Prifysgol Abertawe
Swansea University

Designing Novel Approaches to Personalise Behaviour Change in Intelligent Systems

Darren Scott

Department of Computer Science
Swansea University

A thesis submitted in partial fulfilment for the degree of Doctor of Philosophy

December 2023

ABSTRACT

AI personalisation presents a promising source of innovation for improving the quality of behaviour change technologies. Current approaches are limited in their success, and a proposed solution is the inclusion of intelligent tailoring to best align users with their interventions. This thesis presents three key contributions that explore this promise: A classification system and accompanying survey to examine the current research landscape of intelligent personalisation; The Effect-Led Design process which combines high-efficacy, limitless expert design concepts with focused user discussion and refinement to best explore how to implement high efficacy AI that is acceptable to users; and a conceptual framework, the principles of which are tested in real-world situations to examine whether the intelligent algorithms are able to learn human behaviour and whether proposed systems of personalisation encourage motivation in users. The survey paper identified current trends in the contemporary personalised technology space and explored where the scope for innovation sits. Effect-Led Design showed promise in developing significantly different design concepts to those seen in contemporary applications, and both experts and users commented positively on the process. The studies testing the principles of the experimental platform showed the approaches were positively received by users in terms of motivation and engagement. However, initial implementation issues meant that algorithms did not return any significant evidence of learning. Further explorations into the algorithm through simulated studies using real-world data uncovered alterations that enabled learning. These combined outcomes provided a means to better explore the inclusion of AI in the digital intervention space, with a dedicated design process and investigation of the feasibility of a conceptual framework in this domain showing both the current potential of such a system and where future work can push these ideas to provoke effective behaviour change.

DECLARATIONS AND STATEMENTS

Declaration

This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

Signed: [redacted]
Date: 2[redacted]

Statement 1

This thesis is the result of my own investigations, except where otherwise stated. Other sources are acknowledged by footnotes giving explicit references. A bibliography is appended.

Signed[redacted]
Date: 20/12/2023

Statement 2

I hereby give consent for my thesis, if accepted, to be available for electronic sharing.

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Date: 20/12/2023

Statement 3

The University's ethical procedures have been followed and, where appropriate, that ethical approval has been granted.

Signed: [redacted]
Date: 20[redacted]

CONTRIBUTIONS

The work contained within this thesis is also written up in academic papers either published or awaiting publication:

- Chapter 3 - Digital Personalised Health and Behaviour Change: *A Survey of Personalised Digital Health and Behaviour Change Interventions*, targeting TOCHI in 2023/24.
- Chapter 4 - *Effect-Led Design: Flouting Values to Design Effective AI Behaviour Change Applications*, targeting NordiCHI 2024
- Chapter 5.2 - Champions for Health: *Brown M, Hooper N, James P,* ***Scott D****, Bodger O, John A. A Web-Delivered Acceptance and Commitment Therapy Intervention With Email Reminders to Enhance Subjective Well-Being and Encourage Engagement With Lifestyle Behavior Change in Health Care Staff: Randomized Cluster Feasibility Study. JMIR Form Res 2020;4(8):e18586. DOI: 10.2196/18586*
- Chapter 5.7 - Experimental Examination of Intelligent Behaviour Change: *Intelligent Tailoring of Techniques and Parameters to Promote Physical Activity and Increase Motivation in Step Counter Applications*, targeting UMAP 2024

ACKNOWLEDGEMENTS

This thesis document, and all of the work that has contributed to the work and findings within these pages, would not have been possible without a number of individuals invaluable to either the work conducted or my own ability to conduct it.

I owe a great deal of thanks to my lead supervisor, Matt Roach. While we have not always seen eye to eye on experimental details and especially not on the place of images in my work, you have always provided me with great support, and I will miss our weekly meetings of debate and laughter in equal measure. From helping me with my personal struggles, to challenging my work at every turn, to choosing different doors to the office because you knew I would be looking out for you, to engaging general chatter about my love of the NFL through the musings of BBC's Jason and Osi, this thesis and the work contained within would not have been possible without your assistance and guidance throughout.

I am additionally thankful to my secondary supervisors. To Stephen Lindsay for his endless help, frankly unsettling writing ability and cross-cutting ideas to bring about the best balance in my work, and to Gareth Stratton for fanning the initial flames of this project, giving me my first insights into this behavioural world I find so fascinating, and working closely with me in the early stages of this work to allow it to flourish into both what it has become and what it will become in future years. Further thanks to Chat, Gemma and Bertie for your help in reviewing and refining this work into its final form, your input was invaluable to creating this final thesis. I hope that somewhere down the line, wherever our careers and research have progressed, we will be able to collaborate in future.

My thanks also to the Swansea University Postgraduate Research team, in particular Hannah in my early years and Jo and Katherine in the later ones, as well as Andrea and Julie for their help. It has been a pleasure working with you on various matters both as a representative and as a general colleague. Furthermore, my thanks to both the university funding and the ESRC Wales DTP for agreeing to fund this project and for the various matters of lenience and extension I have been granted, they were very much central to the ability to conclude this work and this thesis.

I must thank the multiple students, be they further in their journey or catching up to my years, that have helped me in this process and helped me either learn the new process of work or supported my attempts to wrap up my own work process. Specifically, I must give thanks to Menna for letting me be a part of her work in my early time and in turn providing me with my first named publication of work, and to Peter for his immeasurable help with building my work platform and helping to finally get my work off the ground at a time when it was truly stuck. It feels only right that the two mentioned here bookend my PhD journey, and while these two deserve special thanks, there were many more between these that contributed and helped, and I am grateful to you all.

To my friends and fellow colleagues in and around the Computational Foundry, you have made this process fun and interesting at every turn, be it our hours spent together demonstrating on whatever modules would have us, or chatting about this, that and whatever instead of doing the work piling up for us. From my mish-mash collection of desk parts and inherited plants in Faraday, to the whole wall window overlook in the Foundry, to coffee mornings and reading groups from my own home, you have all added character and colour to this process that has enhanced these past few years immeasurably.

I am immeasurably thankful to my many friends outside of my work life, for helping my hobbies and interests stay alive despite the ever piling pressure of work. Be it a joke-laden chat, a quick lunch out, a few games into the evening or a weekend meet up for whatever we decide to do with our time, it has helped keep the stresses of this process in perspective. For all the pressure this PhD process has brought about, the friends around me have helped keep this weight manageable, and it's been interesting seeing your lives grow as mine has chugged along. These friends have found love, explored new career paths, gotten engaged and even gotten married during the course of my time completing this thesis, and I hope that all these friends will continue to be an integral part of my life as much as they have allowed me to be a part of theirs.

To my family, and in particular my loving Grandmother, I thank you for your support despite the *very* minimal knowledge you hold of what exactly it is I do. From the early days of trying to nail down exactly what it is I'm doing, to how long it will take, to how long exactly I have left (I promise it's pretty much over now, no more university courses for me please), you have never wavered in your belief of me and your support that I will finish and flourish following the completion of this thesis. And to my Mother and Father, who have been gone far too long, I thank you for allowing me to grow and be whatever I wanted to be, and I hope that I have made you proud.

To my partner Lauren, my love. Despite me forever claiming I cannot finish this work, and that I'll fail, and that I'm not capable of writing a thesis, you always trusted I'd see it through and you never stopped helping me realise that. We have seen each other through periods of mass uncertainty, and through the darkest points of each of our lives, and as we both progress to places of greater responsibility and hardship, I hope we will continue to support each other for years to come.

And lastly, my thanks to Ollie, who's pretty cool.

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CHAPTER 1

INTRODUCTION

This research aims to provoke designs for artificial-intelligence-enabled personalised digital health and behaviour interventions that are grounded in scientific evidence and based on established behavioural change techniques. In this thesis, we use 'personalised' to mean a system or elements of a system which are customised based on user characteristics. This characteristic may not be completely unique to the user (such as age or medical condition), but the needs of the user are still personal and as such are what the system addresses.

The hope is that these designs will have the ability to promote greater levels of behaviour change, keeping users engaged throughout their process of changing behaviour. This work explores the use of reinforcement learning to tailor interventions, moving beyond altering elements of single behaviour change techniques to intelligently selecting active motivational ingredients based on user response. The outcomes of these experiments also provide some insight into how machine learning algorithms must be aligned with users and behaviour change techniques to optimise algorithmic learning and effectively adapt intervention content. The impact of these designs is also analysed in two contexts: the impact on the specific design 'space' of digital health and behaviour interventions, and the impact on the overall research 'landscape' of interventions and behaviour change. The research within this thesis focuses solely on the use of these technologies to address physical inactivity and sedentary behaviour and does not endeavour to explore their impact on mental well-being or other areas of the health and behaviour space.

As the world embraces digital revolution in ever-changing forms, the 'typical lifestyle' becomes increasingly sedentary. An individual can now have everything from basic groceries to luxury cars delivered to their doorstep, and the widespread adoption of social media and video consulting software means that human interaction can be a remote, digital action. With such services pushed further into the public eye by events such as the COVID-19 pandemic, this sedentary lifestyle can create a problematic outlook for the health of those entrenched within it.

With individuals becoming ever more sedentary, can the same digital world that promotes this lifestyle take steps to mitigate its effects? Digital platforms possess the power to alleviate negative behaviours and encourage healthy lifestyle choices. This idea is not new: In 2019, the global fitness application market was valued at an estimated \$3.15 million [291] and was estimated to grow each year.

However, so far this interest has not translated into effective design - optimised, sustained behaviour change is often challenged by *"low usage, high attrition and small effect sizes"* [262]. Additionally, the number of people using these applications is not increasing either, tracking fitness application usage over six months in 2016 found little to no growth across even the most popular applications, and observed that *"fitness tracking apps are generally losing users just as fast as they can add them"* [339]. There is a clear and necessary need to address the design of contemporary digital interventions such that the desired impact can be delivered.

1.1 Research Questions & Aims

One way to address the ineffectiveness of digital health systems is the inclusion of artificial intelligence (AI) or machine learning (ML) to bolster or outright replace existing methods. The rapid advancement of AI has led to confidence in their ability to improve many facets of health and wellbeing, such as service delivery of health care and patient outcomes [61]. Despite these significant advancements, especially in secondary care settings, the implementation of AI in behaviour change contexts such as within wearable personal activity trackers is only recently emerging, and the outcomes of such systems are not clear. There are several challenges surrounding the design and development of artificial intelligence and health technology which must be addressed to allow these technologies to enhance behaviour effectively.

The core, overarching research question of this thesis is as follows:

How can AI be designed and utilised in the personalised physical activity intervention landscape, and what alternative approaches to designing such systems best harness the potential of intelligent algorithms?

In an endeavour to resolve this central research question, the thesis breaks the question down into three smaller sub-questions, or *SQ*s, each of which establishes a core pillar of the eventual answer:

1. *SQ1*: What AI implementations exist currently in the landscape of health and behaviour change, and where exists scope for AI innovation?
2. *SQ2*: How can current intervention approaches be redesigned to best harness the potential for innovation afforded by machine learning?
3. *SQ3*: Do these intelligent interventions have a significant impact on those using them compared to standard approaches?

The first of these questions, *SQ1*, is addressed in Chapter 3, exploring the overall space of personalised interventions for influencing health and behaviour change. By establishing a method for exploring what approaches these systems take and what approaches may not be as adequately explored, we can find where potential gaps exist and whether approaches possibly utilising AI and similar intelligent algorithms may help to more effectively drive positive behaviours. The second and third questions presented here have been revised and expanded upon based on the findings of Chapter 3 and the development of the overall research methodology. These refined research questions, or *RQ*s, are as follows:

1. *RQ1*: Will the approach of pre-design in the focus space of behaviour change theory result in more effective technique designs, and will these present patterns in desired techniques and approaches to using these techniques that work within the scope of the system?

2. *RQ2*: Can a machine learning algorithm function on a mobile device in real-world situations and learn user patterns?

3. *RQ3*: Will the two experimental approaches - technique and parameter switching - influence motivation and engagement?

RQ1 is a refinement of *SQ2*, which is more closely linked to the work presented in Chapter 4 on the design process of **Effect-Led Design**. As such, *RQ1* is answered in Chapter 4 by the research studies into the **Effect-Led Design** process and how both designers and users responded to the process and its resulting designs. *RQ2* and *RQ3* both expand upon *SQ3*, focusing on the two main elements of the experimental system described in Chapter 5 - *RQ2* focuses on the quantitative outcomes in terms of how effectively the on-board AI algorithm works and to what extent it is able to learn user behaviour and drive improvement, while *RQ3* focuses on the qualitative elements of how the system engages with user motivation and interest in the system and its approaches to encouraging behaviour change. Both *RQ2* and *RQ3* and answered through the main experimental study as described in Chapter 5.

1.2 Thesis Methodology

The thesis ahead endeavours to answer both the initial sub-questions and further research questions by exploring the space of intelligent behaviour change systems and developing new approaches to both the design and implementation of intelligent algorithms in such systems.

Chapter 3 answers *SQ1* through a survey of the research landscape, exploring existing literature through the lens of a novel classification typology developed as part of this research. The literature in the space is examined and placed into multiple classification dimensions, and these dimensions are then used to compare the literature within the space to find where potential dimensions may be underutilised. This classification typology also includes dimensions relating to the outcomes of systems both in terms of absolute efficacy (change in behaviour) and user experience (motivation, engagement, etc.), which can be cross-referenced against the approaches to personalisation to find any emerging trends correlating approaches to personalisation with positive efficacy and experience.

Chapter 4 resolves *SQ2* and by extension *RQ1* through the development and subsequent testing of a novel design process structured around a focus on theory linked to high-efficacy outcomes. This focus on theory, as well as the encouragement of extreme approaches to behaviour and inclusion of intelligent algorithms where possible, serves to answer these questions by removing possible blockers to finding whether this new approach is able to best harness the potential for innovation and produce more effective technique designs. The core design method of **Effect-Led Design** is defined following an exploratory design workshop which utilises the core philosophies of theory-driven design and inclusion of extreme methods and intelligent approaches as additive elements to a more generalised participatory design approach. The development of the design process, which posits itself as an inversion of typical participatory design by using user feedback to guide systems which strive for outcomes, is evaluated by designing systems using both the new process and an existing process using the typical approach in Value Sensitive Design.

Chapter 5 resolves *SQ3* and the two refined follow-up questions in *RQ2* and *RQ3* by developing a system which utilises intelligent algorithms to drive behaviour change, and examining it regarding both the performance of the algorithm and the explicit change in activity within each user, as well as user feedback regarding their engagement and motivation resulting from the actions of such algorithms. The testing of the intelligent actions of the system is split into two separate experimental conditions; a set of techniques to test the selection of individual approaches based on user response, and a single technique with a set of parameters to test the tuning of behaviour change strategies to the needs of a given user. In the true realisation of the conceptual blueprint, these features would be implemented alongside each other and work in tandem, but for the purposes of the experimental platform, keeping these separate allows us to ascertain whether each condition is individually effective and whether one of the two approaches to adaptive intervention content is more effective in encouraging increased motivation and behavioural outcomes. These are tested over multiple weeks with continuous data capture to ensure outcomes reflect real-life use rather than single isolated data capture sessions which could impact the ability to align outcomes with the performance of the system in a day-to-day context.

1.3 Key Contributions

The work contained in Chapters 3, 4 and 5 forms the key contributions of this thesis and answers the research questions presented in Section 1.1:

What AI implementations exist currently in the landscape of health and behaviour change, and where exists scope for AI innovation?: This thesis presents three contributions from this question: a personalisation typology positioned within a wider classification structure for digital personalised health and behaviour change systems; the identification and discussion of gaps within the research landscape that may drive greater behaviour change outcomes if explored; and a conceptual blueprint to challenge the current perception of personalised digital intervention design. As personalised and digital interventions both increase in prominence, this typology allows for personalisation to be broken down into its mechanical components and allows these personalised systems to be compared and contrasted to find future gaps for innovation. The conceptual blueprint encourages the inclusion of AI and urges designers to focus on all forms of personalisation in future designs, challenging them to push the design space further and uncover effective solutions for health and behaviour change.

How can current intervention approaches be redesigned to best harness the potential for innovation afforded by machine learning?: This work presents the methodological contribution of **Effect-Led Design**, a three-phase process for developing intervention concepts that effectively consider both high-efficacy approaches and the core values of users. This process encourages both sides to drive the elements that are key to them - Designers are encouraged to explore designs with the best chance of promoting behaviour, while users are encouraged to identify and reclaim their core values within these high-efficacy designs. The current space of intervention design is often constrained by either users or designers overstepping the lines: Designers may limit their systems to respect what they believe to be user values, and users may overestimate their own values if they hold concerns about the intervention approach. These limitations are especially pronounced where AI is involved, and **Effect-Led Design** allows for these limitations to be discussed openly, letting both sides see the true limitations required which may leave solutions more chance to operate effectively. The studies on **Effect-Led Design** found that the process generated significantly different results, designers expressed surprise at what users accepted in the pursuit of better behaviour change, and the process was seen to reflect its key tenets in a validation study against another participatory design method. Both the method of **Effect-Led Design**, as well as the findings of these initial design studies, are treated as key contributions of the thesis.

Do these intelligent interventions have a significant impact on those using them compared to standard approaches?: This thesis presents an empirical study to investigate the core principles of the experimental platform, itself a single instance of the conceptual blueprint presented to guide intervention thinking. The study presented qualitative evidence of positive outcomes on motivation and engagement resulting from the technique and parameter switching systems. This work also outlines how intelligent algorithms struggle to learn effectively in messy real-world environments. Further simulated studies on real-world data show that redesigning the learning objective and reward structure of the AI to combine physical (active behaviour) and mental (explicit motivation) demonstrates that in this instance, the AI is capable of learning despite the real-world noise by including both data types in the process of learning.

Advances in personal technology mean that personal interventions now have the potential for more complex approaches, which are demonstrated by the conceptual blueprint and accompanying experimental platform. Identifying how these systems function, both in terms of their physical performance of learning human behaviours and their mental performance of encouraging increased motivation, helps show the potential afforded by these systems and serves to reinforce the concepts outlined in the conceptual blueprint as a legitimate standard of intervention thinking for the wider research community.

1.4 Thesis Outline

This thesis will expand upon the field of intelligent personalisation, and the potential integration of machine learning approaches into the behaviour change land-

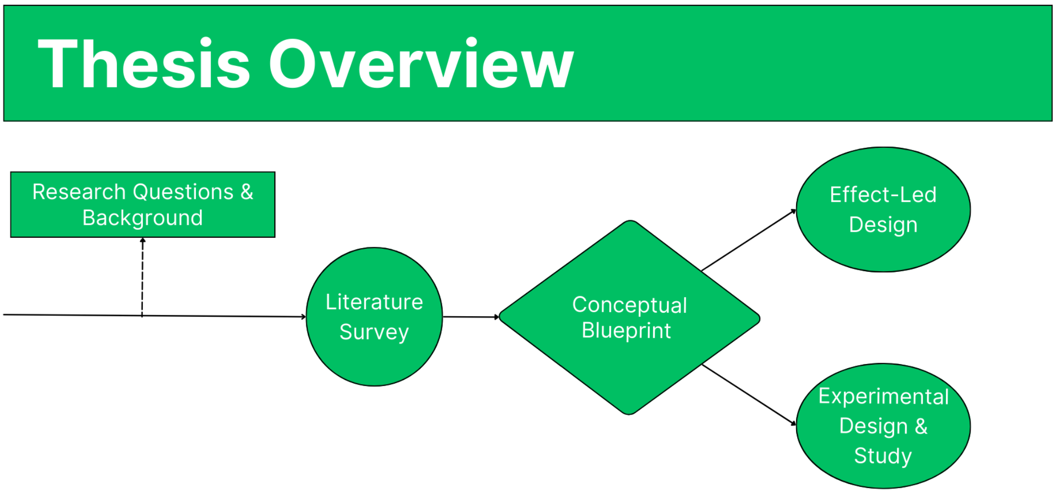


Figure 1: A high-level overview of the thesis chapters and how they relate to each other

scape. This chapter, Chapter 1, has established the core of this thesis - a set of research questions which structure the overall investigation into intelligent physical activity and behaviour change interventions.

Chapter 2 presents the digital intervention space and the issues these interventions aim to resolve. This chapter covers health concerns stemming from physical inactivity and sedentary behaviour, existing digital health systems and how they influence behaviours, as well as why current approaches may prove ineffective. The current uses of AI, mainly in secondary health, will then be examined along with the many concerns and questions that currently surround the use of AI in a field that interacts directly with people's health and well-being.

Chapter 3 conducts an in-depth survey, examining a wide range of digital personalised health and behaviour interventions. This examination is conducted through the lens of a typology developed to better analyse personalised interventions. This typology is used to explore the landscape, finding where gaps with the greatest potential for innovation sit. Current ideas around intelligent personalisation are discussed following the survey outcomes. This chapter finishes with a conceptual blueprint built upon key components established at the beginning of the chapter, which stands as a lens through which to view and challenge the field of personalised intervention design.

At this point, as illustrated in Figure 1, the thesis splits its investigations into two isolated arms. This is a potential source of confusion, as the conceptual blueprint and experimental platform diagrams which will be presented in Chapters 3 and 5 suggest both research arms are part of the same continuous workflow. This difference is due to these two elements - the investigative thesis and the structured conceptual blueprint - representing different stages in designing within this space. We position the conceptual blueprint as a suggestion for how the systems being explored should be approached and designed going forward from this thesis, but before we can make that claim in earnest, it is necessary to explore whether these elements are beneficial in their own right. The work presented in Chapter 4 covers an innovative approach to design that would theoretically form a key element of the conceptual blueprint going forward by ensuring future platforms utilising intelligent approaches are built with theory and effect at their forefront, but to position it as only a supportive element within the thesis risks undermining its potential importance and impact in isolation as an approach to design. Additionally, the work in Chapter 4 was not considered at the time to be supportive to the work in Chapter 5, so presenting it as such would risk confusion as to why elements from the design process do not translate to the eventual design. As such, while future implementations would utilise the work seen in Chapter 4 to enhance the eventual system design, an example of which is seen in Chapter 5, the thesis treats them as separate elements to allow for the research into each to be presented independently.

Chapter 4 presents Effect-Led Design, an innovative design process that uses participatory design to meld outcome-driven AI algorithms with acceptable behaviour change methods. The process is tested through two experiments: a design study on the theoretical idea of efficacy-driven AI system design that forms the basis for Effect-Led Design, and a validation study against Value Sensitive Design.

Chapter 5 covers the development of the behaviour change implementations and AI algorithm. This chapter describes the two approaches of Parameter Switching and Technique Switching to tailor intervention content and discusses selected techniques and their implementations. The AI algorithm is also outlined, both in its operation and its connection to the wider system. Four experimental conditions are then established, and compared across several weeks. These systems are examined in terms of their impact on step counts, the performance of their machine-learning algorithms, and qualitative responses surrounding motivation and overall interest in the system. Chapter 6 follows this by exploring potential changes to the machine learning algorithm to drive better learning outcomes.

Chapter 7 considers the outcomes of Effect-Led Design and the intervention experiments in relation to the experimental platform and conceptual blueprint. The questions established here in Chapter1 are examined. This chapter then expands upon the impact of this work on the research landscape of digital personalised health and behaviour systems. Finally, this chapter explores where future work should progress.

1.5 Chapter Summary

In this chapter, the general outline of the thesis has been discussed: The overall research questions and aims of the research described; the methodology through which the thesis will address these questions and aims; the key contributions that will be discussed in chapters 3, 4 and 5; and a general outline of the thesis. The following chapter, Chapter 2, will outline literature that is necessary to understand the work ahead, with a focus on physical activity research, behaviour change methods with a focus on motivation, current digital approaches to improving behaviour, and the current applications of AI in this space and related spaces.

CHAPTER 2

BACKGROUND - HEALTH, DIGITAL INTERVENTIONS & AI

2.1 Active & Sedentary Behaviours

Human genetics, shaped over 40,000 years ago, are tailored for movement - our ancestors would routinely travel up to 20 kilometres a day [352]. In contrast, modern sedentary lifestyles have led to a sharp decrease in physical activity in our professional and personal lives. Globally, 25% of adults do not meet recommended physical activity targets [393] and the problem is not limited to adults - 81% of 11- to 17-year-old's do not meet physical activity guidelines [141]. The cause for this sedentary crisis is, in part, employment changes. In the United States of America, the number of people in sedentary professions grew by 20% between 1960 and 2008 [65] and working adults in France now spend 10 hours per day seated [316]. The COVID-19 pandemic severely impacted activity levels, with a decrease of self-reported physical activity by 41% for moderate-to-vigorous physical activity, and 42.2% for vigorous physical activity [383].

Examining the landscape of physical activity and sedentary behaviour is essential to determine how to best combat negative behaviours. Behaviours like inactivity and sedentary behaviours have seen past response of guidelines and interventions, which have seen numerous updates and variations as new understanding emerges. The terminology that will be used around physical activity and sedentary behaviour is presented in Table 2.1. By examining the current definitions and guidelines on these behaviours, as well as the health risks they may influence, we can better understand the need to combat these behaviours, and identify whether there are specific denominations of behaviour that need to be focused upon.

2.1.1 Physical Activity & Sedentary Behaviour Definitions

Physical activity is any movement produced by muscles that requires energy expenditure [393]. This energy expenditure is measured in 'metabolic equivalent task' units (METs). METs are the measure of the amount of oxygen used by

Physical activity	Any movement produced by muscles that requires energy expenditure
Physical inactivity	A situation where an individual is not meeting the recommended guidelines for physical activity
Metabolic Equivalent of Task	A measure of energy expenditure in activity, specifically the amount of oxygen used by the body at rest
LPA	Light-intensity physical activity (1.5 to 3 METs)
MPA	Moderate-intensity physical activity (3 to 6 METs)
VPA	Vigorous physical activity (>6 METs)
MVPA	Moderate-to-vigorous physical activity, the type of activity commonly used in health guidelines
Sedentary Behaviour	Periods of time expending less than 1.5 METs
Stationary Behaviour	A behaviour that, while close to sedentary in nature, falls within the boundaries of light-intensity physical activity

Table 2.1: Definitions for Physical Activity and Sedentary Behaviour

the body at rest, providing a practical measure for the energy expenditure of activities as a quantity of 'resting metabolic rates' [179]. METs can be used to divide physical activity with light, moderate and vigorous physical activity denominations for different actions. All levels of activity still expend energy, but there are questions of whether all METs are equal in terms of the associated activity [165]. Most recommendations use moderate-to-vigorous physical activity (MVPA) in their guidelines.

Sedentary behaviour is classified as long periods without moving, specifically expending less than 1.5 METs, such as sitting or lying down [355]. Lifestyles can be both physically active and highly sedentary [78] - someone who spends three hours each day walking and 10 hours each day sitting in front of a workstation or TV would be both highly physically active and sedentary. Some behaviours require additional distinctions, such as separating sedentary behaviours and 'stationary behaviours' like standing, which possess a low energy expenditure but do not fall within the bounds of sedentary actions. Sedentary behaviours are further divided into passive and active sedentary behaviours, separating watching TV (passive) from computer use or reading (active), which may impact mental health differently [147]. The level of granularity in these terms can create difficulties in establishing guidelines, as these may have to account for multiple behaviours equally. Experts may have to recommend adjusted guidelines such as increasing from moderate to vigorous activity for the advised times to counteract high sedentary time [43].

2.1.2 Health Risks of Physical Inactivity & Sedentary Behaviour

Despite an incomplete knowledge of all dangers [54], there are known health risks associated with both physical inactivity and sedentary behaviour. Reducing physical inactivity by 10% could avoid over 533,000 deaths each year [214]. These risks cover both physical and mental ailments.

Many prevalent chronic diseases and health conditions are negatively associated with inactivity [92]. There are clear links between physical inactivity and conditions such as coronary heart disease, type-II diabetes and cancer, as well as a general 'risk of death' [214]. There are also many psychological complications associated with inactivity [389], with Tremblay *et al.* finding connections between physical inactivity and depression [356]. Depression and inactivity were also notably linked for some during the COVID-19 lockdown - Silva *et al.* found those who were regularly inactive during lockdown presented higher levels of anxiety, depression and overall stress [327].

Sedentary behaviours have emerged as a significant health risk in recent years - King compared the risks of sedentary behaviour to regular tobacco smoking, for which the risks are well known [193]. Sedentary behaviour has been linked to cancer [81, 404], cardiovascular disease [233] and overall risk of death [97]. There have also been links between sedentary time, anxiety [10, 350] and depression [147, 169], with stronger associations seen with passive sedentary behaviours [10, 147, 169, 350]. Sedentary time is connected to negative mood [101], with this connection even present when sedentary time is artificially increased [102].

There were specific notable improvements in cancer-related biomarkers when individuals increased their physical activity [142,229], and Paivarinne *et al.* identified higher health-related quality of life with high amounts of leisure-time physical activity [276]. In some instances, physical activity is seen to improve health in instances where said health has been affected by sedentary activity - Katzmarzyk *et al.* found that reducing risk of cardiovascular disease requires increasing MVPA, as well as reducing sedentary behaviours [190] and Kandola *et al.* presented a reduction in the odds of depression when sedentary behaviours were replaced with MVPA [185]. While physical activity may only be one small part of a solution to improving mental health, Bell *et al.* suggest that increasing activity may mitigate factors which lead to such problems [30].

These findings illustrate the need to address these problematic behaviours, but also indicate the need for a specific type of intervention. As the most problematic sedentary behaviours are passive and some risks can be at least partially addressed by increasing MVPA, an intervention must be timely and able to address behaviours at the perfect point to provide the individual with the push they need, and perhaps present an activity that may drive them from passive sedentary behaviours (reclining or watching TV) to active behaviours (increasing physical activity).

2.1.3 Physical Activity Benefits & Current Guidelines

Systematic research on the importance of **physical activity** has been visible since the late 1950s. Despite this, guidelines instructing the general public on necessary levels of activity only began to emerge in the late 20$^{\text{th}}$ century [34]. The American College of Sports Medicine (ACSM) released the *Guidelines for Graded Exercise Testing and Exercise Prescription* in 1980 [13], which presented recommendations for frequency, duration and intensity of sessions of aerobic physical activity. The latest edition, released in early 2021 [14], recommends 30 minutes of moderate-intensity aerobic physical activity five days of the week, or 20 minutes of vigorous-intensity aerobic activity three days of the week [14]. National Health Service (NHS) guidelines recommend 150 minutes of moderate-intensity activity or 75 minutes of vigorous-intensity activity per week, with reductions in time seated or lying down to break up long periods of non-movement [271].

Sedentary behaviour is distinct as it focuses on general movement rather than intensity of activity. Both absolute sedentary time and sedentary bouts and breaks are important factors, attention to which can be seen in the NHS guidelines instructing breaking up long periods of non-movement as well as reducing time overall [271]. Sedentary behaviour guidelines are “less available, comprehensive, implemented and effective than PA policies” [199], an issue stemming from the nature of sedentary behaviour itself. Physical activity has moderate and vigorous activity levels with desirable frequencies and timings, but as sedentary behaviour represents the general absence of energy expenditure, time requirements are difficult to quantify. This is exacerbated by the need for longitudinal targets - sedentary behaviour presents most of its issues through extended periods of non-movement - which are harder to set and maintain.

Chaput *et al.* argue that guidelines for sedentary behaviours are overdue and necessary [54]. In contrast, Stamatakis *et al.* present a more cautious outlook, advising advancements in sedentary research to “prevent enthusiastic but premature guideline development" [335]. Quantifiable targets for sedentary behaviour do exist in some countries, as seen through the work of Pogrmilovic [199]. However, only 11% of the examined countries have them, and only 40% of countries present any form of national sedentary guidelines.

The consistent evolution of these guidelines presents a simple message - it is necessary to encourage the reduction of sedentary behaviour and the increase of physical activity to combat the related health effects. The need for these guidelines shows that this is an important health issue and that pushing these behaviours to be changed is a key health concern. The lack of consistent guidelines, and the repeated updating of those that do exist, demonstrates the potential benefit of a system that can alter targets and approaches during use, to maintain relevance and ensure the necessary behaviours and guidelines are promoted.

2.2 Motivation in Behaviour Change

Motivation is typically essential to behaviour change. Guidelines can outline the required levels and intensities of activity, but user commitment and motivation are required to initially engage with these guidelines. User motivation may also represent a true reflection of attitudes towards a behaviour since it is less likely to be impacted by surrounding factors, and as such motivation can function as a key target to try and influence improved behaviours. Users are typically driven by either intrinsic or extrinsic motivation. Intrinsic motivation is internal, performing an action for individual improvement, while extrinsic motivation is external, performing an action to receive a reward or societal approval [31]. For example, school students who work hard primarily to improve their knowledge are intrinsically motivated, while students who work hard primarily to receive better test results and better grades are extrinsically motivated. Teixeira *et al.* show extrinsic motivation predicted short-term uptake and engagement, while intrinsic motivation predicted long-term participation and adherence [348].

Older adults who regularly engaged in recreational and culturally-motivated activity presented higher motivation for physical activity compared to those with a preference for directed exercise and sporting activity. These same adults were also more likely to fulfil physical activity requirements. Greater intrinsic motivation was observed in cultural and recreational individuals, with sport and exercise individuals presenting greater extrinsic motivation [301]. Gender may also be a predictor of where motivation is derived; Zervou *et al.* observed male participants were more likely to hold competition and ego motivations for activity, while female participants more typically held physical appearance motives [401]. This connection is supported by van Uffelen *et al.* who found women were more likely than men to engage in physical activity to lose weight, improve appearance or be social while men were more likely to engage in competitive and high-skill activities [366]. However, physical appearance motives can be partially construed as extrinsic due to a desire to adhere to societal standards of appearance - Zervou further observed that individuals with low self-esteem and high BMI engaged in activity for appearance motives, and high self-esteem individuals engaged for ego motives, regardless of gender [401]. The influence of self-esteem on motivation is further explored by Wilson *et al.*, finding that self-observed competence and autonomy positively correlated with levels of activity and attitudes towards physical fitness. However, it can be suggested that intrinsic motivation and exercise regulation contribute to self-held levels of competence and autonomy, and it was found that high levels of intrinsic motivation effectively predicted overall attitudes towards exercise [387]. This demographic-based variation in motivation, as well as the influence of believed capability, indicates that the impact of some approaches may be heavily limited in ways separate from their specific mechanisms of action. Behaviour change interventions need to be able to address these demographic differences to ensure all groups can benefit from the system.

Collectively, the literature indicates that intrinsic motivations are required to maintain long-term behaviour. However, this does not mean that people with solely extrinsic drivers of motivation are unable to pursue behavioural improvement. Cheval & Boisgontier present the Theory of Effort Minimalisation in Physical Activity (TEMPA) [60] which builds upon the Theory of Energy Cost Minimalisation, the theory that human beings have evolved to reduce unnecessary physical activity wherever possible, and unconsciously aim to minimise the energy expenditure required for certain rewards. This was initially desirable to conserve energy for actions central to survival but has become a mental barrier to activity in the modern day [40]. Brand *et al.* use the theory of Energy Cost Minimisation to call for a focus on small in-the-moment associations between stimuli and action by eliminating small negative associations stemming from habits or adverse attitudes and fostering positive associations that may help support positive behaviours [40]. Lee *et al.* suggest a possible approach to improving these associations is to restructure environments to increase functional physical activity and promote a greater overall perceived purpose of physical activity, creating positive associations to exercise [212].

Digital activity trackers are overall extrinsic systems, as intrinsically motivated individuals would not require the call-and-response nature of a system to maintain their behaviour, instead relying upon their own positive response. This explains the fragility of behaviours that are built upon activity trackers, as the extrinsic source of motivation requires the tracker to be effective in promoting this motivation throughout the process. This also highlights how problematic the low evidence of tracker efficacy is: while intrinsically motivated individuals may be able to maintain their behaviour if a tracker is ineffective, extrinsically-driven individuals are likely to abandon the behaviour altogether without a device supporting their behaviours in the long term. If technology can facilitate the small positive associations as described by the Theory of Energy Cost Minimisation, and reduce the in-the-moment cost of an activity, this could lead to greater positive change and potentially increase the longevity of the device and the behaviour change by establishing a more permanent habit. The comments of Teixiera *et al.* also present an interesting design idea here - If an approach to behaviour that promotes intrinsic behaviour for a user can be found, then this could be used to encourage long-term usage. There is the potential for a system to leverage extrinsic motivation from the device itself to maintain interest long enough for this particular intrinsically motivating approach to be found, at which point this internal motivation could help drive more long-term motivation and engagement.

As Fritz *et al.* suggested, even extrinsically motivated individuals may be able to build enough of a habit to eventually not require the device [119]. Building a habit typically requires an effective solution that provides the exact reward and response required to engage with the behaviour and maintain this engagement. This idea is described in Pinder *et al.'s* Habit Alteration Model. This model explains that habits are formed when conscious efforts become unconscious - the transition from an intentional and structured approach to behaviour to a response that feels natural, and therefore does not require as much intent and mental effort [289]. However, current trackers often introduce a 'fragility' to the behaviour change efforts of users [307]. The potential for extrinsic motivation is there in behaviour change systems, but at this stage, this requires a re-framing of the design of behaviour change applications to better drive habits and ensure interest and motivation are maintained.

Many other behavioural models could be applied to the space of behaviour change interventions. One such model is the Transtheoretical Model, also known as the 'Stages of Change' model. This model, originally defined by Prochaska & DiClemente in 1983, outlines five phases through which an individual progresses during behaviour change [325]. This model is one of the most common lenses through which behaviour change can be discussed, but the model is primarily focused on intrinsic drivers - The progression from contemplation to action to maintenance is a progression of motivation, and is based on the internal stance of the individual. For the research of this thesis, which focuses primarily on the persistent influence of an external system, the Stages of Change model is less effective. There may be some interesting discussions to be had around whether the stage of change has a significant impact on whether an extrinsic system is effective for a given user, but regarding the overall design of these systems, the theory of habit formation which focuses specifically on taking extrinsic influences and using those to establish intrinsic habits over time is a better fit. Another lens through which to view behaviour change is Social Cognitive Theory as initially presented by Bandura in 1986 [24]. Social Cognitive Theory revolves around the concept of 'reciprocal determinism', the dynamic interaction between an individual, their environment, and their behaviour. A core issue with applying Social Cognitive Theory in this context is that this theory does not focus on motivation, instead revolving around the impact of social influence and reinforcement. For the purposes of theorising large-scale sources of motivation, this theory is not particularly well suited. The Habit Formation model [289] was chosen here to focus primarily on individuals who may require an extrinsic motivator to actively change their behaviour. In this space, the Transtheoretical Model is focused too heavily on the intrinsic state of mind and Social Cognitive Theory is structured more around the continued regulation of behaviour. The Habit Formation model, on the other hand, presents exactly what is required for those without the internal drive to improve their behaviour - The use of external influences which over time transition to unconscious, internal influences.

2.3 Behaviour Change Techniques

A concept that may help to drive motivation is that of behaviour change techniques. The initial exploration of Behaviour Change Techniques was driven by inadequate details of the design of behavioural interventions. This made it difficult to examine the nature of techniques or the reasons for their place within the wider intervention [321]. Abraham and Michie, aiming to provide the means to faithfully recreate interventions and to identify techniques that contribute to effectiveness across multiple behaviour change interventions, generated a taxonomy of 26 BCTs which covered numerous approaches to behaviour [2]. Following further investigations, Michie *et al.* developed first the CALO-RE taxonomy which built upon the initial 26 BCTs with a focus on health and physical fitness [252], and subsequently designed the Behaviour Change Technique Taxonomy v1 - a full taxonomy of 93 BCTs across 16 distinct clusters to guide the comprehensive examination and classification of behaviour change interventions in the space [254]. The BCTTv1 provides a detailed guide through which to understand the mechanisms of action of any given intervention, which helps better connect elements of an intervention system with their outcomes. Much as the typology in Chapter 3 provides the means to connect the mechanisms of a personalised system (method, frequency, specificity, data) with the outcomes, the BCTTv1 allows us to better understand behaviour change interventions and to isolate the effective elements of an intervention for optimal future design.

The BCTTv1 provides the means to map conceptual ideas of behavioural influence to mechanisms of action. Barker *et al.* use the BCTTv1 to examine the delivery of hearing aids for use by audiologists, specifically the techniques used to ease the introduction of the device. These findings could then easily be cross-referenced across locations to create a unified effective approach using the best selection of techniques [26]. Scott *et al.* use the BCTTv1 to identify active ingredients of pharmacist interventions to improve the outcomes of patients receiving these interventions. Meta-reviews which push certain BCTs as more effective in intervention contexts were used to identify the potential outcomes of these pharmaceutical interventions [324]. As well as directly coding interventions, research has been conducted examining the need for effective training to examine BCTs in interventions: Wood *et al.* examined the importance of training to 'improve reliable, valid and confident application of BCTTv1 to code BCTs in intervention descriptions'. Training was found to improve the confidence of assessment, and the likelihood of participants agreeing with expert consensus assessment of BCTs, but did not have a significant effect on inter-coder agreement. This indicates training can help understand existing statements on techniques, but does not increase the likelihood of two individuals seeing a piece of work as exhibiting the same BCTs [391].

There have also been attempts to use the BCTTv1 to increase the scope of what can be rated within the taxonomy or to increase the ability to reliably code more specialist intervention content. Presseau *et al.* developed an additional set of coding rules and examples which supplement those provided with the BCTTv1, as they felt the examples contained with the BCTTv1 were not sufficient for making accurate links between content and techniques in more specialist scenarios [295]. Dugdale *et al.* addressed a flaw in the research surrounding the development and use of the BCTTv1, namely the notable gap between the standardised approach of the taxonomy derived from health psychology research and the complex, real-world intervention space of treating substance use disorders. Rather than a straightforward set of connections between the taxonomy and what was observed within the space, researchers developed a full list of clinical techniques within a notable substance abuse system and conducted an exploratory mapping session with the intervention developers to map the BCTTv1 in its base state to the clinical techniques observed within the system. This allowed for the development of more direct examples and highlighted any areas where further considerations were required [95].

The implementation of BCTs is highly varied, and the selection of BCTs within a given system can be decided through numerous means, from explicit relation to theory to techniques being seen as popular or desirable. This will be discussed further in Chapter 4 concerning the rationale of the Effect-Led Design process.

2.4 Digital Health and Human Influences

Digital systems, especially those for actively tracking user behaviours, present a more effective approach to behaviour change than traditional methods due to their ease of implementation, scalability and ability to provide individualised feedback [230]. Many digital health solutions exist, both for physical behaviours and other ailments (which will be covered in more detail in Chapter 3, specifically in Section 3.7.2), but many struggle to directly and effectively influence the behaviours of the individual or to see sustained use [262, 339]. The following section will examine the efficacy of existing digital health systems and how they operate, as well as look at adherence and abandonment of these systems to find where changes could be made to find sustained impact and usage.

2.4.1 Digital Health Systems

Digital health systems are technologies that aim to boost our health and well-being, including smartphone apps and wearable devices [272]. These systems may have several issues to be addressed but are still capable of imparting behaviour change. Xie *et al.* found around 30% of adults reported recently using a wearable device, and the use of these devices was positively associated with higher levels of physical activity [394]. Tang *et al.* in their systematic review found connections between fitness trackers and physical activity levels [345], and Wong *et al.*, found the majority of interventions targeted at obese adults presented moderate to high impact on waist circumference, body mass index and overall physical activity [390]. Laranjo *et al.* further found a trend of positive influence across 28 interventions utilising applications or fitness trackers [204]. These 'minimal contact interventions' - passive interventions without outside communication or influence - present evidence of improving behaviours; Hajna *et al.* found increases in physical activity, energy expenditure and overall fitness from the use of these systems [145]. Coughlin & Stuart found evidence of positive changes in both physical activity and weight within wearable trials, but this evidence lacked the long-term samples required to determine whether this persisted with continued use [75]. Jo *et al.* observed effective facilitation of motivation and increased physical activity, but evidence of other health benefits was unclear [180]. Brickwood *et al.* presented evidence of efficacy for physical activity, step count and energy expenditure in cases where the tracker is either solely used or used as part of a wider intervention. However, no impact on sedentary behaviours was observed and all studies examined presented results and discussion in the short term, making it difficult to ascertain whether these benefits carried over in prolonged cases of use [42]. Monninghoff *et al.* present the potential effectiveness of mHealth systems for improving physical activity in the long term, but argue that these long-term impacts diminish and possibly even cease entirely. A lack of evidence across varied backgrounds and use cases makes it difficult to state these diminishing returns for certain [257].

A possible reason for this lack of significant impact may be a disconnect between the individual and their device. Li *et al.* found a general trend of fitness trackers effectively influencing conscious active behaviours but found that any observed impacts were heavily dependent on the characteristics of the user, although these factors required further investigation to determine their true impact [217]. Cheatham *et al.* found that wearable-enhanced health weight loss programs provided greater impacts in older populations for physical activity and other active behaviours than standard approaches, although younger adults responded far less favourably [58]. Ringeval *et al.* presented similar findings, finding positive impacts on MVPA and steps from the inclusion of Fitbit devices in health interventions, although much like the outcomes observed by Cheatham *et al.*, this was mostly limited to adults and older subjects [309]. This outcome was further supported by the work of Jakicic *et al.*, who found that digital fitness trackers presented no evidence of improved fitness outcomes for young adults when used to supplement an existing weight-loss intervention, and presented further evidence that this addition potentially negatively impacted the outcomes of these interventions [174]. Age is not the only factor observed to affect intervention outcomes; Lugones-Sanchez *et al.* observed intervention groups using fitness trackers saw improvements to body weight, body fat mass, percentage body fat and BMI, but these improvements were significant only for female users with a prior history of physical activity, while male participants saw no significant impacts on their behaviours [226]. Western *et al.* found that those with low socio-economic status show no evidence of efficacy from behavioural interventions regardless of intervention content, while higher socio-economic status individuals found greater chances of positive change [378]. Again, this suggests that certain intervention approaches may be limited to certain demographics and that considerations for these demographics in design, such as different approaches specific to each group, may be required to see a significant impact.

Digital health systems may provide greater benefits by tailoring their content and approach to the individual user. This idea is touched upon by Gasparetti *et al.* who present emerging evidence that the common approach of steady increments of physical fitness levels may not be the optimal approach for all users. Further research into adaptive and personalised strategies may help to uncover more effective approaches [126]. Personalised and adaptive approaches to fitness are further explored by Castro *et al.* looking at the difficulties of connecting lifestyle and behaviour change as 'lifestyle' is an unclear and unrefined target which is difficult to focus upon for a digital tool or set of tools. Castro *et al.* highlight the approach of connecting lifestyle behaviours to health impacts, to better tune systems to problem spaces [49], but more innovative solutions lie beyond this. If personalised and adaptive systems could themselves bridge this gap between the adverse behaviours of a user and the subsequent impact on their health and well-being, these systems could in turn integrate themselves within this unrefined lifestyle space and avoid obsolescence altogether. Digital health interventions present high levels of potential on all levels of prevention [49], but the space of adaption and personalisation presents a clearer means for how this potential can be best realised. There are some emerging examples in the research of adaptive health systems which will be discussed further in Section 3.7.2.

2.4.2 Technology Adherence & Abandonment

There is a school of thought that research on personal health trackers should put less emphasis on the lack of long-term success, and focus instead on the wealth of short-term outcomes. Lazar *et al.* argue that eventual system abandonment should not diminish short-term improvement and that any degree of behavioural influence should classify the system as a success [210] - Quoting Rooksby *et al.*, "to track over the short-term is not necessarily to give up or fail" [311]. Allowing these systems to be abandoned provides new avenues of insight into where the space should move.

However, even if short-term effects are positive, there is a wealth of evidence that the majority of effects wane in the long term. Xie *et al.* lacked evidence to establish a connection to long-term clinical outcomes in adult users of fitness trackers [394], with Tang *et al.* similarly finding no strong evidence linking digital health systems to long-term activity and weight loss [345]. Coughlin & Stuart found evidence of short-term impact evidence lacked the long-term samples required to determine whether this persisted with continued use [75]. Jo *et al.* observed effective facilitation of motivation and increased physical activity, but evidence of the success of other health benefits was unclear [180]. Brickwood *et al.* found all studies of fitness tracker efficacy examined presented results and discussion in the short term, making it difficult to ascertain whether these benefits carried over in prolonged cases of use [42]. Monninghoff *et al.* present the potential effectiveness of mHealth systems for improving physical activity in the long term, but argue that these long-term impacts diminish and possibly even cease entirely. A lack of evidence across varied backgrounds and use cases makes it difficult to state these diminishing returns for certain [257].

Generally, the goal of a health intervention is to help people change their long-term habits. As outlined above, the Habit Formation model describes how short-term intentional actions eventually transition into long-term unconscious habit responses. This idea is accompanied by an argument that technologies should view abandonment not as a failing of the device, but rather as a logical end point of use as tracked behaviours transition into lived habits. Fritz *et al.* question whether activity trackers should be viewed as tools to support effective positive behaviours over time, or as temporary aides to be abandoned once habits are formed [119], a view which reflects the ideas of the Habit Alteration Model as described by Pinder *et al.* [289]. Research consensus indicates that while the formation of habits is the ideal end goal, these systems may not be effective at promoting these habits. The most common reason for abandonment of fitness trackers was loss of motivation to track behaviours. Loss of motivation was strongly linked to permanent abandonment of trackers and linked behaviours, as opposed to temporary abandonment resulting from aesthetic or privacy issues [20]. Guilt when the tracker was not adhered to also increased abandonment [44]. Stawarz *et al.* found detailed tracking of behaviours does not promote the formation of habits but rather creates problematic connections between behaviours and specific features of the application that drive these behaviours [336]. These connections may indicate that the lack of habit formation may be an intended feature, keeping people using the system as opposed to abandoning it once the behaviour is established. As described by Stawarz *et al.*: "In their current form, habit formation apps do not support habit formation" [336].

The usage of digital health systems is a question of adherence and abandonment. Hawley-Hague *et al.* found four metrics for adherence across 37 different papers: retention, attendance, duration of exercises and intensity of exercises [154]. Within this thesis, the definition of adherence as retention will be used, as this allows for a direct link between reduced adherence and eventual system abandonment. Different definitions of adherence can also create difficulties in synthesising research, as different measures can return varied findings of success. Tang *et al.* examined step data using different measures of what would be deemed as the system being adhered to for each day. Changing adherence measures had a significant effect both on the level of adherence and the magnitude of behaviour change during these periods of adherence. This also affects study outcomes elsewhere as the definition of adherence further defines valid data for analysis, which can heavily alter the strength of conclusions [344]. Xu *et al.'s* work on successful adherence listed rewards and fostering system engagement as positive measures to increase adherence and retention, but the definition of 'retained user' was vague and the system itself required no behaviours that would contribute to abandonment [395].

Henriksen *et al.* point to the key benefits of digital systems being increased user knowledge on the connections between behaviours and positive outcomes, accurate tracking of behaviours and promoting conscious acknowledgement of daily activities. This research reported high adherence but acknowledged these numbers may be inflated due to users actively maintaining interest as part of a study rather than unconsciously integrating the system into their routine [158]. These benefits, as well as others, may influence the ability of digital health systems to retain user interest and promote adherence. This conscious acknowledgement of activity is supported by Burford *et al.* reporting the added 'sense of achievement' as a positive factor for users of wearable trackers [44]. Lazar *et al.* echo the benefits of quantifying behaviours, while further presenting system novelty as a factor for greater user engagement and use [210]. Li *et al.* and Hermsen *et al.*

mirror findings that long-term system success is heavily dependent on the user; Li *et al.* found personal and psycho-social factors as key contributors to long-term engagement [220], and Hermsen *et al.* listed factors such as age, household background and self-held goals as influential factors for adherence [161]. Further research on what users require from an activity tracking system may be a missing piece in this space. Shin *et al.* theorize that exploring the "more existential interrelationship between people and their information needs" may help these systems to better serve user needs and increase adherence [326].

Prolonged usage of fitness devices is a complex interaction, with numerous factors contributing to loss of engagement. Design and aesthetics were a major cause of reduced engagement, as observed by Attig & Thomas [20], Burford *et al.* [44], and Henriksen *et al.* [158]. Burford *et al.* and Attig & Thomas further shared the observation of data accuracy and privacy as concerns for both users and non-users [20, 44], which may affect the desire for users to engage with the system. Lazar *et al.* further outline the difficulty of integrating intervention systems into a daily routine as a driver of abandonment [210].

2.4.3 Personalisation in Behaviour Change

The use of personalisation in behaviour change is becoming more widespread and may provide more positive outcomes from behaviour change systems. Personalisation in many contexts has already been seen as highly effective - Early research on advertising personalisation found double the rate of click-throughs to products, and while the majority of content may attract individuals early on, only personalised items continue to attract the attention of potential customers [292]. Mobile health interventions have seen limited effects from 'one-size-fits-all' interventions [354], and their ubiquitous nature places the mobile platform as an attractive means for facilitating large-scale positive behaviour change [176]. Tong *et al.* further found that personalised mobile health interventions presented a moderate positive effect on lifestyle behaviour outcomes, mostly through the personalisation of intervention content with other forms of personalisation rarely identified [354]. Celis-Morales *et al.* further show the positive impact of personalised nutritional recommendations based on individual lifestyle [51].

There are some considerations required in this space to ensure beneficial behaviours. Tong *et al.* found that despite both system-reported behaviours and user-reported behaviours being prominent in the space, there was a clear benefit to interventions using system-captured data [354]. Regarding the specific personalised content, Jankovic *et al.* found an interesting divide between perceived and actual persuasiveness in the context of personalised messages to encourage behaviour change. Some participants displayed instances where messages would be marked as highly persuasive, but this would not translate to actual action [176] - This 'nuanced relationship between the personalisation and persuasiveness' could require a focus on surrounding context to identify where persuasive elements are not able to be acted upon.

Further to this, Alslaity *et al.* in their panoramic view of personalisation found that while designers in the space have displayed increased attention to personalising persuasive interventions as time has progressed, there are still several areas where further progress is required. This work presents some recommendations, such as “integrating a combination of personalisation techniques... to increase effectiveness for motivating behaviour change" and highlighting the importance of designing interventions that “continuously monitor the user so that the system is kept up-to-date about the user's habits and motivation" [12].

Personalisation presents a means to help increase the applicability and potential efficacy of digital health systems. However, even personalised content may fall victim to the abandonment that these systems often see. Lazar *et al.*'s focus on novelty [210] and the comments of Shin *et al.* around more effectively aligning user and intervention [326] seem to suggest that there is a need for personalisation to change over time. The ability to adjust personalisation to maintain the alignment of user and system may be the key to increasing engagement and adherence, but continuously updating the personalised aspects of a system works in direct opposition to the promise of reduced direct interaction. Artificial intelligence (AI) and machine learning (ML) present a possible solution here, allowing for these updates to be automatic and therefore allow for updates to persist long past direct interaction with healthcare professionals.

2.4.4 Personal Informatics

‘Personal Informatics’ is an area where the combination of behavioural systems and AI is emerging. Personal Informatics systems are defined as systems which "help people collect personally relevant information for the purpose of self-reflection and gaining self-knowledge" [218]. Personal Informatics systems, and particularly the self-tracking of information, can help to personalise interventions predicated on self-management, but being able to take advantage of this collected data is an additional skill unto itself. Pure self-reflection on behaviours is often flawed [218], and while personal informatics systems assist in collating and storing behavioural data, reflecting on this data requires additional motivation and literacy [121].

There are a number of issues with current personal informatics implementations. A major issue is that there are often high levels of burnout and eventual disengagement that simply come from the need to track information and the resulting outcomes of this tracking. Users inexperienced in collecting and utilising self-tracking data can find the process “burdensome with no beneficial reward", especially once the initial curiosity around “playing with the data" subsides [303]. Some users reported losing interest in manually tracking data and potentially felt discomfort with what the data revealed and how it was used within the context of the application [103]. A potential solution to this is to approach interventions as multi-faceted systems, with the potential for flexibility in how data is collected and presented [218]. There is also the need to maintain interest in what the system is presenting - To quote one user from the work of Rapp & Cena, “It was interesting for the first times, but what else is there?... after a few days it became boring reporting my information every day... seeing more or less always the same things, the same graphs, that's not much" [303]. It is suggested that designs need to sustain motivation by leveraging both extrinsic and intrinsic motivations, echoing the transitional ideas of the Habit Formation Model [289]. Epstein *et al.* further suggest focus on allowing users to return to the system at a later point, exploring how to “appropriately facilitate re-engagement and how designs can support a more successful experience in returning" [103], but this may not be a necessary element of system design - In line with the comments of Rooksby *et al.* in Section 2.4.2, to only track in the short-term is not to fail, and as presented by Epstein *et al.* themselves, many users cease using the system because the behaviour is learned, again reflecting the ideas of the Habit Formation Model in that the habit is formed and the once-central system is now surplus to requirement.

AI and ML are being approached as potential solutions to some of these issues. Mitchell *et al.* utilise ML to resolve the need for more interactivity and feedback in personal informatics systems by generating goals based on individual health data. The inclusion of ML is further supported as greater support for user action can also support, augment and inform the eventual reflection on the collected data [121]. Mamykina *et al.* further praise the potential of ML and AI in personal informatics systems as a means to reduce the cognitive burden of engaging with personal informatics systems [235]. This would serve to resolve the concerns of Rapp & Cena [303] as well as those of Epstein *et al.* by reducing the potential for burden and burnout, simplifying the process of collecting and processing data and allowing the user to engage to a greater extent with the insights obtained from this collated data. There are even some emerging ideas in the personal informatics space that could be better implemented through the inclusion of ML and AI. In the work of Karanam *et al.*, motivational affordances and personality types are found to be strongly correlated, suggesting tuning intervention content to the personality and tracked behaviours of the user may provide a path to more positive outcomes. For example, those tracking ‘Anxiety’ found a stronger benefit from ‘Feedback’, and those tracking ‘Health/Fitness’ found ‘Challenges’ to be most positive. They believe that “Applications designed to accommodate multiple experience tracks for different personality traits could contribute to the sustained use of the application and enable users to better meet their personal goals" [188]. The use of ML and AI could strengthen such an approach, either by allowing the active aligning of these elements based on currently-present user factors, or enhancing the ability to determine these personality traits in use rather than forcing the user to present behaviours up front which could fluctuate throughout use.

Mamykina *et al.* present what they call “Grand Challenges" for the inclusion of AI within the space of Personal Informatics [235]. While some of these are widely applicable to the space of AI implementation, two of these challenges are particularly interesting to the space we are investigating:

1. “Limitations of self-tracking data in AI models" - A potential use of AI in this space is to ease the burden of collecting behavioural data on the user, but this relies on the ability of the model to accurately and effectively track this data. Two ideas presented by Mamykina *et al.* are interesting to highlight here - Difficulties with passive tracking of behaviour that may result in noisy datasets, and the suggestion of triangulating between passively and actively captured data to get closer to what is deemed ‘correct’ by the user and their circumstance.

2. “Personalisation" - The key application of AI in this space is to personalise intervention content, as supported by the presented use case of Mitchell *et al.* [121]. However, Mamykina *et al.* suggest that the nature of personalisation is crucial and that some personalisations may weaken the impact of the intervention. The key questions here are what opportunities exist for

personalisation such as timing, form and tone of intervention content and, in the specific context of 'human-in-the-loop' systems, what different user actions could enhance the functioning of the algorithms contained within these systems?

Many of the ideas and questions presented within these two "grand challenges' will be explored in Chapter 5 within the experimental implementation, and as such these challenges serve as an interesting current overview of the emerging space which this thesis aims to explore.

2.5 AI in Health

2.5.1 AI in Healthcare

One of the key application areas of AI is in secondary healthcare, with great optimism that AI could substantially improve all areas of healthcare [37]. This prominence in healthcare aligns well with the health focus of physical inactivity and sedentary behaviour where this research places its focus. One of the key areas for AI in secondary healthcare is the use of ML approaches, most frequently deep learning (DL), in the detection and analysis of cancers. Deep learning systems consist of numerous layers to effectively learn from data and allow for independent analysis compared to typical neural networks which act to support decision making. This approach provides a model that can detect issues without the need for human intervention [171]. Rodriguez-Ruiz *et al.* found that compared to the average of a sample of 101 radiologists, the performance of a deep-learning AI system outperformed 61% of the sample in the detection of cancer from patient data [310]. Makalesi *et al.* found that as well as effectively detecting cancerous cells for early detection and treatment, deep learning approaches could accurately distinguish between cancerous and non-cancerous cells, allowing these systems to act independently [234]. This ability for autonomy is further supported by Chan *et al.*, who present deep learning as an exciting breakthrough in the field of patient care and medical analysis, especially in the detection and treatment of cancers. This breakthrough is seen both as a treatment tool and as a means to reduce doctor workloads, although both applications require the effective integration of AI systems into the clinical workflow [52]. The ability of these intelligent systems to work autonomously positions them as promising solutions for behaviour change systems, as these need to be able to operate without human input due to their in-the-moment nature. Their success also illustrates the potential to successfully promote behaviour change where previous digital solutions have failed.

Research into AI in secondary healthcare settings is a continuously evolving field of interest, with the COVID-19 pandemic seeing several intelligent solutions presented regarding both treatment and prevention of the virus. Zhou *et al.* present a Deep Learning approach to the diagnosis of COVID-19 cases, specifically in differentiating between cases of COVID-19 pneumonia and typical influenza pneumonia which may present with identical symptoms. The system developed returned an AUC of 93%, presenting this as a highly effective system to reduce misdiagnosis and in turn, more accurately represent the severity and the spread of COVID-19 [403]. Bhattacharya *et al.* explore the wider applications of

Deep Learning to the COVID-19 pandemic, from direct diagnosis and treatment to the discovery and examination of vaccines and effective drug responses. Past the limits of secondary healthcare, Deep Learning has been used to predict incidences of virus outbreaks and the spread of infections, which demonstrates the many benefits afforded by AI both in the direct treatment of COVID-19 cases and in higher-level response to reduce overall incidence [32]. The ability of AI to predict these behaviours in real-world environments suggests an ability to effectively operate in these settings, which may reflect an ability to effectively process data and determine optimal actions in free-living behaviour change situations.

2.5.2 Questions and Concerns on AI in Healthcare

Despite the evidence of positive AI implementation in the healthcare field, and initial explorations surrounding implementing AI into the Personal Informatics space [1], concerns surrounding AI may limit uptake. These concerns exist both as direct responses to examples of problematic AI implementation and as concerns for what AI could be capable of, especially when in contact with vulnerable populations. It is necessary to consider these concerns to ensure that potential users are willing to engage with future beneficial implementations of AI. These concerns represent key barriers to integrating AI into the behaviour change space, and it is necessary to address them to allow for the best potential outcomes for users.

AI Metrics and Problematic Deployments

A major concern is the tendency of AI algorithms to focus explicitly on efficacy metrics, which could lead to shortcomings in other areas. The 'AI arms race' described by Armstrong *et al.* encourages the repeated under-cutting of safety and ethics to further increase the overall efficacy of the system [19]. This then leads to situations where systems achieve optimal levels of efficacy, but the ethical requirements of users are not considered [191, 308]. Amodei *et al.* highlight how this focus on a single metric rather than the full environment leads to an AI showing indifference to other aspects of that environment, which can lead to failure to fulfil the needs of the users, or even active endangerment depending on the purpose of the system [16]. Even when these user needs are considered, an AI system without complete knowledge of these needs can present unwanted side-effects due to incomplete knowledge of user requirements [318].

Premature and problematic deployments of AI in user-facing contexts have led to growing feelings of scepticism in the space, which could negatively impact the potential efficacy and uptake of future AI deployments regardless of their individual merits [400] leading to increased focus on the design and implementation of fair and ethical AI [247]. This focus could help to create systems that protect the needs of those interacting with the system but may sacrifice some level of efficacy in the process. There may be a requirement for a new approach to design that effectively balances these two schools of thought, such that efficacy is driven as a focus of the system but the system is still able to support and protect the needs and values of the user.

Human Attitudes and Perceptions on AI

Public concerns surrounding AI have become more widespread in recent years, especially surrounding the loss of system control to a potential intelligent agent [110]. These concerns have been exacerbated by popular media portrayals presenting optimistic or pessimistic extremes of AI [351]. Some of these portrayals, such as those in *Terminator* or *2001: A Space Odyssey*, spark fear that the natural progression of AI will lead to all-powerful systems, with over one-fifth of people believing an AI uprising is likely [50]. This translates into difficulties in the design process, as users may actively fight against AI. Co-creation workshops were significantly inhibited by difficulties in understanding intelligent systems [167], and even when these systems were understood, participants were unwilling to provide data to AI systems [164]. These perceptions, however, also impact users' awareness of the positive impacts of AI - in fact, most individuals do not understand the core fundamental benefits of AI systems [282].

Members of the public interviewed by McCradden *et al.* held mixed opinions of the use of AI in healthcare settings. Most individuals admitted to having low levels of AI knowledge and negative perceptions of AI before discussions. These individuals endorsed the use of their data in AI research when there was strong potential public benefit, as long as privacy concerns and commercial motives were addressed. Increased accuracy, as well as the ability to process larger amounts of data, were key benefits observed. Fears of reduced human involvement and resulting loss of skill were mentioned, as well as desires to know exactly how their data would be used by the AI [245]. These opinions held by non-involved individuals varied depending on who was involved in the process of AI implementation and regulation. Some viewed AI as a helpful tool to reduce the workload of medical professionals, letting physicians 'do what they were trained for'. Certain individuals even felt that AI tools were a necessary progression of healthcare as long as explainable AI tools were utilised to ensure doctors were effectively engaged rather than sidelined from treatment. Contrasting views were held regarding the involvement of private companies with the deployment of AI in healthcare: Some felt that a focus on company profits could lead to harm to patients similar to the over-aggressive pursuit of efficacy by AI algorithms, while others felt these concerns were unwarranted given the existence of ethical frameworks intended to prevent this [241].

These perceptions of AI are also visible in the healthcare field, making it difficult to introduce highly beneficial AI systems to an existing workflow. Opinions towards AI in this field also vary based on the stakeholder in question. Lai *et al.* examined the opinions of these groups, finding that while health researchers who specialised in AI research held pragmatic views focused on transitioning AI technologies from research to established use, other groups were more hesitant: Healthcare professionals focused on the wellbeing of their patients, with or without the aid of AI technologies; industrial partners balanced the observed benefits of AI technologies with the legal barriers of user data required to make them effective; and members of the public with no vested interest held significant concern on the balance of health, social justice and freedom that they felt would be significantly impacted by the introduction of AI systems [203].

Scoping professional attitudes to AI, Chew *et al.* found many saw AI as a tool promoting availability and ease-of-use, as well as improving efficiency and reducing cost in delivering health care. These professionals also held concerns around not trusting AI data privacy, risks to patients, the readiness of the technology to be trusted with healthcare services, and a wider concern around the automation and eventual replacement of their own positions [61]. Mehta *et al.* and Teng *et al.* both explored medical students' attitudes towards AI, representing the group that will see the full potential of these technologies in their field. Mehta *et al.* highlighted optimism towards the use of AI, especially in clinical care and administrative duties [248], but both groups found students were concerned about the potential of AI in fields that required personal attention and empathy such as counselling, social care and midwifery. [248, 349]. Students currently in education were overall more positive towards AI than those in existing professions [349], but an overall opinion was that all groups required education into AI and its integration into medicine to be adequately prepared [248, 349]. Professionals in the NHS felt that while opinions were mixed on AI, a key barrier to implementation was placed on the service as a whole, citing funding and technical infrastructure as solutions to be resolved before AI could be utilised effectively. People-centred concerns were also raised, such as a lack of AI knowledge and confusion as to whether AI would supplant or support existing medical structures, mirroring the desire for increased AI education seen in current medical students [261].

This work demonstrates that scepticism on AI usage is not limited to the average person and that even experts in their fields may work to limit the effective usage of AI. To return to the example presented by Yardley *et al.* of users identifying unacceptable intervention features in their Person-Based Approach, it is entirely possible users would frame any inclusion of AI as unacceptable due to only viewing its inclusion through the negative lens of the public conscience which would limit any possibility of it being used positively to benefit behaviour. It may be necessary to address these concerns on algorithms head on, by having potential designers explore and conceptualise these extreme solutions and having potential users react directly to the 'evil' applications of AI they are concerned about, which can help them to have a significant benefit to healthcare while still ensuring the actively problematic elements are addressed. This may resolve some of these mixed public and professional opinions by actively demonstrating the interactions of the AI to create a rounded and accurate understanding of how AI may be applied.

Ethics of AI

Rigby *et al.* proclaim that "AI systems can diagnose skin cancer faster, more efficiently and more accurately than a dermatologist, and only requires a suitable collection of data rather than a costly and prolonged medical education" [308]. However, current ethical guidelines for AI technology have not progressed to the same degree. Despite attempts to engage in ethical conversations about this technology, medical professionals remain ill-informed of the complexities AI technology introduces to the field of medical ethics [308].

For an AI system to be effective in health scenarios, patients must trust the system. Human beings naturally aim to reduce uncertainty in their daily interactions, and as such may be hesitant to welcome AI into their process of treatment. Trust and accountability are key considerations for AI implementation, with further societal risks such as an intelligence divide between human doctors and AI systems. Ethical risks stemming from AI algorithms overlooking human values to make what it deems optimal decisions - similar to issues explored by Amodei *et al.* - are also seen as important concerns in AI integration [139]. AI ethics surrounding these concerns is well reported upon in the field of organised healthcare in developed countries, but there is a severe lack of literature on AI ethics in low- and middle-income countries, as well as in population and public health. This lack of knowledge on AI usage in lesser-developed and more widespread healthcare may lead to potential occurrences of bias against these groups and calls into question whether ethical frameworks are equipped for these scenarios [265].

Mittelstadt *et al.* highlight difficulties in integrating medical ethics into AI systems, as these ethics are often based on human concepts such as beneficence and non-maleficence that a digital system may struggle to account for [256]. Much as Gerke *et al.* questioned whether the current interpretation of informed consent was equipped to deal with AI systems, Ganapathy calls for regulatory requirements to be established that can manage AI systems even as they change and adapt. It is accepted that laws and regulations cannot keep up with the rate at which AI innovation progresses, and any attempts to strictly regulate these systems come at a cost to the ability of the AI system. An important consideration is to differentiate between algorithmic errors and training errors and to establish accountability in the event of decisions made by the algorithm that negatively impact patients [122]. There are frameworks of regulations that exist to try and guide the design of AI systems [181], but these often create issues of their own. Hagendorff *et al.* found significant gaps in frameworks [144], and Whittlestone found that many sets of regulations were internally inconsistent and may limit the ability of AI to perform effectively [382]. McLennan *et al.* suggest 'embedded ethics' as a potential solution, integrating ethical experts throughout the design process to ensure considerations are made during the initial design that will prevent serious ethical shortcomings during future use. This is seen as especially important in healthcare, where black-box algorithms directly engaging with vulnerable populations will require effective ethical consideration. Integrating ethicists into the process of design also helps these same figures predict and anticipate social frictions that may arise as these technologies evolve [246], and may be able to adapt the design of problematic issues like informed consent [130] and AI regulations [122] accordingly.

These concerns stand as barriers to widespread AI implementation in the healthcare field, but it is also important to weigh them up against the potential benefits in these fields. Focusing too heavily on outcome metrics may cause significant harm to users, but pivoting too harshly into strict regulations causes significant harm to the ability of the AI algorithm to be effective. These arguments must be resolved, and the design of AI systems for health and behaviour change must adapt to account for these concerns and resolve them, such that the best balance between system efficacy and user acceptance can be found. It is important for this balance to be found, as the potential benefits of AI are too great to abandon them entirely. As stated by Alex Zhavoronkov, CEO of Insilico Medicine, "...Once you realize what kind of impact this field can have, and what kind of tragedy a delay could cause, stopping... would be a crime against humanity" [392].

2.6 Designing Behaviour Change

Participatory Design could aid in designing new AI-enabled behaviour change apps, with a strong track record in messy domains as part of third-wave HCI approaches [35] and a history of dealing with sensitive ethical issues [128, 333]. Using PD in the development and deployment of AI has shown potential in healthcare [269] and can encourage responsible co-design by closing gaps of expertise [331]. However, a lack of understanding about AI can undermine the efficacy of the systems that are co-designed. Poel *et al* observed that when someone says they will never engage with an AI, it can appear disrespectful to include one in subsequent designs [361].

In addition, in participatory work, designers' assumptions about the efficacy of previous designs and user values can also constrain the design space in unhelpful ways [330]. For example, designers' assumptions that older users want to avoid technology locks in limited scope for use in their designs [77]. Current behaviour change systems are not effective, so basing designs on them can undermine designers. There are examples in real-world contexts of designer assumptions having a negative impact on the quality of the device [149], but generally this assumption-driven approach leads to reusing 'tried and true' designs while challenging assumptions leads to smarter design and smarter products [330].

2.6.1 Designing for Effective Behaviour Change

Presseau *et al.*, in examining connections between clinical techniques and free-living interventions, stressed the importance of implementation science to enhance the real-world impact of health behaviour change interventions. Presseau *et al.'s* research placed focus on the means through which the intervention is delivered as well as the outcomes in controlled settings, and stated that the surrounding context of the intervention played a major part in determining how this should be approached [294].

French *et al,* present a four-step approach to transform evidence-informed ideas into effective and practical solutions. This takes a slightly different approach to intervention design in that these four steps place their central point of reference in theory, considering what is best practice based on existing theoretical underpinnings and evidence and avoiding what they deem as 'pragmatic, rather than theoretically informed, solutions' [116]. This references a statement by Rothman in 2004 that theory and intervention must be treated as interdependent factors - Interventions must be based on theoretical foundations to give the best potential for successful outcomes, but additionally, theories must be rigorously tested through intervention and therefore open to alteration or rejection based on the subsequent outcomes [314]. The key to successful behaviour change is to combine solid foundational theory with well-informed design to ensure that the intervention has both evidence-supported means to influence behaviour, and solid implementation to allow for this evidence to be effectively presented.

2.6.2 Users & Designing Intelligent Systems

Focus groups and participatory design sessions can help shape ideas around the nature of a behaviour change technique. Participatory design in the field of co-designing behavioural interventions has already been explored to a high level. John *et al.* explore the benefits that co-design may bring to social learning and the associated theories, with the outlook that an effective system can not just be designed with optimised efficacy in mind. The inclusion of users helps long-term use behaviour change systems to avoid design that leads to short-term success but long-term failure, as said users are central to the motivations and outlooks that lead to failure and can therefore explore how to best avoid these issues [182]. Carvalho *et al,* present participatory design for behaviour change as a necessary step to combat arising issues within the field of behaviour change design. The necessity for grounding intervention design in behavioural theory has been rightly emphasised, but Carvalho *et al,* note that directing too much focus to behaviour change theory and the rigid implementation of these techniques as written undermines the potential of the system to influence. Directing interest too heavily towards quantitative research with minimal interest in the process of development effectively silences qualitative approaches that explore the reception of these techniques to provide complementary perspectives, with stakeholder participation wrongly diminished as a result of this [48].

There are a number of existing design techniques that provide the potential to integrate these intelligent solutions into participatory design without the same degree of backlash from users. User-centred design (UCD) is a widely used process, first outlined properly in the 1970s as a design method to create systems that aligned with the requirements of the user. As soon as techniques are implemented in a user-facing system, users would be required to ensure optimal design of this system for their use - Wever *et al.* liken this to the design of a diesel engine, in that the design and construction of the engine require no user input, but sound and feel once the engine is in the car require user engagement to adequately resolve any arising concerns [380]. Gaynor *et al.* use UCD to design intelligent systems as a two-pronged approach, by both examining general ideas and desires in the application space and by discussing methods through which researchers could improve upon common examples of these applications, finding both what is desired and what is currently missing [129]. Arguing the need for user-centred AI in radiography settings, Filice & Ratwani describe the potential for additional issues where intelligent technologies are implemented without user input, mainly in the case of unexpected errors as a result of limited consideration for how the outputs of these technologies synergise with the people using them - similar to Wever *et al.'s* diesel engine analogy, the intelligent technology may be highly effective for the sole purpose of its design but will present many unexpected errors once exposed to the requirements of the user, as each requirement would require a thoroughly different approach to design and implementation from the outset [112]. An additional consideration presented here is the need to plan for all use cases; While the case of radiologists reading results directly from the algorithm may be the primary point of communication, other points of communication with patients and other doctors are also frequent and would require vastly different levels of presentation which must be considered during design [112]. An article by Guszcza on the benefits of user involvement in AI development further supports this idea of relevant data presentation, while also presenting the necessary considerations of possible psychological impacts an AI left to work without necessary restrictions can inflict. Guszcza also discusses the 'Paradox of Automation' where as a system becomes more effectively automated, the few instances where user engagement is required must be given more consideration, as the values and motivations of the user will become more complex and more central to the maintained operation of the system [140].

Experience Based Co-Design (EBCD) attempts to integrate social and cultural factors into design. EBCD was used by Fylan *et al.* in the design of intervention for safer medicine use, where the experiences of the users both in the general context and in previous uses of interventions are integrated into the design. EBCD is typically used in isolated scenarios to resolve issues in design, but Fylan *et al.* approach design from a more abstract level to assess real-world issues. Their work examined resulting co-designed systems at a component level against the taxonomy of behaviour change techniques to understand the theory below each design decision, before combining successful components into a core intervention [120]. This process of approaching design aligns with the intended approach of our conceptual blueprint, by designing individual components rooted in behaviour change techniques and then presenting either single components or component combinations based on the potential for high efficacy. Integrating the experiences of users into the design of each component is essential to ensure that they are perceived to be effective and feasible, but also that they present good potential for long-term impact. Another approach designed specifically to suit this purpose is the Participatory Action Research process based on theories on Behaviour Change and Persuasive technology (PAR-BCP) as presented by Janols & Lindgren [177]. The PAR-BCP derives its approach from a small subset of behaviour change strategies as presented in the work of op den Akker *et al.* [274], using these as a foundation for the makings of a successful real-time behaviour change application. These strategies are then thoroughly explored through the eyes of the end-users involved in the process, with each strategy used as a focal point for user experiences, attitudes and desires. This produces a comprehensive idea of how the user views technology in this space and what they would both require and desire from a designed system for long-term use. These idea of integrating user attitudes and outlooks into the design of the system through the lens of established effective concepts is crucial to optimise the chance of success, and they represent a key focal point of the design work within the development of this system.

Analysis of current approaches to connect user needs with the design of intelligent systems presents some ideas of how to approach design in this space while also outlining certain issues. However, the current approaches all lack the means to challenge assumptions and better understand the core values of both experts and users. Processes such as PAR-BCP and EBCD are more effective in understanding the theory behind design, but this focus on theory is still potentially limited by unfounded concerns held by those involved in the process. Only by directly addressing these misconceptions and more directly leveraging values and efficacy against each other to understand their relationship can we uncover a more effective design space and develop more efficacy-driven behaviour change concepts. There are other processes which attempt to blend design with user input, with the Person-Based Approach proposed by Yardley *et al.* being a prominent example [397]. The key premise of the Person-Based Approach is the development of 'guiding principles' based upon in-depth qualitative discussions with users which state the key objectives and features of the designed intervention to ensure these objectives are satisfied. These principles cover undesirable intervention features and user perspectives on the space which can be used to shape the eventual design. An example provided by Yardley *et al.* is the decision to not include context sensing to detect potential behaviour change moments due to users being sceptical about the potential negative effects of context sensing on their behaviour, instead using it for another purpose [397]. The Person-Based Approach and similar approaches will be discussed further in Chapter 4 in relation to the Effect-Led Design process which serves to resolve some of these misconceptions and disconnects between design and user.

2.7 Chapter Summary

This chapter has explored the literature space which surrounds the outlined topic of the thesis, providing a general context with which to immerse the mind to best understand the work going forward:

- Physical activity and sedentary behaviour in terms of their definitions, recommended guidelines to maintain health, and the possible effects stemming from not meeting these guidelines
- The concept of motivation, especially regarding engaging in healthy behaviours, and an overview of behaviour change techniques which may be used to guide physical activity and sedentary behaviour improvement.
- Digital approaches to influencing behaviour, specifically around current system approaches, the space of personal informatics, and overall adherence to systems attempting to promote positive behaviour change
- The introduction of a possible solution in personalised behaviour through artificial intelligence algorithms, covering intelligent algorithms concerning both direct application and their perception in the wider space.

There is a clear need within this space for more effective behaviour change systems, to avoid the common issues of abandonment and lack of long-term success. In this section, we have seen evidence that there is potential for this effect to be driven by adaptive, personalised systems which can better align the approach of the intervention platform with the user receiving this intervention, as well as some early emerging evidence that this adaptation and personalisation could be powered by AI algorithms.

There are a number of challenges to overcome in the space of adaptive AI approaches. The main issues with the inclusion of AI are problematic deployments which do not properly account for the user on the receiving end and said users being generally sceptical towards the use of AI in a system intertwined with human health and behaviour. These issues cannot be resolved in implementation alone - They must be addressed at the point of design, ensuring systems are properly tailored to maximise positive outcomes for users and that the needs of these users are accounted for and their concerns are properly addressed.

We expand upon these early conclusions further in the following chapter, Chapter 3, which will present a literature survey which follows on from the final bullet point raised - Current approaches to personalised behaviour change, both with and without AI algorithms, to find where impact is currently seen and where there may be potential for greater impact in spaces not currently effectively explored.

CHAPTER 3

A TYPOLOGY AND LITERATURE SURVEY OF DIGITAL PERSONALISATION FOR HEALTH & BEHAVIOUR CHANGE

Digital healthcare is rapidly cementing itself as a central pillar of public health. This is supported by wider opinions, with many enthusiastic about the ability of digital health technologies to "revolutionise and 'disrupt' medical and public health practice and produce better outcomes for patients" [228]. A major characteristic of digital healthcare systems that must be considered is that of individual applicability. A potential route to increase this applicability is the use of artificial intelligence and big data to allow for decisions to be made on an individual level by utilising voluminous, heterogeneous and noisy data [208]. However, research on AI with personal digital health and behaviour change is scarce.

Figure 2 provides an outline of the key components of an AI-driven, behaviour change system, including work prior to design and various factors that influence the actions of the system. This system uses regularly captured user data to tailor content to the user and best work to improve both the ability of the user to change and the ability of the system to promote such change.

The concepts set out in Figure 2 bring together disparate ideas and concepts found throughout the literature on how digital systems should be approached to encourage better behaviours. The 'Approach to Personalisation' component (in purple on the left-hand side) represents the theoretical ideas presented by Behaviour Change Techniques and personal informatics, as well as different models of behaviour alteration which may impact the selection of approach depending on how they are perceived to impact individual users. The inclusion of a dedicated component regarding design (in green on the far left-hand side) is to ensure that extensive research into design methods and the design of personalised technologies is represented within these technologies. The focus on the design of these systems is also included in response to concerns unearthed within the secondary healthcare space - many of the concerns surrounding the design and deployment of AI algorithms within healthcare would be effectively addressed through an in-depth

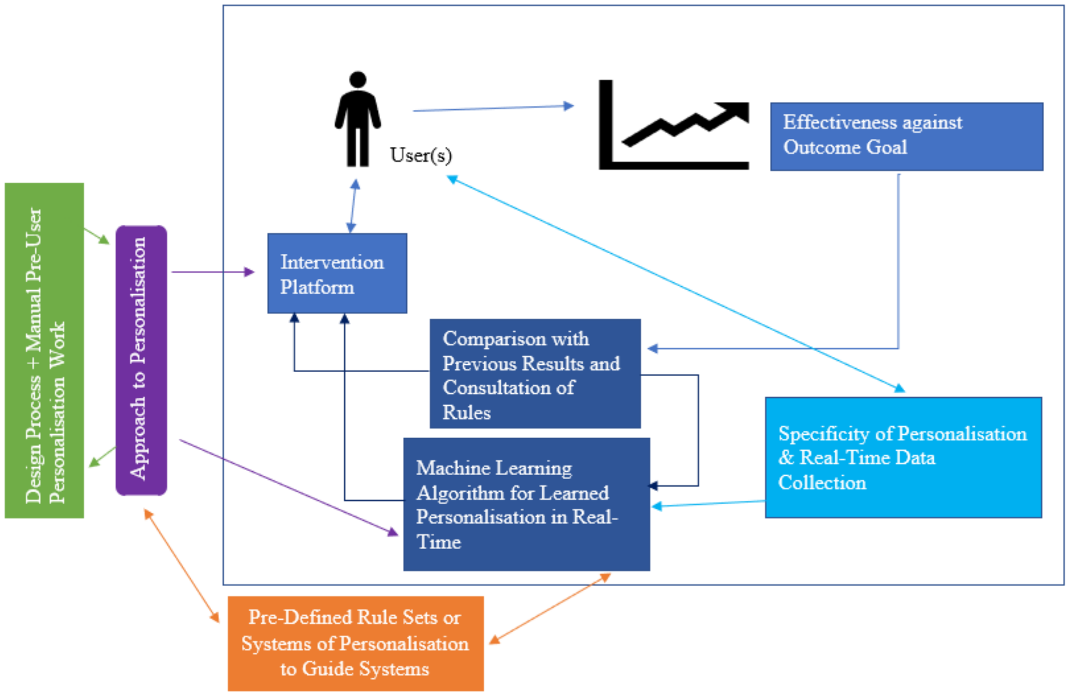


Figure 2: Key components of an AI-driven behaviour change system

and inclusive design process. The inclusion of pre-defined rule sets for certain approaches (in orange at the bottom of the diagram) reflects the general discussions on the need to tailor content to individuals, as well as specifically reflecting the comments of Castro *et al.* on connecting lifestyle and health approaches [49] which links the theoretical basis of approach and design to the tangible intervention platform.

The intervention platform is not specified, as literature on connecting lifestyle to approach and exploring the relationship between people and their information needs [326] indicates this platform is heavily dependent on the context in which the intervention is deployed. The generalised approach of analysing the effectiveness of a shifting outcome goal reflects the ideas of Stamatakis [335] and Pogrmilovic [199] that the concept of the ideal goal is undefined and the measure by which effectiveness is determined may need to adapt and evolve along with the user and their situation. Comparisons against previous results (dark blue) are not only essential for the functioning of both a repeated behaviour change intervention and an intelligent system relying on user response to improve the model but also connect to elements of adherence by allowing a reflection on previous success and predicting upcoming disengagement. Additionally, the benefits listed by Henriksen *et al.* in the interest of adherence - accurate tracking, knowledge of behaviours and conscious acknowledgement of activities - may be most effectively reflected in active and passive comparisons to previous behaviours. The inclusion of machine learning exists to serve the necessary shifting of goals and approaches as described by Shin *et al.* [326]. Additionally, the use of machine learning (dark blue) in combination with dedicated rule sets (orange) and contextual information (light blue) furthers the ideas described in Section 2.2 on scaffolding the efforts of the Habit Formation model in transitioning behaviours from extrinsic to intrinsic

- Having multiple rule sets for behaviour change, combined with a knowledge of contextual factors, allows for the system to select best-fit sets for maintaining motivation engagement, reflecting the closing statement of Section 2.2 in 're-framing the design of behaviour change applications'.

The extent to which contemporary behaviour change research reflects the ideas set out in Figure 2 is unclear. Many systems make use of a single static approach to personalisation which remains either unchanged or undergoes minimal alterations at set intervals. Users are effectively woven into the design of these approaches, but we believe intelligent, real-time personalised systems represent what designers should build around going forward. Such systems may exist, but it is difficult to identify such systems given their rarity and the associated difficulties in drawing out these lesser-seen systems from the wider design space.

Due to the relative immaturity of the area, these difficulties are exacerbated by the lack of a clear structure of classification for the approaches included within personalised digital health. This chapter builds the foundations of this typology by examining the literature with regard to approaches and the exact nature of system personalisations. This chapter will then conduct a survey of the literature using the newly established typology to identify trends in personalisation approaches and find where innovation can be pursued.

This chapter and associated literature survey serve to answer question *SQ1*:

What AI implementations exist currently in the landscape of health and behaviour change, and where exists scope for AI innovation?

By exploring not only if AI implementations for personalised health and behaviour are currently visible in the research space, but also what exists more generally - By establishing a clear picture of the overall landscape of personalised health and behaviour change, we gain a clearer picture of what methods currently exist, intelligent or otherwise, which allows us to further identify spaces where innovation is possible. The typology and subsequent classification of the space presented here create a more structured view of the research space with which gaps for innovation can be more clearly identified. It should be noted that the content of Figure 2 does not contain a direct parallel to the literature classification presented in this chapter. This survey does not exist as an element of this key components diagram, but rather as a means to align this diagram with the wider research space. If the literature described in Chapter 2 serves to illustrate the direction we believe the research landscape should progress, then this classification serves to provide a much clearer lens through which to see if this proposed direction lines up with the current state of contemporary research.

3.1 Literature Review Method

3.1.1 Need for Review

This survey establishes the beginnings of a classification system for personalised digital health and behaviour change systems. The need for such a classification and review is simple: the technique content and digital components of digital health systems, as well as the exact personalised approaches, are difficult to describe in an easily comparable way. To reiterate, this classification uses the term 'personalisation' to mean a system or element of a system that is based upon or targets a personal characteristic of a user.

By providing the ability to compare personalisation approaches, designers can better observe the current space; A typology of personalisation approaches could allow designers to identify opportunities for future research, using these opportunities to fully explore and optimise personalised digital health and behaviour change in future implementations.

3.1.2 Search Strategy

Literature search terms captured personalised systems and a health and behaviour change focus. These search terms were developed by analysing a small subset of literature and finding terms which commonly appeared within this literature, as well as expanding certain terms to words assumed to be regularly used within the same area, e.g. including the term 'app' alongside the commonly used 'application', as well as allowing for expanded versions of 'personal', e.g. personalised, personalize, personalise. One search term was used originally, which was then updated based on initial findings and the discovery of literature not captured within the first term.

1. ((personali* OR tailor*) AND (custom* or bespoke) AND (intervention* OR app OR application OR trial) AND (behavio*) AND (design* or hardware)) - This term was used initially to scope out the space. This set of terms captured the important elements desired for the survey, but also inadvertently eliminated possible papers from being included. 'Personalisation' and 'tailoring' were captured in the initial search terms, but common synonyms observed in later papers were not captured here. 'Intervention', 'trial', and 'design/hardware' often returned human-delivered personalised interventions, which were outside the survey scope.

2. ((personalis* OR personaliz* OR tailor* OR individualis* OR individualiz* OR adaptive OR adaptable) AND (ehealth OR e-health OR mhealth OR m-health)) - The refined term, capturing the majority of the papers included within the survey. This search removed terms which produced irrelevant results, as well as including additional search terms seen in referenced literature not captured by our terms. Outside of 'personalisation' and 'tailored', individualised and adaptive systems were added to the search as these were often found in the titles and abstracts of relevant papers missed by the initial terms. The collection of terms such as intervention, behaviour and design were collated into m-health or e-health, which is also a commonly observed term both in papers found in the initial search and relevant results not captured.

These search terms were used on the PubMed, Web of Science, IEEE and ACM digital libraries. Following this, the ResearchRabbit literature searching tool was used to find papers linked to those already found.

The scope of our survey covers digital interventions focused on health or behaviour change, where the major component of the intervention is personalised. Only papers published between 2000-2021 were included to effectively capture recent developments in the field. Inclusion criteria covered any paper presenting a digital intervention which used personalisation to change health or behaviour. These interventions had to be delivered on digital platforms, and the personalisation had to be a core aspect of the research being conducted, although the personalisation did not have to be conducted by the digital system to be included. Exclusion criteria covered papers published before 2000, papers which did not present a defined intervention, e.g. a theory of how to change behaviour, or suggested innovations to systems for changing behaviour, and papers which presented human-delivered interventions without digital components.

3.1.3 Paper Overview

Literature searches resulted in 238 papers, 37 of which were out of scope. Following further analysis, 174 papers were examined in this survey from 91 different journals and conferences. Figure 3 shows the most prominent of these journals and conferences, indicating which disciplines are spearheading personalisation research. 11 of these journals/conferences covered a computing discipline, representing 15 of the 174 papers (8.6%). The majority of published papers covering personalised digital health and behaviour change originate from health or sport science backgrounds. The three most prominent authors across the papers included, those being Hein de Vries (12 papers), Corneel Vandelanotte (11 papers) and Lilian Lechner (9 papers), are all primarily health researchers, although they present specialities in the digital systems domain (Vandelanotte in app-based interventions and Lechner in computer tailoring).

The majority of papers focused on Physical Activity and Health Management, both at 26% of the 174 papers. Smoking Cessation (7%), Weight Management (7%) and Wellbeing (6%) were present in at least 5% of papers.

3.1.4 Limitations

Personalised systems are relatively new and as such their content is less reported upon. Additionally, health and behaviour change systems are more commonly reported upon in non-computing fields such as behavioural science and medicine. This reduces the likelihood that computing-specific elements will be reported upon in high detail, which limits the ability to discuss these features in-depth within the classification itself. This will require additional insight when reading papers in these fields to draw out any computing elements, and how exactly they factor into system personalisation. There is also potential that the search terms were still too broad, although this is difficult to navigate as narrowing the space requires the subsequent typology to know what to search for.

3.2 Personalisation Typology - Core Classification

A key contribution of this survey paper is a typology for personalised digital health and behaviour change interventions. The typology specifies how a system's

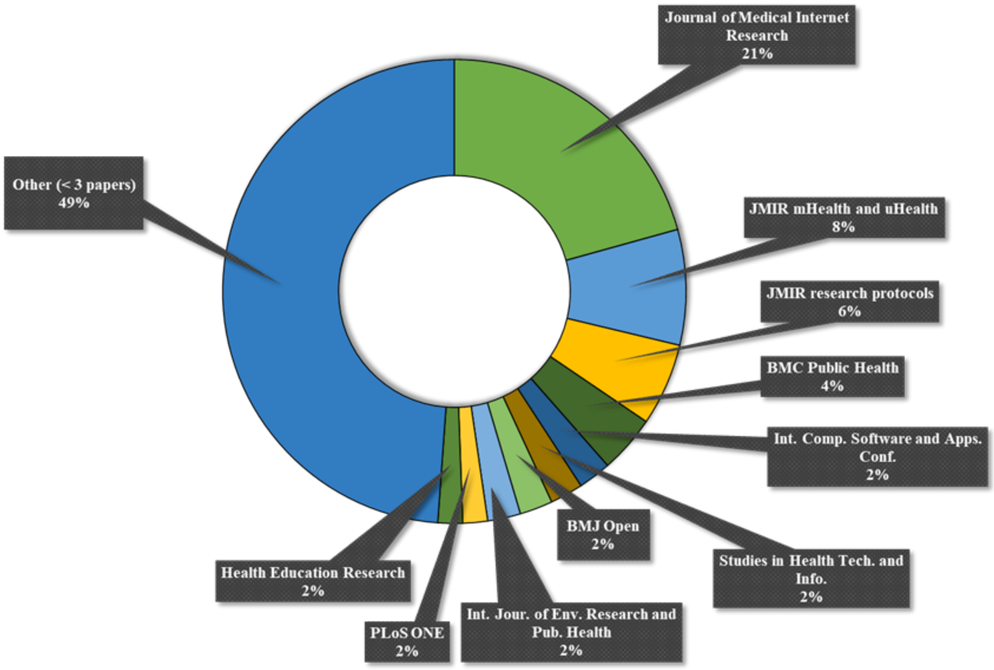


Figure 3: Journal and conference prevalence in included papers

personalisation is implemented, as well as providing insight into personalisation outcomes. These categories are broken down further into specific labels which clarify the nature of the personalised system, the data and methods it utilises, and whether this personalisation results in a positive outcome.

This section covers the core classification dimensions of the Personalisation Typology structure, which covers the high-level classification of such systems for the main points of comparison. A visual description of this structure can be seen in Figure 4.

3.2.1 Core Classification Development

The 'core classification' provides a set of dimensions to directly compare how personalisation is approached within a system. This set of dimensions was developed by identifying examples of personalisation in the literature, and in what ways these differed from each other. For example, Noar *et al.* [273] present an online system which records lifestyle choices to present recommendations for safe sex practices, and Lim *et al.* [222] present a smartphone-based fitness intervention which uses real-time environmental tracking to provide in-the-moment recommendations for positive behaviours. On the surface, these may appear unrelated, but certain comparable factors can be drawn out:

- Noar *et al.* base their intervention upon a single data point, while Lim *et al.* use multiple data points collected in real-time at the point of need;
- Noar *et al.* use a fixed set of rules to respond to certain lifestyle choices with certain recommendations, while Lim *et al.* learn over time the needs of the

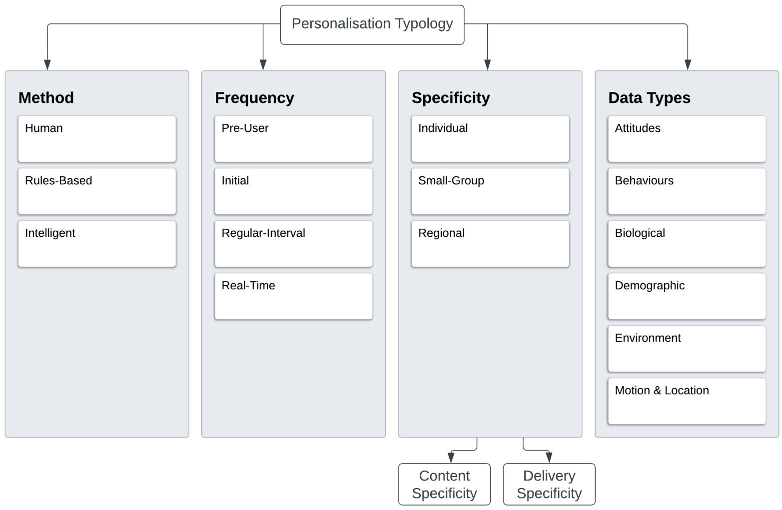


Figure 4: The high-level structure of the Personalisation Typology level of the classification

user and how to best provide behaviour recommendations;

- Noar *et al.* tailor their content generally based on shared lifestyle characteristics, while Lim *et al.* base their tailoring on specific user features obtained through use;

- Noar *et al.* tailor recommendations to the attitudes of individuals, while Lim *et al.* use contextual information and in-the-moment behaviours to determine which recommendations are made

Differences such as these provide the core classification dimensions of the typology as described in Section 3.2. The specific classifications within these dimensions were developed using an iterative, bottom-up approach defined based on what was observed within the space. These were also developed to uncover certain ideas about behaviour change technologies as seen in the literature - Comments on the need to adapt personalised goals and to change approaches over time informed how the space may be perceived, e.g. the dimensions of **Method** being: fixed personalisation by a human designer; personalisation which can adapt based on defined rules as implemented by a human designer; and personalisation which can adapt based on the in-use observations of the system. These classifications were also challenged when papers were analysed which did not fit into the classifications or classifications were unclear or rarely seen. For example, **Intervention Specificity** was divided into **Content** and **Delivery** when it became apparent that different interpretations of where personalisation was observed could change where a paper was classified.

3.2.2 Personalisation Method

- **Human Personalisation** encapsulates personalisation approaches which are established manually in the system during design, and therefore represent a fixed personalisation of the system. These types of personalisation are often based on a specific disease or culture, which would have a standardised response and could therefore be 'hard-coded' into the system. An example of this would be intervention content personalised to region-specific barriers and culturally-specific norms to directly target challenges in changing behaviour [371], or tailoring materials to male audiences, such as using males in example videos or trying to match humour and tone males respond more positively to [399].

- **Rule-Based Personalisation** is personalisation that is not hard-coded to a single group or single approach, but the rules for personalisation are hard-coded, and cannot intelligently change through use. Algorithmic personalisation such as specific pre-written feedback and educational materials selected based on specific barriers are examples of Rules-Based Personalisation. Examples include an automated system which selects a small number of messages from a large bank of motivational text based on user answers during a start-up questionnaire [104], or an automated system to provide personalised feedback on dietary intake, including a method for the system to select the best-matched health goals to target behaviours [153].

- **Intelligent Personalisation** represents data-driven personalisation through machine learning. Examples of this include creating 'life profiles' and intelligently altering these profiles to best target problem behaviours, or selecting methods based on prior user outcomes and responses. **Intelligent** interventions often use more advanced approaches due to the wider range of possible applications provided by learning capabilities. This can be using prior actions by all users to assess the best intervention content and timing [5], selecting optimal comparisons with other users through the learned patterns of the user [89] or even creating situational models directly linked to states of behaviour to provide more accurate tracking of behaviour [45].

3.2.3 Personalisation Frequency

- **Pre-User Personalisation** defines personalisation before system use. This covers cultural personalisation, as well as personalisation specific to health conditions. Pre-User Personalisation follows a similar train of thought as **Human** Personalisation, allowing for aspects of personalisation that would be unchanged such as information on targeted conditions to be implemented for immediate user benefit. Examples include lifestyle recommendations to address common genetic health markers and tailored information specified to the target culture and associated norms [64].

- **Initial Personalisation** covers systems tailored based on a single data point obtained from user input upon first use. An example would be an on-boarding questionnaire which determines barriers to behaviour, and then tailors messages or techniques to target these barriers. Examples include developing a 'risk profile' from an onboarding questionnaire which informs the selection of intervention modules [362] or allowing a user to develop their own profile for the system to base selection of content upon [365].

- **Regular-Interval Personalisation** includes interventions which select personalised content based on regularly-calculated values. For example, a personalised daily goal that is calculated based on user actions in previous days. Regular-Interval Personalisation covers numerous applications, from the previously defined daily goal assignment [3, 370], to selecting expert-designed modules at time intervals to respond to symptoms and situations as they arise in the user [364], to more niche uses such as daily recordings of UV levels used to encourage changes in behaviour to avoid excessive levels of UV depending on provided skin type [156].
- **Real-Time Personalisation** applies to systems that personalise content in real-time. Real-time personalisation covers approaches such as live feedback to actions or just-in-time notifications in proximity to problematic locations. This level of personalisation can be used to recommend real-time fitness plans with accompanying feedback [304] or to provide real-time behavioural recommendations based on immediate context such as time and location [160, 222].

There is some potential confusion distinguishing Real-Time Personalisation from Regular-Interval Personalisation, as while a system may work with real-time data capture and calculations, the presentation of the personalised content limits this. A system that collects fitness data and behavioural habits in real-time, but uses these to present once-a-day feedback, is a Regular-Interval Personalisation system as the user-facing personalisation is only presented at regular intervals.

3.2.4 Personalisation Specificity

Personalisation Specificity is divided into two subcategories - **Content Specificity** and **Delivery Specificity**

Intervention Content Specificity covers the degree of specificity of intervention content tailoring. Individual Specificity in Intervention Content Specificity is often seen in **Real-time**, **Intelligent** systems as content is ever-changing and tailored specifically to the user, although less intelligent solutions such as comparative metrics between user-specific values and user-specific goals would also classify as individual.

Intervention Delivery Specificity covers how the system delivers personalised information. This covers factors feeding into which tailored messages to send to the user, or using contextual information to determine when content would be best received. Individual Specificity in Intervention Delivery Specificity is the more commonly seen, as this simply means that personalised content is selected based on individual factors. This would cover pre-designed personalised content selected for a given user based on individual factors such as questionnaire responses or demographic data.

- **Individual Specificity** covers personalised materials specified to an individual user. This includes presenting techniques that apply to specific user barriers or providing user feedback based on positive or negative actions against the presented goals. Individual feedback covers a very broad area of the scope, including implementations such as messages populated with information sourced from progress diaries [67], aligning materials with personally-held barriers to behaviour [69, 79, 143, 157], or learning specific information about the user to tailor materials and timings more directly [136, 146].

- **Small-Group Specificity** describes content specified to a group within the intervention scope. Groups may be clustered based on age, education level or specific conditions, with content tailored to the group generally, e.g. educational materials for a given condition or materials presented in easily digestible ways for lesser-educated individuals. Small-Group is common in interventions that base their approaches on Stages of Change [183, 189, 206, 280], but also is used for groups of similar conditions or condition severity [72,106,197,224] or to address conditions which could affect ability to engage with interventions [8, 251].

- **Regional Specificity** covers broad elements of personalisation. A good example of Regional Specificity is cultural tailoring, where personalisation materials are developed to apply to a given race or culture, which could in theory apply to a wider group than a condition that other interventions may target [7, 168, 319, 371].

Personalisation Specificity is selected based on the deepest level of personalisation - while elements of Regional Specificity are present in the majority of applications, these tailored interventions frequently present more specific examples of personalisation at Individual or Small-Group levels.

3.2.5 Data Types & Context Specificity

Data Types covers categories of data used by the system for personalisation. This helps to determine which avenues of data are most prevalent in personalisation requirements, and if there is any possible correlation between the collection of certain data types and positive or negative outcomes in terms of efficacy and user interaction:

- **Demographic** - High-level user classifications related to personal characteristics separate from conditions. Demographic data covers data such as age, sex and location. This data is central to tailoring manually tailored interventions assigned to age or culture but is also present in personalising feedback and information presentation. Demographic data has a variety of uses including using demographic data obtained on start-up to tailor materials [90], selecting tailored content based on demographic and social contexts [29], or using demographic data to inform a trained model as to which information is most relevant [237].

- **Biological** - Bodily characteristics or values that would affect courses of treatment, and in turn, influence selections of intervention content or help to personalise feedback and technique selection. Biological data would include medical conditions [98, 132, 133, 163, 184], risk of disease [84, 238] or more quantifiable metrics such as heart rate [73, 91, 369], blood pressure [63] and weight [72, 105, 170].

- **Motion & Location** - Accurate tracking of user movement for use in refining intervention content or providing tailored feedback. This can be high-level movement tracking such as GPS tracking distance travelled [358], or more specialised movement tracking such as mobile phone accelerometers [402] or dedicated activity trackers [219, 320, 328].

- **Attitudes** - Attitudes users hold towards their behavioural change, be it positive intentions towards changing behaviour [59, 175, 211, 259], or self-held barriers to engagement [38, 79, 157, 270, 381]. This covers common psychosocial correlates such as motivation [21, 117, 186, 206, 284], self-efficacy [39, 136, 259, 267, 273] and self-held beliefs [38, 53, 88, 90, 170], as well as selecting intervention content that is specifically designed to target given user issues [59, 90, 143].

- **Behaviours** - User behaviours used to select intervention approaches. These are mainly collected to determine a necessary intervention starting point, using baseline behavioural engagement to assign relevant content [151, 219, 277, 299, 320, 363, 370, 377, 385]. However, this is also used to record necessary risk behaviours e.g. diet [67, 114, 136, 153, 375], activity [17, 76, 134, 148, 300, 365] or drug use [74]. This data type may also apply to behaviours captured during the intervention, used to reassess and tune intervention content, tailoring goals or feedback to user actions [63, 80, 320] or using user feedback to determine content selection later in the process [5, 166, 315, 398].

- **Environment** - Contextual information is used mainly to optimise the delivery of selected intervention content or to determine ideal content for given conditions. Environmental Context includes data such as time of day [113, 232], weather [160] and location data [45, 134, 198, 222, 268, 300] for making sensible suggestions - activity recommendations during work hours or bad weather may be ignored. Factors such as the availability of stairs over elevators or alternative walking routes over bus transport to replace behaviours are also included [198].

Contextual Information Specificity indicates the specificity of the information gathered for personalisation. This typically aligns with content specificity, but there are minor edge cases that require these to be recorded separately. **Contextual Information Specificity** is recorded as one of **Individual**, **Small-Group**, or **Regional**.

3.2.6 Comments on the Core Classification Dimensions

A discrete system of classification allows for direct comparisons between interventions. This system can then be applied to both developed intervention areas and those with a high potential for innovation and advancement. The core classification dimensions defined here allow researchers to view personalisation with greater granularity, which then allows them to see how this process is conducted and whether changes need to be made.

These discrete levels of personalisation can then be connected to outcomes of personalisation (as defined below) to view the outcomes of the most common approaches, as well as view whether there are rare combinations with frequent positive outcomes which deserve further investigation.

3.3 Personalisation Typology - Personalisation Outcomes

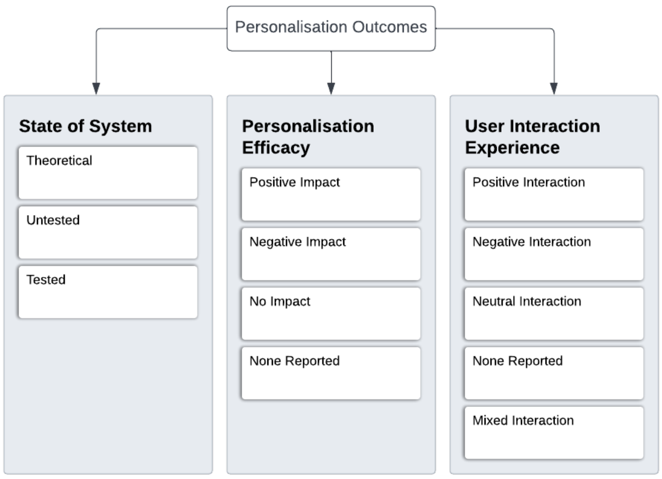


Figure 5: The high-level structure of the Personalisation Outcomes level of the classification

As well as the core classification dimensions of the typology, there are further observations within this survey which cover the nature of the intervention system itself and the related study outcomes examining these interventions. The structure of the outcomes dimensions can be seen in Figure 5.

3.3.1 Personalisation Outcomes Development

As well as the actual mechanisms of personalisation used by a system, an important part of a system to explore is how the system performs. The core classification dimensions allow for the effective sorting and comparing of personalised digital systems, but an important additional consideration is whether certain classifications or combinations result in more effective systems. As such, the outcomes of the systems were included as an element of the typology so it could be established where certain elements may translate into consistent effective outcomes.

The overall state of the system was included to both explain many papers with no results and also to give an indication of whether certain levels of classification were prominent within the space or should be perceived as an upcoming trend within the literature. For example, if **Intelligent** systems were listed on their own, a high number may indicate that these are commonplace and would raise questions about the high levels of **Rules-Based** systems existing concurrently. However, if these **Intelligent** systems are simultaneously shown to be mostly **Theoretical** or **Untested**, this suggests a new point of experimental focus that may soon become more commonplace.

Both efficacy and user experience were included in line with the literature, and concerns surrounding the current state of these systems. In much of the literature on behaviour change systems and in particular work on adherence and abandonment (seen in Section 2.4.2), there was a clear trend of systems which may have been positively received but showed limited examples of effective behaviour improvement. Similarly, in the field of secondary healthcare specifically relating to intelligent systems (as seen in Section 2.5.2), many concerns were around the potential lack of user consideration if these systems were designed to be highly effective. By considering both system efficacy and user experience within the typology, it can be seen if certain classifications report high positive responses in either area and classifications or combinations of classifications which report positive outcomes in both can be taken forward as highly desirable systems within the space.

It must be acknowledged that any single positive outcome could be subject to uncertainties stemming from empirical studies. However, this fact is true of all research, as it is the nature of research itself. A single positive outcome may not be strong enough to establish the perfect solution to digital health personalisation, but some positive outcomes which share similarities within the scope of the typology could indicate a potential space for positive innovation which should be explored further.

3.3.2 State of System

State of System covers where the personalised system sits within the process of initial conceptualisation to being completed and tested:

- **Theoretical** discusses systems presented mostly as concepts or possible approaches to a personalised system. Physical implementations may not exist due to time or technical limitations, but the system must be outlined in terms of an exact implementation.

- **Untested** describes a system with a digital implementation that is yet to be tested by users. Much of the Untested literature is study protocol papers or similar outlines of studies yet to be conducted with details of planned user studies outlined later in the paper, although some are presented instead as proof-of-concept implementations without the intention to test.

- **Tested** covers systems with real-world digital implementations that have been tested with end users to determine effectiveness and user experience.

3.3.3 Personalisation Efficacy

Personalisation Efficacy, applicable only to **Tested** systems, covers how effective the personalisation was in driving the target behaviour:

- **Positive Impact**, where the personalisation within the system resulted in a more beneficial outcome in terms of behaviour change than a non-personalised equivalent.

- **Negative Impact**, where the personalisation reduced the overall effectiveness of the system.

- **No Impact**, where the personalisation did not affect behaviour.

- **None Reported**, where the results do not touch on efficacy - such as studies focused on acceptability and feasibility - or pre-test literature where there are no results to speak of.

3.3.4 User Interaction Experience

The other observation from **Tested** systems is **User Interaction Experience**, which covers reports from user participants on the usability and overall experience provided to them by the personalised components of the system. This can cover feelings that personalised feedback is more accurate to their needs, or perhaps personal feelings on the nature of the personalisation and its role within the system as a whole:

- **Positive Interaction**, where user feedback towards system personalisation was positive, and included positive reflections upon the actions of the system and their interactions with it.

- **Negative Interaction**, where users were displeased with their interactions with the system personalisation, be this in feelings towards the system or their direct personalised outcomes.

- **None Reported** is present for Untested and Theoretical systems, but also exists for situations where system efficacy is the only observed outcome and no consideration for user experience or opinion is included within the reported results.

- **Neutral Interaction**, where opinions are captured on the personalised system, but these opinions do not display notably positive or negative attitudes.

- **Mixed Interaction** covers situations where user opinions cover both positive and negative opinions. This could cover situations where different aspects return different opinions, such as positive attitudes towards personalised feedback but negative attitudes towards the intrusive nature of the personalised system, or mixed opinions on a single aspect such as positive attitudes towards selection of techniques but negative attitudes towards the quality of tailored feedback.

3.4 Personalisation Typology - Personalisation Observations

Further observations serve to elaborate on certain aspects of the examined systems which do not fit into set categories. These data categories are not suitable for large-scale comparisons, but instead provide additional details to allow for the separation of systems within a given classification.

These classifications were established to capture elements of a system or its personalisation which did not fit into discrete, comparable dimensions. For example, where **Data Types** as a dimension captures high-level types of data, the further observation classification of **Captured Data** captures the exact data that is collected which may be central to understanding how the types of data translate into the personalisation. Similarly, a system reported as **Intelligent** simply means it contains some intelligent algorithm, and it is the role of **Personalisation Algorithm** to establish what that algorithm is, helping to further understand how the system operates.

The first of these observations is **Personalisation Algorithm**, the specific intelligent algorithms that are used in intelligent personalisation to examine which algorithms are commonly used in personalisation systems and to see if an association exists between certain personalisation algorithms and system efficacy. If a given algorithm more typically results in an effective system, then recording this association allows for such algorithms to be favoured in future.

The next is **System Platform & Included Devices**, the medium through which the system exists. This exists to note the prevalence of certain mediums (internet-based, mobile-based or otherwise), as well as any external sensors or devices that are included within the scope of the intervention to view whether external hardware is utilised and whether this has a notable impact on the outcome of the system. The most common example of this is a dedicated step counter or activity tracker, although other more specialised examples exist.

The third observation within this area is **Captured Data**, an expansion of the discrete **Data Types** that clarifies the exact data that is being collected to tailor the system. This helps gain extra insight as to regularly occurring data which could be pinpointed as useful to the personalisation process. For example, while **Attitudes** is useful for large-scale comparisons between personalisation approaches, knowing specifics such as motivations or mental barriers helps find how these attitudes are used and which are deemed necessary to personalisation.

Methods of Data Capture captures information on how data is obtained. The majority of these cases will be user input or researcher input in cases of **Human Personalisation**, but cases in which automated data collection is utilised may produce some interesting outcomes in terms of efficacy and user interaction. There is the potential that automated data collection, be it through a mobile device or dedicated sensors (which would be captured by **System Platform & Included Devices**) could provide more nuanced behavioural insights and in turn improve the ability of the personalised system to affect behaviour. Combining this non-discrete method data with the discrete insights of efficacy and user interaction could cast some light on this potential.

The final further observation is **Personalisation Approach** which captures, in essence, what the system does. This is arguably one of the most important observations in the entire system as it covers the personalised actions for the system and how each personalisation is applied to help change the behaviour. These approach observations are not directly comparable due to the broad nature of these systems and the lack of discrete implementation categories. However, these findings can help observe the approaches taken by **Positive Impact** systems, as well as novel **Intelligent** or **Real-Time** systems. These findings can also help to further explore whether novel systems take full advantage of algorithms and user data to present effective intelligent personalisation.

		Method			Frequency				Content Specificity			Delivery Specificity		
		Human	Rules-Based	Intelligent	Pre-User	Initial	Regular-Interval	Real-Time	Individual	Small-Group	Regional	Individual	Small-Group	Regional
Behavioural Science	Annals of Behavioural Medicine		[196]					[196]	[196]			[196]		
Behavioural Science	Behavioral Sciences		[67]				[67]		[67]				[67]	
Behavioural Science	Cognitive and Behavioral Practice			[23]			[23]			[23]		[23]		
Behavioural Science	Health Education & Behaviour		[15]				[15]			[15]			[15]	
Behavioural Science	Int. Jour. of Behavioral Medicine		[386]				[386]			[386]			[386]	
Behavioural Science	Jour. of Nutrition Edu. and Behavior		[189]			[189]				[189]			[189]	
Behavioural Science	Mindfulness		[216]			[216]				[216]			[216]	
Behavioural Science	Translational Behavioral Medicine		[127]				[127]			[127]		[127]		
Health	BMC Public Health		*A*	[166]		[368]	[39, 166] [175, 281] [306]	[21]	[175, 281] [306]	[21, 39] [166, 368]		[21, 39] [368]	[166, 175] [281, 306]	
Health	Int.Jour. of Env. Research and Pub. Health		[53, 59] [85, 373]			[85, 373]	[53, 59]		[59, 373]	[53, 85]			[53, 59] [85, 373]	
Health	Health Education Research		[90, 143] [367]			[90, 367]	[143]		[143]	[90, 367]		[367]	[90, 143]	
Health	Addiction		[242, 267]				[242, 267]		[242]	[267]		[267]	[242]	
Health	Int. Con. on e-Hlth. Ntwk., App. & Serv.		[359]	[63]				[63, 359]	[63]	[359]		[359]	[63]	
Health	Dbts. Educator		[157]				[157]		[157]				[157]	
Health	Dbts., Met. Syn. & Obe..: Tgts. & Thrpy.		[249]				[249]		[249]				[249]	
Health	Drug and Alcohol Dependence		[258]				[258]		[258]				[258]	
Health	EMBS Int. Con. on Bio. and Health Info.		[195]				[195]		[195]			[195]		
Health	European Journal of Prev. Cardiology		[362]			[362]				[362]		[362]		
Health	Gerontologist			[124]			[124]		[124]			[124]		
Health	Health Economics	[72]				[72]				[72]				[72]
Health	Health Informatics Journal			[136]			[136]			[136]		[136]		
Health	Health Promotion International		[117]			[117]			[117]				[117]	
Health	Healthcare		[170]			[170]			[170]				[170]	
Health	IEEE Journal of Bio. and Health Info.	[111]					[111]			[111]			[111]	
Health	Int. Jour. of Cardiology		[197]				[197]			[197]			[197]	
Health	JAMA Cardiology		[17]				[17]			[17]			[17]	
Health	Jour. of Electromyography & Kinesiology			[160]				[160]	[160]				[160]	
Health	Jour. of Midwifery & Women's Health		[123]			[123]			[123]				[123]	
Health	Jour. of Primary Prevention		[273]			[273]				[273]		[273]		
Health	Jour. of School Health		[71]				[71]		[71]				[71]	
Health	Jour. of Substance Abuse Treatment	[172]					[172]		[172]				[172]	
Health	Netherlands Heart Journal		[132]				[132]			[132]		[132]		
Health	Obesity		[313]				[313]			[313]		[313]		
Health	Pediatric, Allergy, Immu. and Pulm.		[106]				[106]			[106]			[106]	
Health	2016 IEEE Int. Conf. on Healthcare Info.		[91]				[91]			[91]		[91]		
Health	Tobacco Control		[379]				[379]			[379]		[379]		
Medicine	Journal of Medical Internet Research	[64, 98] [286, 371] [399]	*L*	*M*	[64, 98] [319, 371] [399]	[104, 238] [365, 375]	*N*	[45, 105] [398]	*O*	*P*	[64, 319] [371, 399]	*Q*	*R*	[64, 319] [371, 399]
Medicine	JMIR mHealth and UHealth	[168, 192] [332]	*B*	[402]	[168]	[332]	*C*	[304]	*D*	*E*	[168]	*F*	*G*	
Medicine	JMIR Research Protocols	[236]	*H*			[236]	*I*		*J*	[29, 133] [251, 364]		[133, 364]	*K*	
Medicine	BMJ Open		[79, 96] [224]	[5]			[5, 79] [96, 224]		[79, 96]	[5, 224]		[5]	[79, 96] [224]	
Medicine	Journal of Medical Systems		[268, 372]				[268, 372]		[372]	[268]		[268, 372]		
Medicine	Trials		[232, 270]				[232, 270]		[270]	[232]		[270]	[232]	
Medicine	Archives of Internal Medicine		[347]				[347]		[347]				[347]	
Medicine	BMC Cancer		[329]				[329]			[329]			[329]	
Medicine	BMC Family Practice		[374]			[374]			[374]				[374]	
Medicine	BMC Health Services Research		[277]				[277]			[277]			[277]	
Medicine	BMC Musculoskeletal Disorders		[284]					[284]		[284]		[284]		
Medicine	BMC Neurology		[184]			[184]			[184]				[184]	
Medicine	BMC Palliative Care		[322]				[322]			[322]		[322]		
Medicine	BMC Pregnancy and Childbirth		[155]				[155]		[155]				[155]	
Medicine	BMC Sports Science, Med. and Rehab.		[227]				[227]		[227]				[227]	
Medicine	BMJ Open Sport and Exercise Medicine		[370]				[370]		[370]				[370]	
Medicine	Clinical and Translational Rad. Oncology		[202]				[202]		[202]				[202]	
Medicine	Critical Care	[46]				[46]			[46]					[46]
Medicine	Geriatric Nursing		[219]				[219]		[219]				[219]	
Medicine	Human Vaccines and Immunotherapeutics		[88]			[88]				[88]			[88]	
Medicine	JMIR Medical Informatics		[183]			[183]				[183]			[183]	
Medicine	Journal of Pain and Symptom Management		[4]			[4]				[4]		[4]		
Medicine	Medicine (United States)		[305]				[305]		[305]				[305]	
Medicine	Preventative Medicine		[334]			[334]				[334]		[334]		
Medicine	Annual Int. Conf. of Eng. in Med. & Bio. Soc.		[151]				[151]		[151]				[151]	

	The Lancet		[363]			[363]		[363]			[363]	
	The Lancet Diabetes and Endocrinology		[134]				[134]		[134]		[134]	
Psychology	BMC Psychiatry		[28]			[28]		[28]				[28]
	British Journal of Health Psychology		[38]			[38]			[38]			[38]
	Frontiers in Psychiatry		[80]			[80]		[80]				[80]
	Frontiers in Psychology			[173]		[173]		[173]				[173]
	Prim. Care Comp. to the Journal of Clin. Psy.			[215]		[215]			[215]		[215]	
	Psycho-Oncology		[384]		[384]			[384]			[384]	
Science and Technology	Int. Comp. Software and Apps. Conf.		[7, 56] [385]	[6]		[7, 56] [385]	[6]	[56]	[6, 385]	[7]	[6, 56] [385]	[7]
	Studies in Health Tech. and Info.		[84, 113] [201]	[222]		[113, 201]	[84, 222]	[84, 201] [222]	[113]		[113, 222]	[84, 201]
	PLoS ONE		[3, 74] [263]			[3, 74] [263]		[3]	[74, 263]		[263]	[3, 74]
	Internet Interventions	[250]	[312]		[250, 312]				[250, 312]			[250, 312]
	Sensors (Switzerland)		[107, 198]		[198]		[107]	[198]	[107]		[107]	[198]
	IEEE Int. Conf. on Multimedia and Expo		[8]			[8]			[8]		[8]	
	Computers in Biology and Medicine		[9]				[9]		[9]		[9]	
	Computers in Human Behaviour		[298]			[298]		[298]				[298]
	Int Conf. on Info. Tech. & Apps. in Biomed.		[264]		[264]			[264]				[264]
	Int. Sym. on Tech. and Society		[369]				[369]	[369]			[369]	
	PICMET Tech. Manag. for Glo. Econ. Gro.	[55]				[55]		[55]			[55]	
	Int. Sym. on Sym. & Num. Alg. for Sci. Comp.			[66]		[66]		[66]			[66]	
	Int. Jnt. Conf. on Web. Int. & Int. Agent Tech.			[358]			[358]	[358]			[358]	
	Int. Conf. on Web Intelligence			[99]			[99]	[99]			[99]	
	Int. Conf. on Adv. in Soc. Net. Ana. and Min.			[89]			[89]	[89]			[89]	
	ACM Int. Wksp. on Use of GIS in Pub. Hlth.		[302]				[302]		[302]		[302]	
	American Control Conference			[115]		[115]		[115]				[115]
	Smart Inno., Sys. and Techs.		[114]			[114]		[114]				[114]
	Conf. on Techs. and Apps. of AI		[357]				[357]	[357]				[357]
	Int. Join. Conf. on Perv. and Ubi. Comp.			[300]			[300]	[300]			[300]	

Table 3.1: Table of all papers within the literature survey, listed in terms of the primary classification measures and grouped by journals and their associated disciplines

A	[21, 39, 175, 281, 306, 368]
B	[156, 211, 239, 240, 244, 280, 297, 304, 328, 338]
C	[156, 192, 211, 239, 240, 244, 280, 297, 328, 338, 402]
D	[192, 239, 304, 332, 338, 402]
E	[156, 211, 240, 244, 280, 297, 328]
F	[156, 239, 240, 244, 297, 304, 328, 332]
G	[168, 192, 211, 280, 338, 402]
H	[29, 73, 76, 133, 153, 163, 251, 259, 364]
I	[29, 73, 76, 133, 153, 163, 251, 259, 364]
J	[73, 76, 153, 163, 236, 259]
K	[29, 73, 76, 153, 163, 236, 251, 259]
L	[11, 18, 25, 69, 94, 104, 108, 137, 146, 148, 162, 186, 206, 223, 238, 283, 299, 319, 323, 337, 365, 375, 377, 381]
M	[45, 105, 237, 290, 315, 320, 398]
N	[11, 18, 25, 69, 94, 108, 137, 146, 148, 162, 186, 206, 223, 237, 283, 286, 290, 299, 315, 320, 323, 337, 377, 381]
O	[18, 69, 94, 105, 108, 137, 146, 148, 223, 238, 283, 286, 290, 320, 337, 375, 377]
P	[11, 25, 45, 98, 104, 162, 186, 206, 237, 299, 315, 323, 365, 381, 398]
Q	[11, 25, 45, 104, 105, 237, 299, 315, 320, 323, 365, 375, 377, 398]
R	[18, 69, 94, 98, 108, 137, 146, 148, 162, 186, 223, 238, 283, 286, 290, 319, 337, 381]

Table 3.2: Expanded citations for letter representations seen in table

3.4.1 Analysis

The 174 papers were examined by the lead researcher. The classification was fully explored beginning with the Core Classification, and followed on by Personalisation Outcomes and Further Observations. For each dimension, the paper was read through to determine where it best fit. In many instances, this was unclear due to the novelty of the terms and the heterogeneous terminology of the multiple disciplines the papers were sourced from, and classification was determined based on which best aligned with the available descriptions of the process. For further observations, this was more straightforward due to their non-discrete nature, as these elements were often taken near-verbatim from the paper to ensure accuracy within the classification.

Following the completion of the initial full paper classification, the results were examined by at least one other member of the research team to ensure agreement between reviewers and to clarify any issues where classifications did not align. This finalised the classification presented in this survey paper.

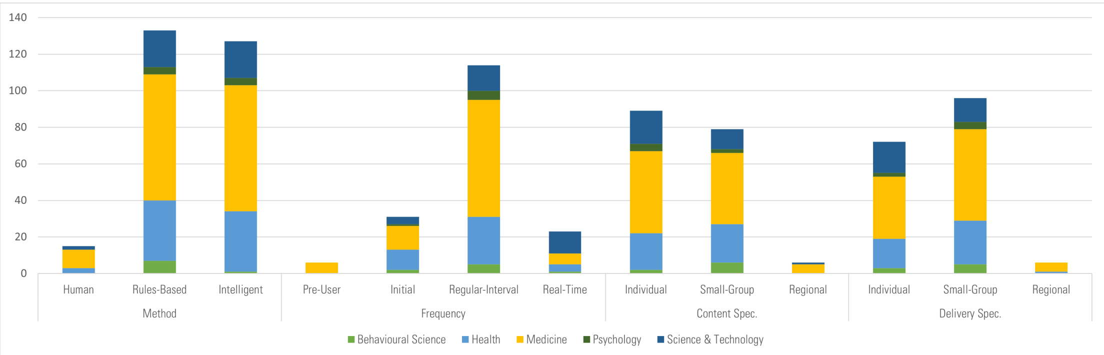


Figure 6: Totals of classifications grouped by journal discipline

Table 3.1 shows the full survey, listed under the primary classification characteristics of Method, Frequency and Specificity, grouped by journal and discipline. Table 3.2 expands any lists of citations which were too long to be presented in the table. This table helps show which disciplines are pursuing certain areas of the research space, as well as identifying at a glance which areas of the classification are highly populated and which present spaces that are either obvious areas to avoid, or uncovered areas of innovation and potential success.

Frequency	Method								
	Human			Rule-Based			Intelligent		
Pre-User	0	2	3	0	0	1	0	0	0
Initial	2	3	0	19	7	0	0	0	0
Regular-Interval	4	1	0	69	25	1	13	1	0
Real-Time	0	0	0	11	0	0	12	0	0
	Individual	Small-Group	Regional	Individual	Small-Group	Regional	Individual	Small-Group	Regional
	Specificity								

Figure 7: A heat map of all 174 papers in terms of their placement in the primary classification - Method, Frequency and Specificity. Red-Yellow-Green scale represents ascending numbers of papers

These areas to consider are further highlighted by Figure 7, which shows the overall spread of the landscape. This table provides the number of papers in each subset of the classification, with the heat map demonstrating where the majority of papers are clustered. This clustering shows some obvious spaces, such as the complete lack of Pre-User Individual interventions (as an individual cannot be tailored to before they are known), but also shows some interesting gaps or limited outputs to be further explored.

3.5 Survey Outcomes

The classification structure developed within this work describes four key elements that contribute to a system's personalisation - how the personalisation is conducted, how often it is updated, to what level of user it is personalised, and what data is used to drive this personalisation. By examining how these elements interact, we can find in what ways personalisation is currently approached, and find areas which are currently lacking exploration, potentially leading to uncovering possible areas of innovation.

3.5.1 Method, Frequency, Specificity

Rules-Based/Regular-Interval/Individual is the most common classification across the scope of the survey. This is closely followed by **Rules-Based/Regular-Interval/Small-Group** which presents a clear majority for **Rules-Based/Regular-Interval** systems. These systems would cover any that provide regular feedback or goals through system rules. The third most common classification of intervention systems was **Rules-Based/Initial/Individual** which further supports the clear focus on **Rules-Based** systems in this space while additionally suggesting that rule systems presenting an initial personalised profile on start-up are a popular approach to influencing health and behaviour.

There are several classifications with no interventions included. There are no interventions within the classifications of **Intelligent/Pre-User** or **Intelligent/Initial** as an intelligent system could not operate before regular user contact. **Intelligent/Regular-Interval/Individual** and **Intelligent/Real-Time/ Individual** represent 13 (7.5%) and 12 (6.9%) of the intervention space, and represent the vast majority of the **Intelligent** systems, which shows the expected

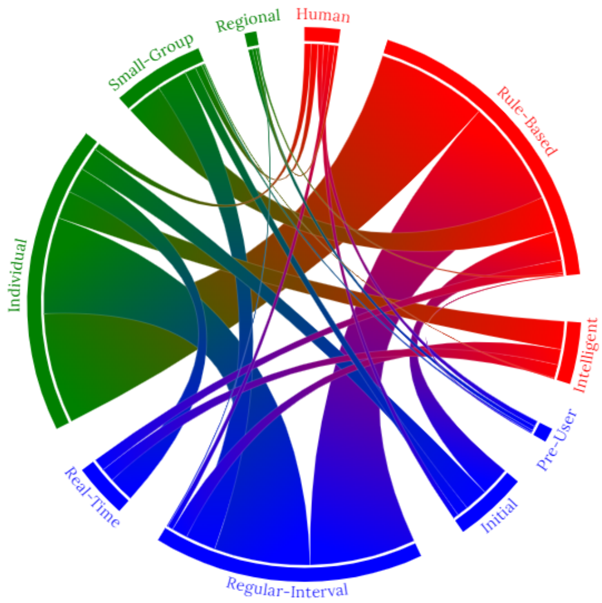


Figure 8: Chord Diagram illustrating the prevalence of connections between areas of Personalisation Typology

trend of **Intelligent** systems operating on **Individual** personalisation as the system would theoretically learn the necessary characteristics of an individual user rather than a collective group.

Figure 8 gives an alternative viewpoint of the space, namely in how different characteristics align with each other in terms of their overall prevalence. For example, It can be seen here that the vast majority of **Rule-Based** systems are **Regular-Interval** and **Individual**, although it can be seen at a glance here that **Rule-Based/Initial** systems are more common than **Rule-Based/Real-Time** systems which may provide more immediate benefit. To compare, Noar *et al.* tailor feedback to the lifestyle factors of the user through an onboarding quiz upon sign up [273], while Ali *et al.* use a rule-based reasoning algorithm built on the real-time collection of data to provide personalised recommendations for wellbeing and health management [9]. Both present lifestyle recommendations based on obtained user behavioural data, but Ali *et al.* [9] are able to alter these recommendations over time while Noar *et al.* [273] have to continuously rely on the potentially outdated information collected when first using the system, while cannot account for any behavioural progress.

Intelligent systems are predominantly **Individual** specificity, with the exception of Hors-Fraile *et al.* using the intelligent algorithms to align the likelihood of success of messages based on their content, without any individual content based on the user [166]. The focus on **Individual** allows for **Intelligent** systems to provide the greatest level of specific benefit to each user: Twardowski & Ryko use personal fitness levels and fatigue to recommend activities and intensities best suited to the user [358], Burns *et al.* create situational models to deliver appropriate mental health aid at the point of need [45] and Dharia *et al.* go so far as to use collaborative filtering to link individuals based on their specific behavioural habits, driving competition and increasing activity as a result [89].

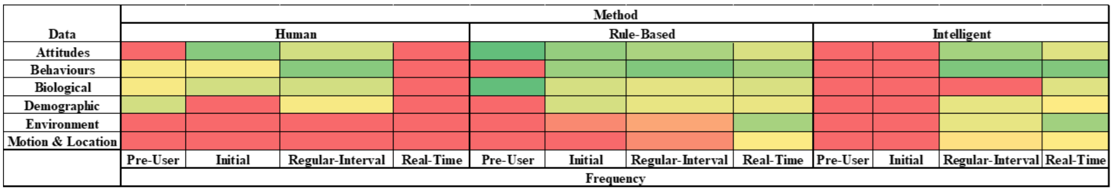


Figure 9: A heat map of the data types used in personalisation, compared against **Personalisation Method** and **Personalisation Frequency**

A point of interest is the relative frequency of **Human/Individual** and **Human /Regular-Interval** systems. There is no explicit negative to these systems in terms of their outcomes: These systems either had positive reported outcomes or no outcomes to speak of. However, one of the leading potential benefits of health personalisation is the reduction in financial and time expenditure, allowing for this money and time to be spent elsewhere to improve medical overall [243]. This benefit is realised by systems such as **Human/Initial** or **Human/Small-Group** as these allow for infrequent updating if not a single point of personalisation. **Human/Individual** and **Human/Regular-Interval** systems involve high levels of continuous human input, and many of these systems do not effectively harness the abilities of digital technologies - Pfirrmann *et al.* [286] and Charoensiriwath both present what is, in essence, a personalised fitness plan that only uses the digital system as a more convenient form of delivery, with the ability to input data without having to directly contact the clinician. Several of these systems could also see some benefit if they utilised the same approach with the advancements afforded by **Rule-Based** or **Intelligent** approaches. Fico *et al.* regularly assess and update manually developed plans and Kim *et al.* set activity intensities and overall goals based on comparisons between current activity and expected levels, both of which could be implemented as **Rule-Based** systems similar to those of Dobrican & Zampunieris tailoring exercise intensity based on biological feedback [91] or Downs *et al.* determining whether interventions continue as structured based on user progression [94]. Ingersoll *et al.* take some advantage of the digital medium, allowing for users to enter their own motivational content and overall aims of progression [172], but this still could benefit from the affordances of **Intelligent** approaches, such as those seen by D'Alfonso *et al.* tweaking user-generated content based on subsequent feedback [80] or Manuvinakurike *et al.* presenting motivational stories which are best aligned with stage of change and current progress [237].

3.5.2 Patterns in Data Types

The average number of **Data Types** is between 2 and 3 - an exact value of 2.35 - with **Behaviour** and **Attitudes** being the most prevalent of these. This makes sense as these would be the two main barriers to engaging in physical activity or other healthy behaviours, with **Behaviour** being the action itself and **Attitudes** covering factors such as motivation and intent.

Figure 9 shows a heat map representation of the types of data used in digital health and behaviour interventions, grouped by their uses in terms of **Personalisation Method** and **Personalisation Frequency**. The prevalence of **Attitudes** and **Behaviours** is clear to see here, with the two rows presenting the most green spaces and therefore the highest overall prevalence. The colour and therefore the usage of each data type is determined by column; For example, where Biological data is a deep green for **Rule-Based/Pre-User**, this is because there is only a single paper with the classification of **Rule-Based/Pre-User** and this work, an intervention by Samaan *et al.*, uses biomarkers determined by race and cultural background.

In the **Human** method space, as well as **Attitudes** and **Behaviours**, **Biological** data is frequent here. This usage of **Biological** data is typically focused around data on weight, such as seen by Cook *et al.* using a description of BMI to drive behaviour change [72] or Kim *et al.* comparing user height and weight to the average for their age and demographic [192]. There is also frequent use of **Demographic** data, especially in **Pre-User** systems which are more frequent in the **Human** method space than in **Rule-Based** or **Intelligent**. As well as the aforementioned use of expected body composition by demographic [192], Chung *et al.* use culturally-specific norms to tailor an intervention to try and improve the odds of positive outcomes [64]. These data types, as well as the complete lack of **Environment** and **Motion & Location** use, is to be expected as **Human** personalisation would be based heavily on data which is easily obtainable and can be used by an individual in a situation outside of direct response to intervention use. Factors like **Environment** are very useful to digital systems in **Regular-Interval** and **Real-Time**, such as by Hermens *et al.* generating adaptive goals and feedback which in part uses the current environment to determine best-fit, but these same factors cannot be used by **Human** personalisation systems as this information will likely be outdated by the time the designer has any chance to use them in the personalisation process.

All data types see use in the **Rule-Based** design space. **Biological** and **Attitudes** reduce in usage as the frequency progresses from **Pre-User** to **Real-Time**, likely due to the need for much of this data to be captured through user input, which becomes more of a burden on the user as the frequency of personalisation increases, especially since much of the information from **Biological** data input can be passively determined by **Motion & Location** data alongside further calculations e.g. using sensor-based PA data to determine progression during exercise activities [369] rather than relying on user-input times and intensities [238]. On the other hand, **Environment** and **Motion & Location** steadily increase due to their ability to be better utilised with greater automation and repetition allowing this data to be utilised at the point where it is most useful. Interventions like Finkelstein *et al.* recommending specific ways to be active based on workspace and time of day [113] and Attwood *et al.* marking specific weak spots where problem behaviours may be more likely to occur [21] show how this data can increase the scope of health interventions. However, the lack of this data in **Regular-Interval** systems where it can still prove effective, as well as the limited use of **Motion & Location** more generally, are gaps that may provide effective outcomes if explored.

Intelligent systems, comprising of only **Regular-Interval** and **Real-Time** subsets, show a generally similar spread to that of the equivalent **Rule-Based** approaches, showing that the change in method impacts less so the data used to guide interventions and more so how this data is used. A notable change is that

Figure 10: Chord Diagram illustrating prevalence of connections between data types and **Personalisation Method**

Motion & Location is more prominent in **Intelligent** approaches, likely because a system that can learn patterns in behaviour will better use live behavioural input than a system which has to preempt how these values factor into the overall process. Twardowski & Ryzko use **Motion & Location** alongside **Environment** to present suggestions for activity based on all surrounding factors to give the best chance of both following the suggestions and these suggestions resulting in positive behaviours [358]. Similar approaches are used by Lim *et al.* considering time and location in suggesting activities [222], and Aguilera *et al.* select feedback and motivational drivers not only on when they are most likely to be answered, but use differences in activity itself by time to drive the optimal levels of activity at a given time [5]. **Behaviours** are consistently high across methods, and this persists through the **Intelligent** classification, although there is potential for this data type to be more effective here - this data type is no longer just a report of the level of activity engaged in to fuel feedback, but can be used to directly train the algorithm and lead to better selection based on absolute outcomes, such as seen by Codreanu *et al.* selecting activities ranked by prior engagement and results [66] and from Zhou *et al.* using step counts and previous engagement levels to learn which approaches have the best chance of succeeding [402].

A potential gap in this space is the limited use of **Biological** data, especially in **Intelligent** systems. A good use of **Biological** in a similar space can be seen from Varadharajan *et al.*, who use heart rate to determine the suitability of exercise intensity for a given user, which can help guide safety in interventions. **Biological** data is useful in this regard not only as a tool for judging exactly how an intervention is progressing, such as by using Bluetooth-enabled devices to judge weight and using this to tweak the intervention [105, 239], but to ensure interventions are safe and suitable for the user, for example using heart-rate data to ensure heart rates after the prescribed intensity of exercise stay within safe levels [91].

Additionally, as discussed above, there may be more potential in **Intelligent** systems that is not currently being explored. Figure 10 shows a representation of how each data type is represented, with the relative thickness of each chord demonstrating the relative prevalence, e.g. **Rule-Based/Demographic** shows a significant number of the overall instances of **Demographic** data usage, but this is a relatively small section of the **Rule-Based** space which is dominated by **Behaviour** and **Attitudes**. The point of note here is that while we have discussed that **Environment** and **Motion & Location** increase in **Regular-Interval** and **Real-Time** systems compared to **Initial**, the split between the usage of this data in **Rule-Based** and **Intelligent** systems is seemingly even despite the additional potential for such data to be used by algorithms to learn patterns and time- or location-specific responses. These data types do form a larger part of the **Intelligent** space compared to **Rule-Based**, but the overall continued heavy reliance on **Behaviour** and **Attitudes** despite the noted issues that would arise as **Attitudes** data would be required more frequently and consistently indicates that the potential benefits of **Intelligent** systems are not be adequately explored.

		Personalisation Efficacy				User Interaction Experience				
		Positive Impact	Negative Impact	No Impact	None Reported	Positive Interaction	Negative Interaction	Neutral Interaction	Mixed Interaction	None Reported
Behaviour	Annals of Behavioural Medicine	[196]								[196]
	Behavioral Sciences			[67]						[67]
	Cognitive and Behavioral Practice				[23]					[23]
	Health Education & Behaviour				[15]				[15]	
	Jour. of Nutrition Edu. and Behavior	[189]								[189]
	Mindfulness			[216]						[216]
Health	Int.Jour. of Env. Research and Pub. Health	[53, 59, 373]			[85]	[53]				[59, 85, 373]
	BMC Public Health	[281]		[21]						[21, 281]
	Health Education Research	[90, 143]								[90, 143]
	Addiction			[242]						[242]
	Dbts. Educator			[157]						[157]
	Dbts., Met. Syn. & Obe..: Tgts. & Thrpy.	[249]								[249]
	Drug and Alcohol Dependence	[258]								[258]
	European Journal of Prev. Cardiology	[362]				[362]				
	Health Economics	[72]								[72]
	Health Informatics Journal			[136]						[136]
	Health Promotion International	[117]				[117]				
	Healthcare			[170]					[170]	
	IEEE Journal of Bio. and Health Info.				[111]	[111]				
	Int. Jour. of Cardiology			[197]						[197]
	JAMA Cardiology			[17]						[17]
	Jour. of School Health	[71]								[71]
	Netherlands Heart Journal	[132]								[132]
	Obesity	[313]				[313]				
	Pediatric, Allergy, Immu. and Pulm.				[106]	[106]				
	Tobacco Control	[379]								[379]
Medicine	Journal of Medical Internet Research	A_2		[25, 315] [365, 381]	[104, 319]	B_2			[18]	C_2
	JMIR mHealth and UHealth	D_2		[328]	[168, 239, 297]	[211, 240] [244, 332]			[297, 328]	[168, 192, 239] [280, 338, 402]
	Archives of Internal Medicine	[347]								[347]
	BMC Family Practice	[374]				[374]				
	BMC Neurology	[184]								[184]
	BMC Pregnancy and Childbirth	[155]				[155]				
	BMJ Open	[224]								[224]
	Critical Care	[46]								[46]
	Geriatric Nursing	[219]				[219]				
	Human Vaccines and Immunotherapeutics			[88]						[88]

	JMIR Medical Informatics	[183]			[183]		
	Journal of Pain and Symptom Management		[4]		[4]		
	Preventative Medicine		[334]				[334]
	The Lancet	[363]			[363]		
	The Lancet Diabetes and Endocrinology	[134]					[134]
Psy.	British Journal of Health Psychology	[38]			[38]		
	Psycho-Oncology	[384]					[384]
Sci./Tech.	PLoS ONE	[3, 74]		[263]	[74]		[3, 263]
	Int. Comp. Software and Apps. Conf.	[7]	[385]			[7]	[385]
	Computers in Biology and Medicine			[9]			[9]
	Computers in Human Behaviour		[298]				[298]
	Studies in Health Tech. and Info.	[113]					[113]
	Int. Join. Conf. on Perv. and Ubi. Comp.	[300]					[300]

Table 3.3: Table of all **Tested** papers within the literature survey, listed in terms of their efficacy and user experience outcomes and grouped by journals and their associated disciplines

A_2	[11, 18, 45, 64, 69, 105, 146, 162, 186, 206, 223, 237, 238, 290, 323, 337, 375, 377, 398, 399]
B_2	[11, 45, 64, 69, 105, 186, 206, 223, 237, 319, 323, 375, 398, 399]
C_2	[25, 104, 146, 162, 238, 290, 315, 337, 365, 377, 381]
D_2	[192, 211, 240, 244, 280, 332, 338, 402]

Table 3.4: Expanded citations for letter representations seen in table

3.5.3 Personalisation Outcomes

Table 3.3, similarly to Table 3.1, shows the papers within the survey grouped by journal and discipline. Table 3.3 shows the outcomes of all papers under the **Tested** classification, showing both efficacy and user experience to try and give some indication of whether certain disciplines see specific outcomes more frequently, or whether approaches may limit what is being seen. For example, papers in the disciplines of Health and Medicine see frequent exploration of both efficacy and user experience. However, Science & Technology papers more frequently see outcomes on efficacy while the majority of user experience outcomes are under the **None Reported** classification, suggesting a need for more exploration of user response to certain technologies within this field, especially as this is the field appearing to be most actively exploring **Intelligent** approaches in this space as seen in Table 3.1. Figures 11, 12 and 13 present the outcomes of **Tested** systems respective to their place within the Core Classification dimensions to identify whether these suggest trends in positive outcomes from how systems are developed.

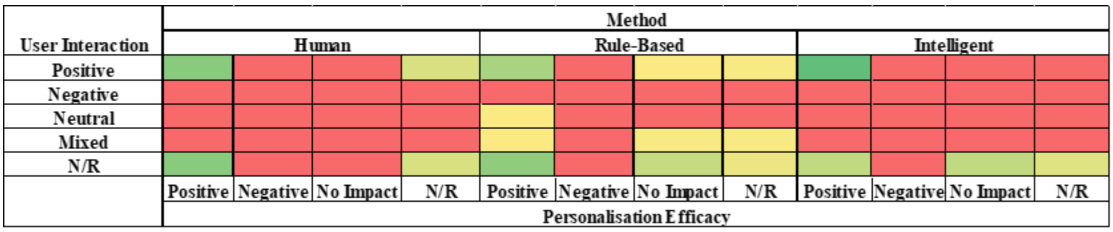


Figure 11: A heat map of all Tested papers, sorted by their efficacy and user experience outcomes respective to the Personalisation Method used

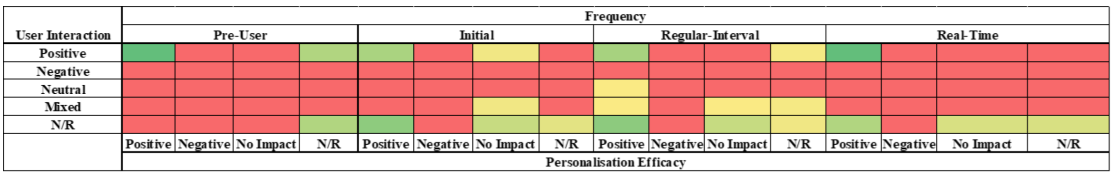


Figure 12: A heat map of all Tested papers, sorted by their efficacy and user experience outcomes respective to the Personalisation Frequency used

The majority (77%) of systems which reported on **Personalisation Efficacy** reported **Positive Impact**. The other 23% reported **No Impact**, with no tested interventions returning a **Negative Impact** on system efficacy. 100% of **Human Personalisation** systems with a reported **Personalisation Efficacy** reported a **Positive Impact**, with 75% for **Rules-Based Personalisation** systems and 78%

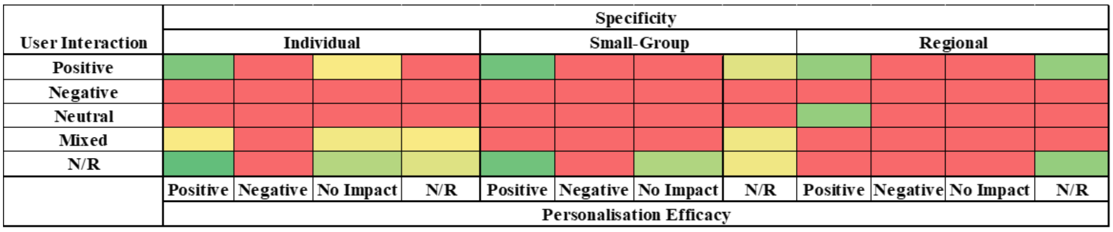


Figure 13: A heat map of all Tested papers, sorted by their efficacy and user experience outcomes respective to the Personalisation Specificity used

for **Intelligent Personalisation** systems. **Human Personalisation** systems are mostly tailored directly from user input to the users and therefore have little chance of being non-relevant and in turn ineffective compared to other approaches. **Rules-Based** and **Intelligent** systems are required to make calculations and present their personalisation based on received information and either pre-written or inferred rules, which leaves a greater chance of error and therefore a greater chance of limited or negligible impact.

There is no visible significant connection between **Personalisation Method** and **User Interaction Experience**. **User Interaction Experience** may align better with **Personalisation Approach**, as this is more down to the specific connection to the user rather than the mechanical elements of personalisation. There are, however, interesting insights regarding the few responses that do not report a **Positive Interaction** with the system. Papers typically focus on either feasibility and acceptability or the efficacy of personalisation over a typical system, but rarely both with efficacy being a more popular outcome to track. Systems which report an interaction outcome for **Human** and **Intelligent** systems are 100% positive, but **Rules-Based** systems return a wider range of responses with a number of **Mixed Interaction** and **Neutral Interaction** responses. This could be due to the nature of an **Rules-Based** system positioning itself as a system that attempts to automate the process of personalisation but does not actively learn the characteristics and needs of the connected user. This coupled with the possible expectations of a system more akin to a **Intelligent** personalisation intervention could result in lapses in accuracy being viewed more critically.

3.6 Further Observations

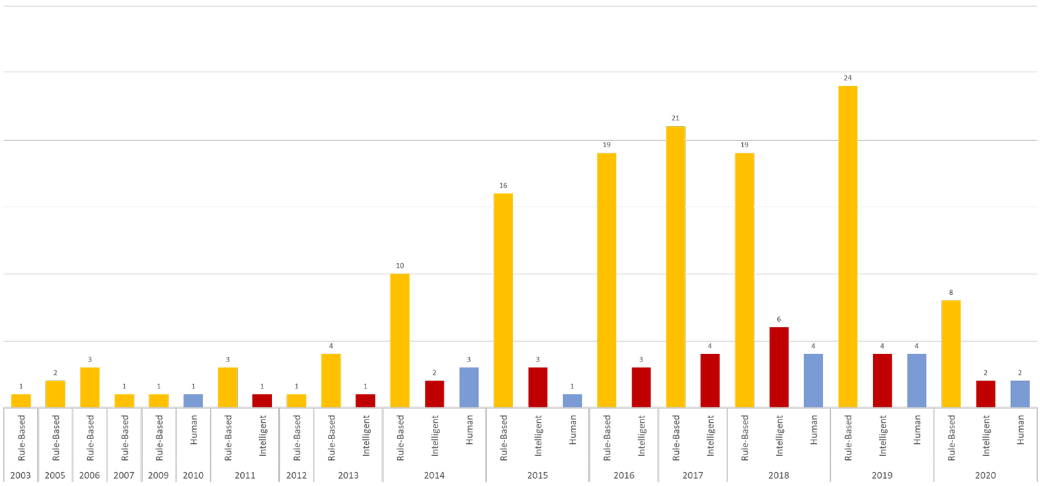


Figure 14: Totals of publications by year, divided by **Personalisation Method**

Figure 14 shows the distribution of dates of publication. The majority of papers in this survey are published between 2014 and 2019 inclusively, with 143 of the 174 (82%) published in these years. The number of papers shows a major increase in 2014 (from 5 in 2013 to 15) and increases up until a peak of 32 papers in 2019 before a significant drop to 12 publications in 2020. A drop in 2020 is expected given the significant impact of COVID-19 in heavily user-focused fields such as health and behaviour interventions. This theory is partially supported by two-thirds (8/12) of papers published in 2020 presenting **Untested** systems which would be unable to be tested under COVID-19 regulations. However, this **Untested** majority is not solely visible in 2020; From 2017 onward, the majority of papers published are presenting **Untested** systems, with **Rules-Based** and **Human** personalisation making up the majority of these systems. Across the scope of the survey, the balance of **Tested** and **Untested** systems is relatively even across all **Personalisation Methods**. As progressing from **Theoretical** to **Untested** to **Tested** is a linear process, this balance of systems suggests that the intervention space is growing year on year, both in terms of newer systems entering the loop and systems progressing to testing. Building on this, the stable number of **Theoretical** systems suggests that as well as the overall size of the space increasing year on year, technology is advancing in parallel, increasing the ability for innovative systems to transition into tangible, **Untested** systems. This is supported by six of the seven **Theoretical** systems being **Intelligent** personalisation systems, suggesting that there are some proposed systems now that are exploring the potential of future systems where intelligent algorithms can truly flourish. The technology to realise these systems is advancing, but these ideas are not yet possible or feasible to implement with current technology.

There is no significant change in the number of **Data Types** used in interventions by year, as the data required is heavily dependent on the nature of the intervention which is unlikely to change on a year-by-year basis. The occurrence of certain **Data Types** does not notably change from year to year. The only notable change is the increasing prevalence of **Biological** data, which could be due to a greater understanding of biological determinants associated with target behaviours. This increase could also be due to a greater ability to utilise such data either through dedicated sensors or system features making use of such information, such as Lim *et al.* using dedicated trackers for biological data to examine changes between learned user models and activity observed [222]. The most common approach to obtaining data is through user input, be this entry questionnaires [25, 198, 219] or regular input of required data such as weight values or activity levels [28,114,148,153]. The prevalence of data input methods varies by **Personalisation Method**. **Rules-Based** personalisation is primarily user input since the regularity of the personalisation means regularly requested self-report data is sufficient. **Human** personalisation is based mainly on large-scale data intake, such as demographic insights or condition-specific information [64, 98, 371, 399], although there are some instances of user input where a system is manually tailored on a **Initial** or **Regular-Interval** basis [72, 172, 192, 236, 250, 286, 332]. **Intelligent** personalisation is more evenly split between user input data and data obtained through application tracking or sensor inputs. Sensor intake allows the data to be obtained and utilised much more frequently to facilitate the high-frequency personalisation required of an intelligent system. User input is reserved mainly for **Intelligent** systems that run on a **Regular-Interval** frequency, and just under half of these also utilise some form of sensor input; The only user input system that runs on a **Real-Time** frequency combines this input with sensor readings to gather necessary tailoring data not obtainable through sensors [45,89,99,222,300,358,398].

The split of **Personalisation Specificity** into **Intervention Content Specificity** and **Intervention Delivery Specificity** creates interesting insights regarding how systems approach tailoring their interventions. The most common combination is **Individual/Small-Group**, this representing individually-personalised content and the delivery personalised to a small-group level. This represents, for example, a system that creates individualised feedback or goals which are presented in uniform intervals for the user group. Following this, the second most common combination is **Small-Group/Individual** which would represent the inverse: materials for a range of individuals (commonly on behaviours or mental barriers) which is delivered on an individual basis, be it upon the completion of an activity or in the event of a context-specific occurrence. These combinations represent the majority of systems, representing 63% of the total interventions. This is an expected majority of the scope, covering interventions with an individually personalised component but without the difficult implementation of a completely individual system. This can be seen when comparing the numbers of **Individual** personalised systems: The broader classification of **Personalisation Specificity** categorises 130 of the 174 systems (75%) as **Individual**, while only 25 systems (14%) have an **Individual** categorisation for both content and delivery specificity. **Small-Group/Small-Group** represents 30 of the 174 systems (17%). A possible explanation of this small number is that implementing a single **Individual** personalisation is feasible and that the benefits of this personalisation are worth any difficulties when compared to combined **Small-Group** personalisations. The related **Personalisation Efficacy** is higher for systems where the **Intervention Content Specificity** is tailored to an **Individual** level, with positive responses for 89% of **Individual/Individual** systems and 83% for **Individual/Small-**

Group systems compared to 50% for **Small-Group/Individual** systems and 55% for **Small-Group/Small-Group** systems. These values contradict the earlier statement that a single approach to **Individual** personalisation is better than none and further emphasises the impact that individual personalisation for the **Intervention Content Specificity** can have.

Intelligent systems utilise a range of machine learning approaches to allow for them to learn user patterns and produce informed intervention content. There is evidence of both supervised and unsupervised learning being used for a variety of intervention purposes. Intelligent Recommender Systems were the most common, in 12% (3/26) of papers. These systems used their intelligent insights to recommend activities and associated aides based on user ability [358], recommend goals based on the learned ability and direction of user improvement [284] or recommend messages with high chances of success based on user interactions [166]. This latter implementation can also be seen in the multiple uses of Reinforcement Learning algorithms within interventions. El-Hassouni *et al.* use reinforcement learning to learn best practice regarding exercises and timings of suggestions based on user needs and user actions [99], and Yom-Tov *et al.* use the same approach to select messages with the highest chance of success based on previous observed impact [398]. This same use of reinforcement learning can be seen from Aguilera *et al.*, although this implementation also employs Thompson Sampling to work with predicted success based on contextual factors relating to the messages and their content [5]. An explore/exploit system is used by Rabbi *et al.* in their intervention, using accumulated knowledge of diet and exercise choices to push effective positive choices further [300]. Some learning approaches make use of other users as well; Ahsan *et al.* use a recommender engine which makes decisions based upon the Euclidean Distance similarity between users, with the messages received by a given user weighted according to their similarity to other users who have responded positively [6]. A supervised machine learning algorithm trained by Decision Tree is used to assign 'fitness buddies' in the intervention presented by Dharia *et al.*, filtering user profiles and matching users and recommending activities through learned user characteristics. [89]. There are limited examples of unsupervised learning present in this domain; Hermens *et al.* make use of a k-nearest-neighbour approach to provide adaptive message timing, content and goals to their system using previous responses and previous spread of actions and activity levels [160].

3.6.1 Classification of Innovative Systems

This classification topology allows for the comparison and alignment of intervention research with the vision of the future of intelligent digital interventions as presented in Figure 2. The exact classification deemed in line with the presented ideal is as follows:

- **Personalisation Method**: **Intelligent**
- **Personalisation Frequency**: **Real-Time**
- **Personalisation Specificity**: **Individual**

- **Intervention Content Specificity** & **Intervention Delivery Specificity**: **Individual**

This represents a truly individualised system running in real-time through intelligent algorithms, which we believe would present the greatest chance of intervention success. Seven systems (0.04%) fit this criteria. This represents a very minimal subset of the overall space, but the fact that these systems are present and observable demonstrates that this innovative space is being explored. The minimal occurrence of these systems can be seen in the state of these systems, with four of the seven being **Theoretical** and a further one being **Untested**. The two that are **Tested** both report positive results for both **Personalisation Efficacy** and **User Interaction Experience**, which gives credence to this being the clear direction of the future of the field. These **Intelligent** systems all utilise sensor intake as a major component of their data collection for personalisation, with four of the seven systems also making use of user input for data such as demographics or psychosocial data.

All seven systems in this subset utilise **Environment** data, as well as **Behaviours**. **Behaviours** are widely common, previously acknowledged as the most prevalent of the **Data Types** and a necessary type of data for a behaviour change intervention, but only 28 of the 174 interventions make use of **Environment**. One-quarter of the interventions that make use of **Environment** are within this innovative space, which suggests the use of context and automatically tailoring systems to the environment around the user is a key part of the future of effective personalisation. These systems are implemented mostly as mobile applications, making use of accelerometers, GPS and contextual information stored on a device such as calendar data. This readily available data and selection of platform allows **Real-Time** elements of the system to continuously assist the user, as they are present on a device that for the most part is a constant presence in the behaviours of the user.

3.7 Refinement of Key Components

3.7.1 Concepts of Personalisation

Much of the work in this survey considers the mechanical side of personalisation, regarding the means of personalisation, the data used and the place of the system in the wider contextual environment. This thesis will refer to such concepts as the **'physical'** side of personalisation, relating to the mechanisms of how personalisation is conducted, actioned and interacted with through our five senses. However, there is another side to be considered, which is the **'mental'** side - this relates to factors such as user values, feelings and motivations, or the internal drive to engage which personalisation can target. This can be seen to mirror the concepts of intrinsic and extrinsic motivation, considering both the internal push and the external pull to drive behaviour. The **Further Observations** of this classification system make some effort to capture this mental side of personalisation, especially in capturing the **Personalisation Approach**, but this is often non-discrete and difficult to compare across different systems as many may use similar mechanics, but implemented or described in vastly different ways. There are some frameworks which exist to try and quantify these ideas, one of which is the framework of Behaviour Change Techniques (BCTs).

BCTs are widely used in the field of behavioural science as a means through which to examine and design interventions for changing behaviours. The most straightforward definition of a BCT is “a systematic procedure included as an active component of an intervention designed to change behaviour" [253] - that is, a technique to change behaviour. The more commonly used definition, and the one that will be used as a standard within this thesis, is “an observable, replicable and irreducible component of an intervention designed to alter or redirect causal processes that regulate behaviour; that is, a technique is proposed to be an active ingredient” [254]. These BCTs range from simplistic methods such as ‘Goal Setting (Behaviour)’, which is as straightforward as setting a behavioural goal (the standard goal of ten thousand steps a day is a perfect example of this specific technique), to more complex examples such as ‘Paradoxical Instructions’ where over-indulgence in behaviour is used to encourage reduced desire to engage in the behaviour (smoking twice as many cigarettes a day or eating twice as much food as typically eaten to induce a negative association).

Preferences and values of users have a notable effect on the outcomes of digital behaviour change interventions [36], which in turn affects how combinations of techniques affect a user - as an additive to the interplay between techniques, the individual applicability of the techniques themselves will have a significant impact on the overall acceptability of the system. The use of multiple behaviour change techniques within a single intervention is well documented and has been observed to have a significant effect on both immediate intervention outcomes [93, 296] and long-term change, especially when larger numbers of techniques are used compared to a single or small collection of techniques [275]. As well as the benefits of additional avenues to changing behaviour, there is research into how certain combinations of behaviour change techniques may provide a greater impact due to interplay [36], such as combining techniques that elicit fear or extreme reactions with technique that increase response efficacy [285], or the idea of combining health or lifestyle education techniques with techniques such as ‘Action Planning’ or ‘Shaping’ which improve the ability of the recipient to put these educational outcomes into practice [70].

3.7.2 Conceptual Blueprint for Behaviour Change Systems

The work conducted in this survey allows us to expand upon the key components presented in Figure 2. Whereas the original diagram is highly abstract and based on general concepts of design and development, the developed conceptual blueprint can align the presented ideas more closely with the information uncovered by this survey. This system can then be used to guide the rest of this thesis, using it as a conceptual foundation from which research can branch off and the potential of such a system can be explored. This updated conceptual blueprint can be seen in Figure 15.

This conceptual blueprint utilises some of the information gathered from the survey. The ‘Techniques’ allow for different approaches to be considered, as many different approaches to changing behaviour within this survey are seen to return

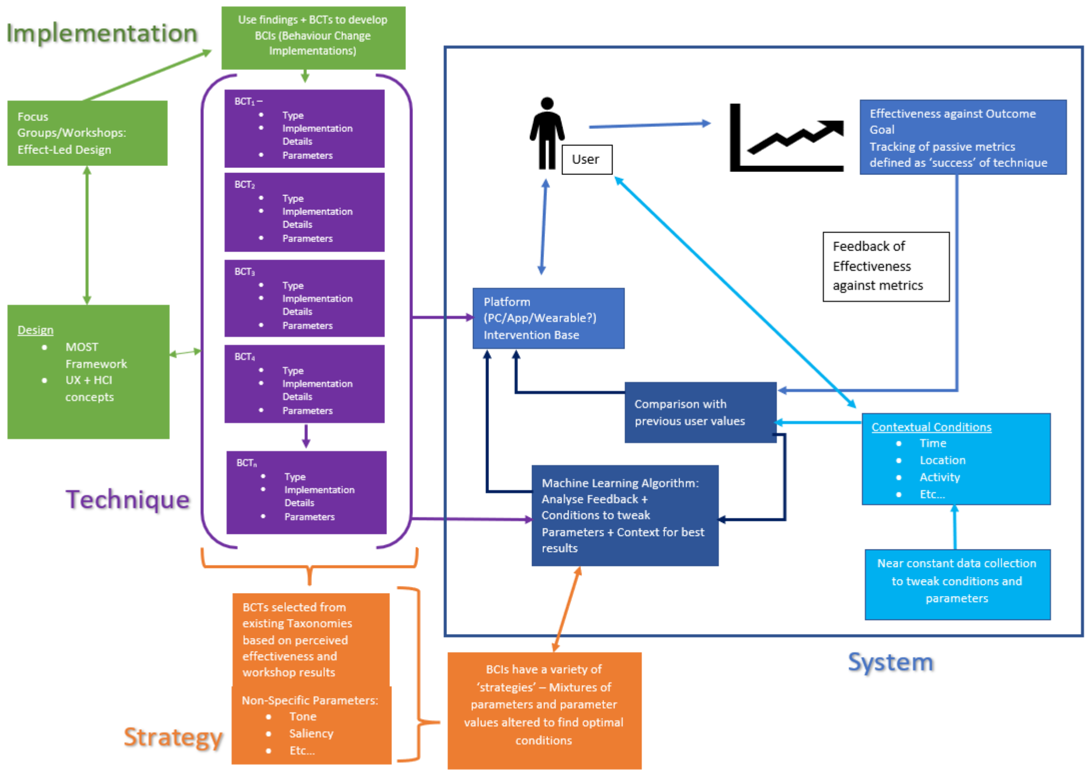


Figure 15: Developed conceptual blueprint, including updates based on survey findings

positive results and these may differ depending on the individual. Accounting for a wide variety of techniques also reflects the non-discrete nature of the **Approach to Personalisation** observation within the typology, as a wide variety of approaches were observed with mixed levels of efficacy, and many of these could be effective for certain users. The 'Implementation' section allows for the inclusion of the best qualities of **Human**-method systems, to ensure these approaches are optimally designed prior to inclusion in the system. By carefully analysing the methods of design described in not only **Human** systems but in systems with *Pre-User* classifications which would heavily involve human design in their approaches, we can find the best approaches for designs which balance positive efficacy with positive user experience. 'Strategy' can utilise different approaches to behaviour and the use of many data types to conduct many different approaches to personalisation as seen in the survey. The 'System' itself uses the **Intelligent** aspect of personalisation to learn behaviours, including multiple data types and focusing on an **Individual** level as seen to be prominent in the space. The non-specificity of the elements within this system, such as platform and machine learning algorithm, again reflects the high amount of variance as demonstrated by the **Personalisation Algorithm** and **System Platform & Included Devices** observations which means these may be heavily dependent on context and user needs. This conceptual blueprint also integrates **Environment** and **Motion & Location** data types, ensuring the intelligent elements of the system can best utilise all available data for personalising approaches to behaviour change.

This conceptual blueprint is presented to challenge the current approach to personalised intervention design. The outcomes of the survey illustrate that the current focus of the landscape is heavily skewed towards **Rule-Based/Regular-Interval** systems, which while effective, may not be utilising the full potential afforded by digital behaviour change solutions. The content of this conceptual blueprint should be taken forward as a core point of consideration in future design, especially in its central inclusion of AI, to trend system design towards this **Intelligent/Real-Time** standard described above.

Several systems in the current research landscape begin to explore some of the ideas presented here. An effective approach to intelligent interventions, the main path of progression as described here, is Just In Time Adaptive Interventions (JITAIs). A JITAI uses system intelligence to react to user action and context to provide intervention assistance at the exact time when it is required, or in other words, 'just in time'. JITAIs are proposed as an effective means to capitalise on intervention engagement and avoid intervention burnout. King *et al.* describe intervention engagement as a state in flux due to interactions between the user, the intervention, and the surrounding context [194]. The intelligent timing of a JITAI is used to combat changes in user and context that may bring about burnout by providing intervention content only at the point of requirement. This context-aware, time-sensitive approach to behaviour shows the potential to outperform doctors or other human actions due to the increased ability to provide helpful feedback at the point of optimal influence [353].

This potential for real-time adaption is explored by Piette *et al.* using SMS messages to promote adherence in medication usage, with these messages being tailored using reinforcement learning to target specific adherence barriers unique to each user. This was perceived to be effective, with a potential absolute improvement to adherence of 5-14% [288]. However, there are some potential issues with JITAIs. Nahum-Shani *et al.* express difficulties in aligning the static and stable nature of theoretical perspectives on behaviour with the dynamic and ever-shifting nature of human behaviour and behavioural requirements that can prevent such systems utilising their theoretical basis effectively [266]. Hardeman *et al.* found issues in the space with reliability and timeliness of just-in-time content, as well as a lack of evidence on reach and sustained engagement [150]. Hardeman also present information in slight conflict with that of Nahum-Shani *et al.* - Where Nahum-Shani *et al.* commented on a key issue of the space being the difficulty of integrating theoretical underpinnings of research into the applications, Hardeman *et al.* found the majority of JITAIs appeared to be designed with no evidence base in mind at all [150, 266].

An approach to best aligning theory-based approaches with contextual considerations is the Multiphase Optimisation System (MOST). The MOST framework was first presented by Collins *et al.* as a method to more effectively develop high-efficacy eHealth interventions [68]. MOST presents the means to refine a set of techniques or concepts into an optimal design. This framework is intended to be completed multiple times before implementation, trialling multiple techniques and multiple conditions in which these techniques are presented to find the best combination, which will in turn give the optimal intervention outcomes.

An issue that can arise within the design of behaviour change interventions even with ideas such as the MOST framework is the issue of *individual* response to system content. The work of De Roos & Brennan [87] presents estimated engagement with a given intervention at 40% of the potential user base. This means that an intelligent, contextually aware system tailoring a single approach would still struggle to overcome this 40% cap on user interest. There are a range of possible reasons for this limit on engagement and overall effectiveness. Tang & Braver in their research on mindfulness interventions found that differences in individual traits, psychological well-being and cognitive functions contributed to “the heterogeneity in mindfulness training effects across individuals" [346]. Part of this issue may be due to the 'ergodicity problem', an obstacle in designing for population health. Lowie & Verspoor outline this problem, which describes that there are key differences between individuals and groups, and as such statistics collected from one group cannot be directly generalised to the other [225]. The majority of behavioural interventions are delivered to large groups with a given health need or condition, and any observed effectiveness is typically then directly applied to the technique. This effectiveness in large-scale interventions, however, does not guarantee this technique will be effective for the individual. As such, even techniques seen to be widely successful may see no effect for a given individual if user needs and the merits of the technique do not align. Advances in intervention design therefore must be centered around how to design a system in such a way that this 40% are given the best possible example of the intervention in front of them, while the remaining 60% are able to benefit in other ways.

3.8 Discussion

The classification topology and further observations outlined in this survey provide the means to observe trends in personalised digital behaviour change and outline where the potential exists for innovation both in terms of effective current interventions and the directions that future interventions may be taking, reflected in theoretical and untested systems within the research landscape. This taxonomy classifies systems in terms of how the personalisation is achieved, how frequently it is tailored and to which level of specificity personalised materials target. It is further augmented by a number of observations as to intervention status and effectiveness, and the data utilised by these interventions to achieve their personalisation.

The classification of 174 papers covering digital personalised interventions in the space of health and behaviour change shows a preference towards **Rules-Based** systems. This may be due to difficulties in generating machine learning algorithms that can produce effective personalised content. Issues such as implementing machine learning linked to a mobile application or integrated into the foundation of the application, as well as required learning times need to be resolved before **Intelligent** interventions can become the expected norm within the space. However, systems classed as 'innovative' show that such systems are currently an emerging focus within the space. The vast majority of interventions are classified as **Regular-Interval** interventions. This pairing suggests a common set-up of a set of rules or coded statements that are executed on regular fixed intervals to generate the personalised content, which would allow for fixed calculations and avoid issues stemming from irregular data flow or the requirement of live adaptation. **Individual** personalisation is the most common specificity, as the ideal level to aspire for regarding specificity is of course to the individual user. However, separating this into content and delivery reveals that a mixture of **Individual** and **Small-Group** is much more common, while both being individually tailored is rare but highly effective.

The findings of Chapter 3 present several gaps in the current research landscape regarding health and behaviour change applications, specifically those utilising intelligent solutions and contextual and environmental data. The conceptual blueprint presented here represents the means to best explore these gaps, and push forward the field of intelligent personalised digital behaviour change to promote greater levels of personalisation and personalisation efficacy.

3.9 Chapter Summary

This chapter presented a literature survey which explored existing personalised approaches to digital behaviour change by defining a typology within the space and using this new classification framework to structure the relatively new and unstructured space of personalised behaviour change. This survey unearthed some interesting gaps within the literature, especially around the use of intelligent algorithms which was a small but highly effective space within the classification. This chapter also presented the conceptual blueprint which functions both as a contribution to help guide future design and as a structural piece which will guide the remainder of the thesis.

The next chapter, Chapter 4, presents Effect-Led Design, a design process developed as part of this thesis to help guide designing for effective behaviour change using intelligent algorithms and behaviour change techniques as core, structural elements. This process reflects the ‘Technique’ and ‘Implementation’ sections of the conceptual blueprint.

CHAPTER 4

EFFECT-LED DESIGN FOR INTELLIGENT BEHAVIOUR CHANGE

The 'Implementation' section of the conceptual blueprint outlined in Chapter 3 outlines the need to explore theory-based intervention design. Furthermore, this focus on theory also allows for a wider exploration of the technique space, past what is currently observed in the contemporary intervention space. This is a necessary change to the process of intervention design as substantial success is rare [262] despite hundreds of examples of digital behaviour change interventions [342]. Less than 20% of users return by the end of day one to new fitness tracking apps and only 7% of users return to health trackers by day 30 [152]. As outlined in the conceptual blueprint (Figure 15), the path we consider for aligning theory with design is the greater inclusion of Behaviour Change Techniques as a central element of system design.

This chapter presents **Effect-Led Design**, a new process for approaching design which places a greater focus on efficacy and the inclusion of intelligent solutions. The chapter first outlines the purpose and usage of Behaviour Change Techniques, as well as examples of blending participatory design and AI design for digital systems. An exploratory study is reported upon in which experts and users were asked to work first individually, and then collaboratively, to develop high-efficacy concepts for behaviour change which still maintained a strong sense of user values. This was developed into the Effect-Led Design process, which was then compared against Value Sensitive Design in terms of the core principles of the process.

This chapter, and the process of **Effect-Led Design**, serve to answer questions *SQ2* and *RQ1* by extension:

- *SQ2*: How can current intervention approaches be redesigned to best harness the potential for innovation afforded by machine learning?
- *RQ1*: Will the approach of pre-design in the focus space of behaviour change theory result in more effective technique designs, and will these present patterns in desired techniques and approaches to using these techniques that work within the scope of the system?

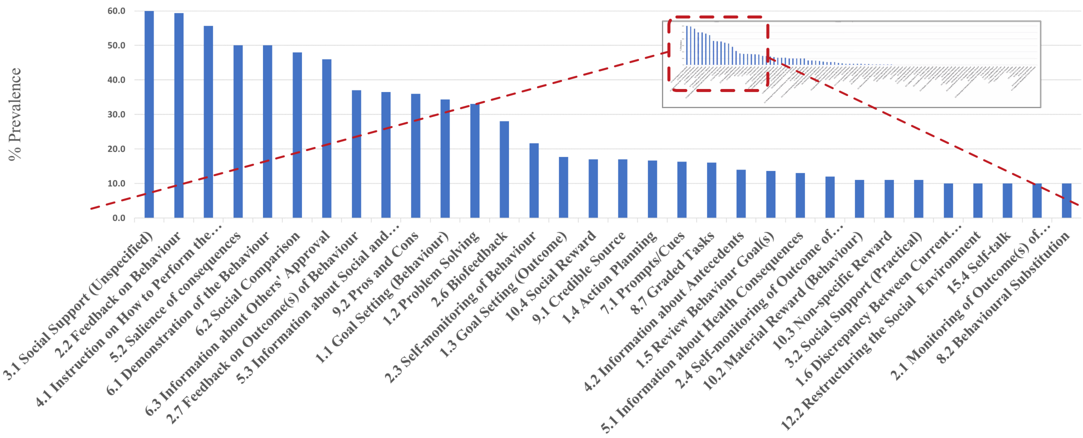


Figure 16: Behaviour Change Techniques by prevalence, the zoomed area shows the top third by percentage of applications they are used in while the un-zoomed area shows the prevalence of all 93 Behaviour Change Techniques, with a long tail of under and unused techniques. n.b. applications can use more than one technique, totals do not come to 100%. Accumulated calculation from [70,125,396]

Establishing a design method which attempts to remove potential blockers within existing design methods allows for more creative approaches which better harness innovation and efficacy to emerge from a participatory design framework. Addressing *RQ1* specifically, the process here uses theory-based behaviour change techniques to guide initial design decisions, with the aim of both developing efficacy-driven designs built up from established theory and unearthing connections between certain techniques and what domain experts see as effective approaches which could indicate paths to higher efficacy through certain techniques in future iterations of design.

4.1 Behaviour Change Technique Prevalence in Contemporary Applications

Behaviour change techniques in contemporary applications (mobile applications targeted at health and wellbeing behaviour change, downloadable as of the time of the study) appear to be chosen because of their prevalence in other popular, contemporary apps and not because of any strong evidence of efficacy. Our analysis of BCT prevalence from [70, 125, 396] shows that technique distribution is heavily skewed (see Figure 16), supporting Yang *et al's* claim that physical activity applications appear to favour techniques with modest to poor evidence of efficacy over techniques with more established evidence bases [396]. For example, educational techniques are widespread in digital behaviour change, but techniques to convert this education into constructive change such as 'Action Planning' (4% prevalence), 'Shaping' (1% prevalence) and 'Motivational Interviewing' (0% prevalence) are rarely deployed [70]. Garnett *et al.* observed that BCTs with proven efficacy were infrequently included, such as 'Self-Monitoring of Behaviour' (29%) and 'Goal Setting (Outcome)' (12%) [125].

There is potential for missed innovation in this space due to the reuse of a small subset of the many available, evidence-based behaviour change techniques. Several effective behaviour change approaches are ignored, potentially because of difficulties in implementing them or because of a lack of awareness of the full range of available techniques. An emerging avenue of research, as seen from our survey in Chapter 3, is focusing on the efficacy of behaviour change applications with Machine Learning (ML), tailoring the experiences of behaviour change to individuals. Furthermore, we believe that widening the design space of behaviour change applications so that designers adopt more interesting, effective techniques would also address the lack of efficacy.

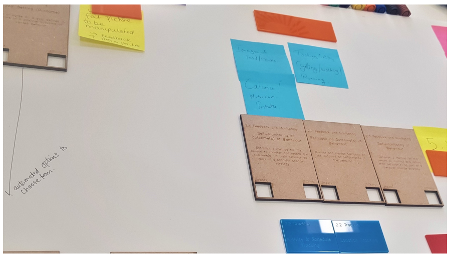
Our research to combine both of these approaches encountered three new challenges. First, linking deliberate alteration of behaviour by an application with machine learning, which users associate with horror stories about rogue artificial intelligence, led to negative responses. Second, designers were reluctant to move out of their comfort zones even at the outset of design and their experiments with more diverse behaviour change techniques were limited. Third, in working with designers and users we observed the values designers embedded into their designs were not aligned with the values that users expressed. When considering trade-offs between efficacy and privacy, designers' decisions were more conservative than users. These three issues resulted in ineffective designs that didn't respect the values of the end-users.

To better approach the space of intelligent intervention design, we have developed **Effect-Led Design** - a participatory design process for domain experts and future users that encourages maximising effect whilst flouting values with domain experts, leading to a range of novel and even absurd design concepts which expand design spaces. These exaggerated design concepts are presented to future users to encourage dialogue about values and effect, ultimately leading to more innovative, acceptable, and effective behaviour change designs.

4.2 Exploratory Study - Designing Intelligent Behaviour Change Implementations

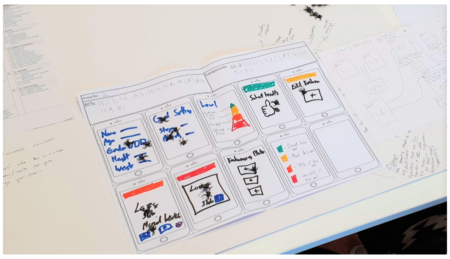
Our first work in this area was an exploratory participatory design study with domain experts taking on participant-designer roles and participant-users. We investigated how we could expand the design space for an intelligent behaviour change system by focusing the approach on 1) the diversity of evidence-based BCTs available and 2) encouraging the experts to deliberately flout what they perceived user values to be in the pursuit of maximum efficacy. The approach tried to encourage a humorous attitude to offset any negativity from the flouting of user values with domain experts encouraged to treat more egregious concepts as jokes. This was supported with playful concepts that mimicked board games such as wooden playing cards representing BCTs, spider tokens for scoring creepiness and dice tokens for scoring designs, as seen in Figure 17a and 17b.

The study included six domain-expert participant-designers from HCI/Interaction Design, two from Sports Science and one from Psychology with a background in behaviour change. Four participant-users took part in the second day with a 50/50 Male/Female split. Participants were university graduates, with prior interests in



(a) BCT and System Feature Cards in use

(b) Spider token system as used by participants



(c) User notes and workings during analysis

(d) Noted alterations made during design

Figure 17: Outputs of the Exploratory Study

becoming more physically active.

In stage one, the three groups of participant-designers were given a presentation outlining challenges in behaviour change and describing the PD process's purpose as being to expand design space and explore AI-driven approaches to behaviour change. Participant-designers brainstormed success metrics to help them select what they thought would be the most effective BCTs from the wooden BCT cards in Figure 17a. This process took 90 minutes plus breaks. They then used the wooden BCT cards to create three concept, progressively shifting the focus to efficacy at the expense of ethical considerations, starting from an **Everyday** design, moving to **Extreme** and finishing by creating a design concept to increase physical activity that they thought was *Cartoonishly* **Evil**. Each design was developed over one hour. To conclude stage one, each group presented storyboards showing their three systems, and other groups voted on the presented concepts in terms of their impact on the target behaviour and their perceived ease of implementation.

In stage two (conducted three days later) participant-users of the system provided critiques of the storyboards through discussions, written notes and the use of the creepiness-measuring spider-tokens in Figure 17b on storyboards to show what they thought were the creepiest aspects of the system over the course of two hours. Finally, participant-designers and participant-users collaborated in a third stage to discuss their concepts and to try to amalgamate their three designs into one effective, acceptable design.

BCT usage was captured from the participant-designers through their storyboards, and through discussion following the creation of the concepts. Impact and Ease of Implementation were captured on a scale of 1-6 using dice tokens (not rolled at random but to align with the study theming). All discussions from participant-users and participant-designers were recorded during both days of the study to identify thoughts behind design and discussions on values in the moment rather than after the fact. Participant-designers were also interviewed upon the conclusion of the second day to understand their thoughts on the process. All discussions were thematically analysed based on characteristics outlined in Section 4.2.3.

4.2.1 Stage 1 Results: Efficacy-Driven Expert Designs

Nine designs were produced by the three groups of experts made up of one Behaviour Change and two HCI professionals. They are labelled as $G_x - C_y$, where x is the group (1-3) and y is the specific concept brief: **Everyday**, **Extreme** or *cartoonishly* **Evil**. In the list below, the developed concepts and approaches to behaviour change are described.

Everyday Concepts

- $G_1 - C_{everyday}$: Users sign a contract with the device agreeing to behaviour targets and receive videos from either themselves or other users praising adherence.
- $G_2 - C_{everyday}$: Augmented reality (AR) overlays scores for taking steps on stairs, and leverages social comparison through AR leader boards that move location, organically increasing step count.
- $G_3 - C_{everyday}$: A picture of the user is edited with 'future predictions' based on activity increasing body fat if the user failed to meet their goals, or decreasing it when they met the goals.

Extreme Efficacy Concepts

- $G_1 - C_{extreme}$: A standing desk changes height based on behaviour change metrics: more adherence means a more suitable height while AR feedback is presented on desktop monitors. Failure is visualised to workplace peers leveraging social guilt.
- $G_2 - C_{extreme}$: Users generate insults and embarrassing content which are posted to social media to elicit social guilt and embarrassment when not meeting goals. Good behaviour gives the option to contribute embarrassing content for friends or competitors.
- $G_3 - C_{extreme}$: Poor behaviours consequences are shown in relation to family members or pets sad that the user's health is deteriorating. Positive behaviours lead to the user happily engaging in playful activity with family.

cartoonishly Evil Concepts

- $G_1 - C_{evil}$: Essential or desirable services such as social media or work accounts are withheld until 'Activity payments' are made, e.g. a five-minute walk unlocks the ability to make a social media post.

Table 4.1: The expert concepts, with BCTs and average ratings of impact and ease of implementation (1-6)

Concept	*Description*	*BCTs*	*Impact*	*Ease*
G1-everyday	Contract, User Videos, Comments on Behaviour	1.8, 3.3, 6.3, 13.1	4.2	4.1
G2-everyday	AR Activity Scoring, Change in Walking Routes	3.1, 4.1, 6.2, 7.1, 7.8, 9.2, 9.3	4.4	2.1
G3-everyday	Comparative 'Altered' Images	1.1, 1.3, 1.4, 2.3, 2.4, 2.7, 10.5, 10.11	3.1	3.1
G1-extreme	Environment Changes, Workplace Comparison	2.2, 6.2, 12.1, 14.2	3.4	4.3
G2-extreme	Social Media Pressure/Insults	1.1, 1.3, 1.6, 6.3, 10.11, 11.4, 14.2, 14.3, 14.10, 15.4, 16.1	4.0	3.7
G3-extreme	Rewards for Surrounding Influences, Use of Regret	5.1, 5.5, 8.3, 9.3, 10.5, 10.9, 12.1	3.7	2.9
G1-evil	Hacking Services, Activity-Linked Unlocking	10.8, 10.11, 14.10	3.1	2.6
G2-evil	Future Predictions through Mass Data Intake	6.2, 9.3, 10.6, 10.11, 12.6, 13.1, 13.5, 14.1, 14.2, 15.3	4.7	4.0
G3-evil	Societal Restructure by Activity, Life Rewards	6.2, 7.7, 8.7, 10.1, 10.5, 12.2	4.0	1.1

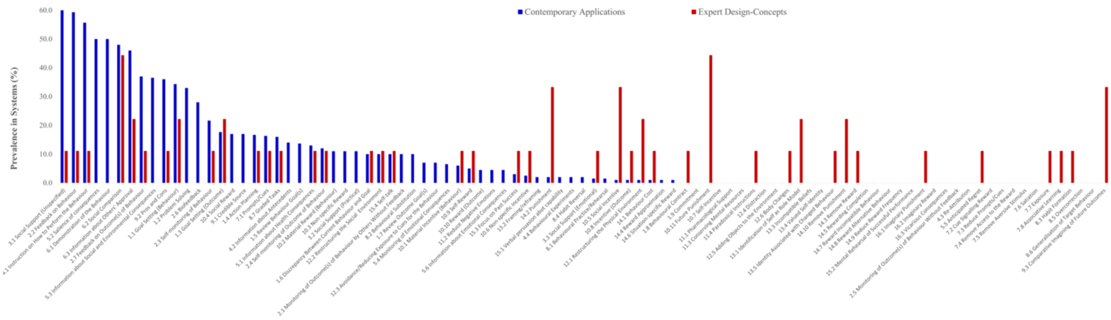


Figure 18: Comparison of the prevalence of techniques used in contemporary applications, from [70, 125, 396] (shown in blue), with prevalence of techniques used in the expert design-concepts generated in this work (shown in red). X-Axis represents behaviour change techniques. Techniques are in order of prevalence according to contemporary systems as shown in Figure 16.

- $G_2 - C_{evil}$: User data, from social media or internet tracking,matches the user to an equivalent older user so they can see how their decisions may affect their health. Less desirable connections are chosen if the user is under-performing.

- $G_3 - C_{evil}$: Users are micro-chipped to collect biometric data and a global leaderboard ranks all users by performance of behaviour. Lifestyle factors such as education, employment and social connections would be dictated by the global rank.

4.2.2 Stage 1 Analysis: Differences In BCT Use

Our nine designers' Effect-Led Designs used 46% (43/93) of BCTs. Figure 18 shows technique distribution by comparing the percentage prevalence of each BCT in our design process against the percentage prevalence in commercial applications (previously presented in Figure 16). The difference between columns in shared techniques, as well as the high number of techniques from expert designs which are not seen in contemporary designs, shows the difference in approaches and technique selection when using the **Effect-Led Design** process.

Figure 18 shows the prevalence of techniques in contemporary and study-produced designs ordered by the popularity of BCTs in contemporary applications.

Table 4.2: Techniques with the highest and lowest prevalence in existing interventions, compared to common techniques in expert designs

Most Prevalent Techniques (Contemporary)	*Prevalence (Contemporary)*	*Relative Prevalence (Expert)*	*Most Prevalent Techniques (Expert)*	*Prevalence (Expert)*	*Relative Prevalence (Contemporary)*
3.1 Social Support (Unspecified)	60%	11%	6.2 Social Comparison	44%	48%
2.2 Feedback on Behaviour	59%	11%	10.11 Future Punishment	44%	0%
4.1 Instruction on How to Perform the Behaviour	56%	11%	10.5 Social Incentive	33%	1%
6.1 Demonstration of the Behaviour	50%	0%	14.2 Punishment	33%	2%
5.2 Salience of Consequences	50%	0%	9.3 Comparative Imagining of Future Outcomes	33%	0%

This demonstrates that Effect-Led Design's technique distribution is less heavily skewed suggesting a broader use of BCTs and again implying a broader design space. Taken together, the findings suggest the Effect-Led Design helped address the limited technique space, by expanding the distribution of techniques from those seen in contemporary systems to include many more that can present effective solutions with intelligent implementations. Table 4.2 shows the top five BCTs by use in both contemporary applications and our study and presents a comparison of their prevalence. There are parallels in technique choice, with socially-inclined BCTs prominent in both. None of the top five techniques from contemporary apps appeared in more than one expert design-concept.

4.2.3 Stage 2 & 3 Outcomes: AI Characteristics

We use the nine AI characteristics of Guidotti *et al's* work [138] to structure our presentation of the results of Stages 2 and 3. This was determined in a top-down manner, as we wished to align the values communicated by the users with the common characteristics of AI design to better integrate these values into AI considerations. These characteristics address the relations between users and the AI, so provide an effective lens through which to investigate user responses to these effect-driven designs. All discussions during the user-centred phases of the design process were recorded and analysed by the research team, using the characteristics to conduct a thematic analysis of the design discussions. Although **Transparency**, **Usability** and **Causality** were not discussed in detail, the other six characteristics helped frame participant feedback and there were discussions of complex interactions between the six characteristics. We observed that values were explored in more nuanced ways when participant misunderstandings were addressed through genuine dialogue.

Efficacy, Privacy & Autonomy

Efficacy was central to discussions and served as a metric for value trade-offs, asking how far users were willing to push their own values in the pursuit of impactful behaviour change. Users generally were willing to push their own values further than expected for the promise of increased **Efficacy**. For example, on the trade-off with **Privacy** in $G_3 - C_{evil}$, Group A said: *"If someone said to me... you're going to look great but you're going to need to be micro-chipped... put it in"*. **Privacy** and **Autonomy** most affected user willingness to engage with concepts as, where sensitive user information was required such as in $G_2 - C_{evil}$ or

$G_3 - C_{evil}$, participant-users were worried. $G_1 - C_{evil}$: *"If it's hacking into your [device], there's no limit to what it could take"*. The term 'hacking' within expert concepts and researcher descriptions exacerbated privacy concerns - discussion of $G_1 - C_{evil}$ changed when 'hacking' was replaced with optional luxuries locked behind a physical 'activity tax'.

Unlike **Privacy**, user-participants were willing to negotiate changes around **Efficacy** and **Autonomy**. Users held an expected degree of autonomy before interacting with the system, so were more certain in how far they were willing to push their **Autonomy** in a trade-off. Group A highlighted the necessity of giving up some Autonomy to reach their goals: *"It's a sense of more freedom... When it comes to exercise... you need less of that"* though Group B were more reluctant to make trade-offs. Discussing $G_1 - C_{evil}$: *"I want to be healthy, and fit, and so on, of course... I'm not going to cut out... important stuff like [emails] for [my health]"*.

Fairness & Reliability - Interacting with Users

Fairness was also a prominent part of the discussion but was typically mentioned in mediating relationships between users. For example, in unequal leaderboards in $G_3 - C_{evil}$, users in Group A were unclear who they would be compared to, and how difficult it could be to climb the leaderboard: *"I also don't think this is particularly fair, how are we supposed to run against professional athletes... What do you [do] then in terms of people who have disabilities"*. Fairness was also associated with preventing discriminatory practices or inequitable support. Group B discussing the design of $G_1 - C_{extreme}$ worried about the inequity of the solution: *"Not everyone can use that app... You've got anyone with any disabilities, then they can't use it"*. This also connected to **Reliability** in relation to $G_2 - C_{evil}$, where Group A thought dietary suggestions could prove problematic without individual considerations: *"They're like, okay brilliant, why don't you just try this diet that is made up of mostly proteins... you're saying that potentially to someone with a dietary requirement"*.

AI Assistance vs. Human Assistance

Beyond AI characteristics, participant-users were asked if this system with its various value trade-offs and enhanced efficacy would be more desirable than a human equivalent, such as a personal trainer. All participant-users showed a strong preference for a human trainer over AI, despite the lack of strong evidence for their efficacy [86]. Mutuality and empathy played into a sense of 'mutual accountability' which allows trust in the human trainer. Participants in Group A envisioned negotiating unreasonable requests saying: *"If [the AI] told me I need to do 30,000 steps a day, I'm going to tell it no"*. Current AI approaches will not effectively mimic these human characteristics but may offer greater degrees of personalisation that effectively mimic empathy and negotiation.

Surfacing ideas and desired characteristics helped the participant-users engage with a wider space of application approaches than they have been exposed to, and effectively quelled concerns around intelligent approaches by showing how the intelligent approaches they may hold concerns about can close the gap between human-driven solutions and their digital counterparts.

4.2.4 Expert Reflections on Process

The process presented in this exploratory study aimed to challenge domain-expert participant-designers' assumptions about user values by making discussion of them focus on specific violations of those values. Participant-users had to "reclaim" their values from designs that flouted them. Unstructured interviews with participant-designers revealed surprise at the participant-users' explanations of their values, particularly when they preferred what was meant to be a *cartoonishly* **Evil** design:

"I was really surprised, firstly like you've just identified... the two top interventions or apps that were designed were the most extreme apps, and that was what they put in for being favourable, the one that tapped into every single potential mechanism and monitoring process, and they were like, yeah absolutely."

"I was surprised... about how, typically health interventions always engage the most consciously active or consciously healthy people anyway, and it always the same questions, the same conclusions from the papers is how do we engage the people that aren't habitually active... I thought this was quite interesting how they were like, absolutely, shame me on social media, they thought was quite motivating which was really counter-intuitive from our perspective."

The designs that, in theory, should have been the most concerning, featuring heavy reliance on AI, got positive reactions and the most interest in using from participant-users. Expert participant-designers found the process engaging, noting that they could limit themselves in their normal work on behaviour change: *"I suppose you've always got to keep in the 'safe zone'... which means sometimes it might be quite passive"*. Another expert noted that surpassing this limitation may be what is required: *"We're always mindful of a person's autonomy, and their control, and their free choice... quite aggressively nudging someone to do or not do certain things may be more effective, or may be what's necessary to instigate change..."*.

Expert participant-designers also reported that the range of BCTs offered early in Stage One expanded their thinking: *"In the first session we looked at different [BCTs] and how we'd give features to those, then we ended up with ideas which we might not have come up with"*. Our approach resulted in a different selection of BCTs in general, as opposed to recreating known systems and searching for BCTs in this amalgamation of popular features:

"People come up with ideas but it's... forced upon what we already know... if you said to somebody to come up with a fitness app, people will start thinking of Fitbits and people starting thinking of Apple Watches and they'll think of those features and bolt them into this big hybrid app which does everything but doesn't really do anything"

These comments from experts show that the approach taken in this exploratory study allowed for more expansive thinking, and presented a means to develop systems that were distinct from contemporary systems. These comments also serve to further support the quantitative findings in Section 4.2.2. Also visible from these comments is the ability of this design approach to alter views on the connections between design and what the user desires, which allows for designers and users together to develop a shared vision of what is desired from a system, reducing misconceptions from both groups.

4.3 Effect-Led Design Methodology

The design approach utilised in the exploratory study was refined into Effect-Led Design. Where the design framework used in the exploratory session used provocative techniques to run participatory design through a lens of high effect and low ethical consideration, Effect-Led Design is a more rounded approach built on creating a low-stakes, playful environment to explore application design within, before using these same feelings to encourage constructive conversation with users to highlight effective and desirable novel designs and uncover necessary value-specific considerations that may reduce acceptability.

The Effect-Led Design approach has three strengths:

1. Creating novel designs by expanding the design space that is explored.
2. Improving understanding of user values on the part of the user and designer.
3. Using real behaviour change techniques to keep system design grounded and effective.

By placing the focus on effect first, designers' assumptions [47] and users' AI misconceptions [50, 282] do not prematurely narrow the design space. Effect-Led Design works to counter designers' reluctance to deliberately flout user values in concept development by creating an environment that encourages discussions of values using absurd, comical concepts that exploit the nature of ludicrous or absurd designs to encourage discussion in ways standard designs do not. The strictly hypothetical nature of systems is stressed to help ensure a broad range of improvements to efficacy are considered. Users come into the process to push back against extreme concepts, reasserting their values and creating a better understanding of them in action rather than presenting their values in abstract terms. These discussions can surprise designers as they may not align with their initial assumptions. These discussions also provide clearer boundaries to AI systems through the precise discussions that emerge. Finally, Effect-Led Design is not mutually exclusive of other design approaches. As seen in Figure 19, Effect-Led Design results in new understandings of the design space, but not polished designs; It is plausible these concepts could be taken through to implementation via additional participatory design approaches.

4.3.1 The Effect-Led Design Approach

Effect-Led Design is made up of six steps, which are separated across three stages: Conceptualise (Steps 1-3), Analyse (Steps 4-5) and Design (Step 6), as illustrated in Figure 19. This division allows for flexibility in running sessions as stages are self-contained and each stage's materials inform the following stages. The six steps of Effect-Led Design are:

1. **Establish Area of Focus:** Designers establish a target behaviour, and metrics to gauge change against.
2. **Select Relevant Techniques:** Designers select BCTs to maximise behaviour change against their chosen metric.

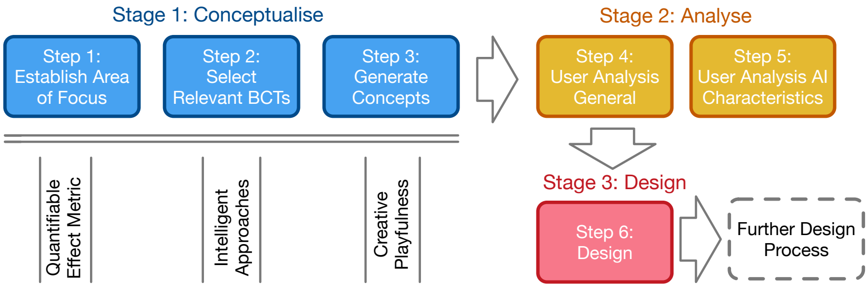


Figure 19: Effect-Led Design: Stages 1-3 Conceptualise, Analyse and Design (Blue, Orange and Red), underpinned by three key pillars of the proposed approach

3. **Generate Concepts:** BCTs act as building blocks to drive design. This step builds up to more extreme designs to capture varied concepts and address any reluctance to flout user values. AI is strongly integrated at this stage to encourage the development of intelligent solutions:
    - *Concept One - Everyday*: Commonly available, or close to normal applications in the area.
    - *Concept Two - Extreme Efficacy*: Unethical yet plausible designs that ignore user boundaries and resource constraints, flouting values to a degree they can't become popular but might see small-scale use.
    - *Concept Three - (cartoonishly) Evil*: Ignores user values and constraints creating absurd concepts, flouting values to an extent that the designers perceive as unacceptable to any users. 'Cartoonishly' indicated designs aren't abhorrent or despicable, but are ludicrous.
4. **User Analysis - General:** Concepts are discussed with users and, where their values don't align, giving them tangible ideas to push back against.
5. **User Analysis - AI Characteristics:** Users consider Trust, Reliability, Usability, Transparency, Causality, Fairness, Privacy, Efficacy and Autonomy [138] to articulate concerns with the concepts. These characteristics ground discussion in the actions of the AI, and create a shared language between users and designers.
6. **Design:** Designers and users discuss concerns about the concepts. Designers learn about users' values from responses to the concepts and participants learn about how AI systems can support behaviour change. Novel, refined designs are co-produced as an expanded design space emerges informed by the pursuit of efficacy and educated user values that surrender less design space to inaccurate assumptions or misconceptions about values.

Effect-Led Design is built on three pillars:

- An atmosphere of '**creative playfulness**' to encourage exploration of ideas without any concerns of judgement or consequences. By creating an environment where all ideas can be entertained and discussed, a wider breadth of the design space can be explored, and high-risk/high-reward ideas can potentially be refined into novel, acceptable designs. Game-like artefacts like spider tokens, dice, and wooden playing cards help foment this.

- Defining **quantifiable effect metrics** to drive behaviour change. Effect-Led Design establishes a key metric that designs influence as opposed to establishing the behaviour to be targeted by the design session i.e., rather than naming 'physical activity' as the behaviour to be changed, naming 'increasing step counts' or 'increasing distance travelled' as the metric. AI systems often act to increase a metric of efficacy and focusing a design process in the same way guides designers to push a metric of effect to its limits through design decisions.

- Adoption of **intelligent approaches** to develop context-aware designs utilising situational information to motivate behaviour change. Creative playfulness develops a space where systems that could be heavily reliant on large amounts of data and user tracking can be discussed, and the effect metric gives a specific target for an intelligent, data-driven system to optimise for.

4.3.2 Comparison to Existing Methods

Effect-Led Design offers an early-stage approach to participatory design that differs substantially from most participatory approaches. Effect-Led Design uses its design concepts to uncover user values, acting in reverse to approaches such as Value Sensitive Design. To maintain a focus on efficacy, Effect-Led Design is strongly directional and does not move freely between phases- if participants were to move back and forth through the process, there is a risk of diluting concepts - unlike Value Sensitive Design [118]. Also in contrast with Effect-Led Design's focus on effect first, Design Thinking [33,82] begins the process by considering users. However, Design Thinking's Ideate phase encourages expansive thinking aiming for similar outcomes to Effect-Led Design but does not have Effect Led Design's focus on efficacy for intelligent systems. In addition, Effect-Led Design also takes deliberate steps to widen the design space through the establishment of a playful atmosphere and through flouting user values. Yardley *et al.* present the Person-Based Approach [397], which utilises in-depth discussion with potential users to understand and enhance the relationship between evidence-based techniques and their eventual users. This utilises some of the ideas presented by Effect-Led Design in centering approaches around directly-applicable values and aligning these with theory. However, this in-depth analysis of values at each stage of the process may still suffer from the same issues described - If values are first sourced prior to any design work, the broad scope of abstract, idealistic values may disrupt early conceptualisation and result in efficacy-compromised designs. Effect-Led Design is not mutually exclusive of other design approaches. As seen in Figure 19, Effect-Led Design results in new understandings of the design space, but not polished designs; It is envisaged these concepts would be further enhanced through more design approaches such as Design Thinking or Value Sensitive Design.

4.4 Validation Study - Comparing Effect-Led Design and Value Sensitive Design

To understand if our Effect-Led Design approach changed designers' work, diversified design concepts and to assure ourselves that it did not lead to the creation of final designs that were insensitive to user values, we compared the process to Value Sensitive Design, one of the leading approaches with widespread use and extensive literature. Value Sensitive Design was specifically chosen as a counterpoint to Effect-Led Design because of its aptitude for negotiating design spaces that are heavily informed by user values while adopting a completely different methodological position. Our results show that the approaches differ, and we speculate on the reasons why this may be. We do not aim to suggest that one approach is wholly superior to another in general terms. Instead, we argue that Effect-Led Design is more capable of presenting the benefits and required affordances of AI in design as these are placed at the forefront of the approach, as opposed to other approaches such as Value Sensitive Design which are agnostic to the technology designed for.

4.4.1 Method

The validation study was a design workshop with 28 groups of 3-4 participants, took place over 15 days, and included two workshops and some external preparation.

Participants

The participants who took part in this validation study were university students, specifically final-year User Experience Design students acting as participant-designers on a shared design brief following either Effect-Led Design or Value-Sensitive Design. All students were given the option to withdraw consent and study-specific materials from analysis at any time, as well as the option to opt out of all participation in line with existing university mechanisms, and all students agreed to take part in the study. Students were asked to work with innovative approaches to design as part of the module structure. Effect-Led Design was presented as one of these innovative approaches, and students had previously participated in workshops using Value Sensitive Design and other participatory design methods. Alternative work packages were available if students did not wish to take part.

Procedure

Prior to the first workshop, participant-designer groups were randomly split between the two design approaches; 55 students in 14 groups of 3-4 followed a Value Sensitive Design approach and 56 students in 14 groups of 4 followed an Effect-Led Design approach. During the study, students acted as participant-*users* for groups running the other approach. Participant-designers were briefed through video presentations, outlining how to perform their respective design approach and describing the format of the final designs.

The first workshops took place three days after the briefing and lasted three hours: Value Sensitive groups performed Value Elicitation, defined value requirements, performed a technical investigation and developed their designs; Effect-Led participant-designers defined target behaviours and metrics, selected BCTs and developed their three concepts - everyday, extreme efficacy and cartoonishly evil (Effect-Led Design Stage 1). Seven days after the first workshop, the Effect-Led Design work was completed in a second workshop. Effect-Led participant-designers engaged in User Analysis (Effect-Led Design Stage 2) of the three concepts and developed the final refined design (Effect-Led Design Stage 3) while Value Sensitive participant-designers refined their final concept. Finally, three days after the second workshop and 15 days after the initial briefings, groups submitted final designs, documents outlining the progress through the steps of each design approach and questionnaire responses.

This study was conducted online as a result of the COVID-19 pandemic. The videos were presented in the same form as lectures to give information in an easily digestible, reviewable form. Design sessions started with refresher briefings on Zoom before moving to Discord groups and voice chat channels for groups to collaborate. Each group of participant-designers had a dedicated voice channel and moved to shared groups when necessary to act as participants. Research and Teaching Staff were on hand to join voice channels for assistance and to provide guidance where necessary. All students were familiar with Zoom/Discord and remote collaboration in design as the studies took place at the end of the module using the same tools and following the same format as other design exercises they had performed.

Materials & Data Collection

Students were expected to provide a single design from their group developed through either Effect-Led Design or Value Sensitive Design depending on which they were assigned. Students were also asked to fill out a short questionnaire based on the principles of the design processes to identify differences. The exact materials produced by each group of students within the workshop were:

- A full 'design document' from each student group detailing their progression through the design process - The content of these documents is dependent on the design process the group worked through:
  - Effect-Led Design designers recorded their initial conceptualisations, the three concepts in detail, the feedback of users when involved and how they related to the specific concepts, and a final design that builds upon these concepts along with a storyboard and techniques utilised.
  - Value Sensitive Design designers recorded the initial values as obtained from user discussions, the progression of these values into design requirements, discussions on technical requirements and the final resulting design along with how it relates to user values.
- A set of responses to an 11-question exit questionnaire, describing their own experiences with the design process rather than abstract thoughts towards both processes.

Output designs were analysed against two major criteria: the diversity of BCTs contained and participant-designers' evaluation of the influence of the design approach on their choices. The BCTs in Effect-Led Design concepts were recorded during the process by designers, so could be taken directly from these documents. Diagrams illustrating concepts were reviewed to ensure the techniques listed were found in the final designs. Value Sensitive Design documents were analysed for BCTs following the study through post-design mapping of techniques (using the BCTTv1 [253]) to identify BCTs in the outputs for comparative analysis. BCT mapping was conducted by aligning design descriptions in participant-designer artefacts with examples and definitions provided in the BCTTv1, as well as utilising student descriptions where technique examples were very similar. Participant-designers using both methods answered questions about their experiences with the approach looking at the impact of the pillars and process on the advantages and risks of Effect-Led Design, comprising:

- Three questions to **validate** that the Effect-Led Design approach works as expected and that the pillars of the process meaningfully contribute to the final designs.
- Four questions identifying where **benefits** over processes such as Value Sensitive Design may be present.
- Four questions identifying whether Effect-Led Design causes notable **harms** compared to user-focused processes.

The specific questions can be seen in Table 4.3. These questions were sent out as an online questionnaire, with students required to return their questionnaires within the days following the workshop session.

4.4.2 Results

Design Process Impact on BCT Selection

Participant-designers working with Effect-Led Design used 39 of the available 93 BCTs across their 14 designs, while those working with Value Sensitive Design used 22 BCTs across 15 designs. Of the 39 techniques found within Effect-Led Design outputs, 18 were shared with Value Sensitive Design, four were unique to Value Sensitive Design, and 21 were unique to Effect-Led Design. The four techniques exclusively seen in Value Sensitive Design were also seen in contemporary applications. The average number of techniques used was 5.5 BCTs for Effect-Led Design and 4.7 BCTs for Value Sensitive Design. The average number of BCTs is similar between the methods but the range of BCTs used in Effect-Led Design was close to twice that of those used in Value Sensitive Design. Despite clear evidence of more novel use of BCTs, a Fisher Exact test on the frequency distributions of BCTs used in both methods did not return a significant difference ($p = 0.064, p > 0.05$, N = 28). Below we present comparisons between the validation workshop design's adoption of BCTs and the prevalence of BCTs found in contemporary applications. Once again, Fisher-Exact tests were run on different combinations of results data to identify differences between the usage of BCTs:

- Effect-Led Design against Contemporary Applications - Technique frequency observed in the concepts of the validation study following Effect-Led Design differ significantly from the techniques observed in equivalent contemporary applications ($p = 0.006, p < 0.05, N = 111$).
- Value Sensitive Design against Contemporary Applications - The technique frequency observed in concepts following Value Sensitive Design was not significantly different from the techniques observed in contemporary applications ($p = 0.087, p > 0.05, N = 111$).

Taken together, the results suggest that Effect-Led Design promotes more diverse behaviour change solutions, supporting the prior results from the expert evaluation and might be more useful for generating these diverse solutions than other common design approaches.

Participant Responses to Effect-Led Design

Participant-designer perceptions of the approaches were assessed to validate the influence of the approach, specific proposed improvements over existing approaches and potential harms of the approach. Results can be viewed in Table 4.3. We highlight expected outcomes (third column, Hypothesis) i.e. the outcome that we deemed most likely given the relative philosophies of the respective approaches.

All 28 groups submitted a final design along with design documents, and 111 students answered the questions presented. Questionnaire responses were converted into numerical scores (Strongly Disagree = 1, Disagree = 2, Agree = 3, Strongly Agree = 4). The responses for the two approaches were compared using Mann-Whitney U tests, with Bonferroni Corrections. The outcome column identifies how the responses compare to the hypothesis, e.g. if the hypothesis states Effect-Led Design and the outcome column states $h = 1$, then for the specific question, more Agree or Strongly Agree responses were seen for Effect-Led Design than Value-Sensitive Design. If the column states $h = 0$, then either the opposite process to the hypothesised process was more agreed with, or there was no significant difference between the two.

The first three questions focused on **validating** the functionality of Effect-Led Design i.e. that the structure of the approach influenced participant-designers as intended. Effect-Led Design was rated significantly higher for Q_1. This suggests that the deliberate ordering of work and guidance on how to approach each stage ensures each step meaningfully influences the next. The lack of statistically significant difference from Q_2 suggests Effect-Led Design does not encourage the selection of techniques separate from user values despite deliberately flouting them. Although selecting approaches to behaviour change based on impact is a pillar of Effect-Led Design, the non-significance of Q_3 suggests our designer-participants felt it did not encourage this more than Value Sensitive Design. However, our quantitative assessment in Section 4.4.2 shows differences in technique selection for Effect-Led Design compared to contemporary work where Value Sensitive Design did not. We discuss why participant-designers might feel this way about both their design approaches because of framing, but only Effect-Led Design leads to a greater diversity of choices, in Section 4.5.

Table 4.3: Participant-Designer Evaluation Questions and Results

Q_{ID}	*Question*	*Hypothesis*	*Outcome* $(N = 111)$
Q_1	*All the stages/concepts within the process influenced our final design.*	Effect-Led	$p = 0.041, p < 0.05, h = 1$
Q_2	*We selected our approaches to changing behaviour based on how well they aligned with the end user's principles.*	Value Sensitive	$p = 0.327, p > 0.05, h = 0$
Q_3	*We selected our approaches to changing behaviour based on the degree of impact they would have on end-user behaviour.*	Effect-Led	$p = 0.697, p > 0.05, h = 0$
Q_4	*We had a clear picture of the change in behaviour that we were designing for.*	Effect-Led	$p = 0.00988, p < 0.05, h = 1$
Q_5	*We had a countable and measurable change in behaviour that we were designing for.*	Effect-Led	$p = 0.854, p > 0.05, h = 0$
Q_6	*The playfulness of the design process made it easy to talk about a wide range of different ways to change behaviour.*	Effect-Led	$p =< .00001, p < 0.05, h = 1$
Q_7	*The design focus on stakeholder principles limited the final design's ability to change behaviour.*	Value Sensitive	$p = 0.153, p > 0.05, h = 0$
Q_8	*During the design process, we spent time thinking about how our designs aligned with the user's principles.*	Value Sensitive	$p = 0.529, p > 0.05, h = 0$
Q_9	*The design process' focus on user's principles made it easy to talk about the ethical implications of our ideas.*	Value Sensitive	$p = 0.258, p > 0.05, h = 0$
Q_{10}	*We produced a design that will align with the user's principles.*	Value Sensitive	$p = 0.084, p > 0.05, h = 0$
Q_{11}	*The design focus on system impact limited the acceptability of the final design.*	Effect-Led	$p = 0.764, p > 0.05, h = 0$

Q_4 - Q_7 cover the proposed benefits of Effect-Led Design to design outputs when compared to alternative approaches. Responses show Effect-Led Design leading to improvements in two (Q_4, Q_6) of the three questions where Effect-Led Design was predicted to outperform Value Sensitive Design. Responses to Q_4 emphasise the positive influence of Effect-Led Design's early stages in establishing clear goals and metrics for designing efficacy-driven concepts. Q_6 shows Effect-Led Design's pillar **creative playfulness**' ability to create an environment to freely explore high-efficacy, ethically-questionable approaches. However, responses to Q_5 suggest that Effect-Led Design does not do enough to set a clearly defined effect metric when the process is followed and that more emphasis on **quantifiable effect metrics** is necessary. The final statement, Q_7, was not significantly higher for Value Sensitive Design as predicted.

The final four questions were designed to check for potential harms introduced by Effect-Led Design's focus on efficacy and flouting values. Our results suggest that Effect-Led Design is no less effective than Value Sensitive in supporting final designs that: think about users, Q_8; explore ethical concerns and implications, Q_9; and align with user principles, Q_{10}. Finally, the results of Q_{11} show no evidence that the acceptability of final designs was limited.

4.5 Discussion

We have used Effect-Led Design to explore alternative designs for behaviour change in health and wellbeing. More research is needed to understand the applicability of the process outside of this domain as both studies presented highly varied selections of techniques from contemporary applications for this single design space. There is clear evidence that our approach fulfils its intent of developing novel and varied concepts. *Effect-Led Design* clarifies values for designers and users by asking users to assert their values to "fix" concepts that explicitly flout them. Where other participatory design methods ask "are you willing to trade this value for this feature?" Effect-Led Design says "We are taking away your value for this feature" and challenges the end users to reclaim what they truly value - casually put "You don't know what you've got till it's gone". The approach helps designers understand and respect the relative strengths with which users hold their values. Our designers held professionally-shaped values that were similar or even derived from heuristic frameworks but did not align with users' values. Our results show designers need to be aware that values should not be treated as additive but as contextually dependent. For example, if users value efficacy over privacy but a designer values privacy over efficacy, a user-centred design should make trade-offs that favour efficacy and not avoid engaging in either because the designers hold privacy in high regard.

Our analysis of BCTs used in Effect-Led Design concepts in both studies showed significant differences from those used in contemporary applications where Value Sensitive Design outcomes did not. We see three possible explanations: 1) the focus on effect widens the design space that experts can explore, 2) the intelligent focus shifts BCT choices, or 3) the fore-fronting of evidence-based techniques forces designers to consider the mechanisms of their approaches more directly. Expert discussions suggest the former and we suggest the ability to put aside limitations on potential solutions is what holds the greatest promise for improved efficacy through *Effect-Led Design.* The expanded design space is further supported by the observable differences between the multiple Effect-Led Design session outputs ($p =< .001, p < 0.05, N = 111$), suggesting Effect-Led Design avoids simply creating an alternative set of homogeneous designs. Our participant designers did not significantly differ in selecting their approaches to behaviour, however, the framing of the Value Sensitive Design process may affect this. Participant-designers may rule out BCTs early in the process, then select ones to design around later on from the reduced space; When they are *selecting* techniques (as opposed to discounting them) they will select for maximum impact.

Effect-Led Design is presented here as a process for exploring alternative designs for AI-driven behaviour change systems, although the further applicability of this process for other areas of design requires further exploration. Furthermore, by design, this process will return vastly different outcomes and values depending on those participating both as designers and users. The studies presented here cover behaviour change for physical health and well-being, with designers and users tailored to this area as to return the most relevant designs and values through the steps of the process. This chapter presents a starting point for this process, and from this point, the full potential of this method - both successful and otherwise - must be explored through a variety of contexts and participant specialisations to grasp all possible uses of this process and how values may be better focused on each area as to best present these varied and interesting system concepts to end users.

Effect-Led Design positions itself within the literature as a new approach to participatory design that harnesses a greater focus on efficacy, engagement with intelligent approaches, and a refined space of user values to create significantly different designs for contemporary applications. The importance of a refined value space reflects comments made by Liao & Muller [221], who found that in designing value sets to be embedded into AI systems, many values were "not universal or held to the same standard", with privacy and autonomy having highly varied requirements. This not only reflects the discussions on autonomy and privacy held in the initial exploratory study but justifies the inclusion of such discussions as a core element of the design process, ensuring the relative standards of each value are unearthed and correctly applied in the resulting designs. Commonly cited issues with integrating intelligent approaches into participatory design are difficulties with comprehending AI methods and difficulties in judging designs which require long-term engagement to understand [41]. Effect-Led Design aims to resolve both of these concerns through the inclusion of efficacy-driven concepts. These concepts help the user to understand the AI and how it functions within the system, and the use of AI characteristics as guiding topics for user assessment ensures these connections are made clear as to how the AI-user interactions must be structured. Additionally, the use of these concepts and accompanying artefacts present these systems as conceptual long-term products rather than abstract concepts, allowing the user to envision the full process of use and react both to the initial idea and its long-term impact.

An interesting comparison to the Effect-Led Design process is the co-design of behaviour change strategies for physical activity with older adults conducted by Janols *et al.* [178], which utilises some similar concepts such as the explicit use of Behaviour Change Techniques as a driver of discussion and the reflection upon exact concepts by the potential users to ensure values are linked directly to the space rather than simply being abstract values. This work effectively highlighted what older adults valued in their behaviour change technologies, which is a core tenet of Effect-Led Design achieved through identifying missing or flouted values within the expert concepts. The inclusion of these concepts is where Effect-Led Design achieves its other goal of high-efficacy solutions with differ significantly from contemporary systems. Janols *et al.*, using the BCTTv1 [253], found nine BCTs included within their systems resulting from the design method - Seven of these nine BCTs are also found within the highlight top end of BCT usage in contemporary applications (as shown in Figures 16 and 18). Effect-Led Design includes concepts prior to user engagement in an attempt to include techniques selected for their efficacy which can then have resulting concepts tuned by user values, rather than the values obtained from the process aligned with behaviour change techniques during the creation of outcome designs.

There are some limitations to be aware of for the validation study. There was potential for ideas to move between Effect-Led and Value Sensitive groups. This was minimised through the ordering of participants' engagement in these sessions: Effect-Led participant-designers acted as users before they began conceptualising and Value Sensitive participant-designers acted as users after they had finished their designs. Second, the validation study participants were students with limited design experience. Also, there is the potential that some questions used to evaluate the process may have been leading due to making assumptions about the process discussed, such as Q6 - *The playfulness of the design process made it easy to talk about a wide range of different ways to change behaviour* or Q11 - *The design focus on system impact limited the acceptability of the final design* - There is an argument these were not leading due to the words not being used in describing the methods and thus not being already associated with a given process, but there is still potential due to the processes being more strongly associated with the concept through their core design.

We observed three areas where Effect-Led Design struggled. First, despite its aim to promote novel idea creation without limitations, some designers struggled to put aside their values even for purely hypothetical, comical designs. Second, some expert designers became fixed on progressing a single design idea, increasing the severity of a single punishment rather than using the full BCT toolkit to explore other approaches. There is also a risk that the promotion of a playful environment may lead to a disconnect between what users establish as acceptable in an enthusiastic and low-stakes environment and what they would find unacceptable in free-living situations. Lastly, while AI and intelligent algorithms were pushed as important elements during conceptualisation and encouraged throughout, many designers did not utilise such algorithms extensively within their concepts. This may require minor changes in how AI is tied into the core of the Effect-Led Design process to ensure such algorithms are suitably considered in the pursuit of maximum efficacy.

4.6 Chapter Summary

This chapter presented the newly defined process of Effect-Led Design, which aims to provide a more focused participatory design approach to behaviour change systems utilising new innovative, intelligent approaches to maximise impact. This provides a means to take the conceptual ideas of technique utilisation and more effective implementation as presented in the conceptual blueprint, and put these ideas into practice using a participatory design approach that promotes these techniques and ideas rather than allowing them to become diminished by too heavily focusing on what the designers believe would be acceptable or the best fit for prospective users. The inclusion of users later in the process serves to find a more accurate profile of values in play and to gain more insightful responses to the methods used within the concepts to find where users' attitudes truly lie within the space of behaviour change innovation. This process, and the studies which explore its potential and evaluate its structure presented in this chapter, provide an interesting new approach for intervention designers going forward to develop innovative, intelligent approaches to changing behaviour.

The next chapter, Chapter 5, provides a particular instance of the conceptual blueprint which presents the rationale for the core experiment of this thesis. This chapter then outlines some early exploratory work on alternative approaches to behaviour change, before describing the experimental system in detail regarding the core platform, technique implementations and machine learning algorithms included. The latter half of the chapter then describes the main experiment of the thesis.

CHAPTER 5

EXPLORATION AND IMPLEMENTATION OF INTELLIGENT BEHAVIOUR CHANGE

The previous chapter on the process of Effect-Led Design presents a means for us to explore the potential of AI integration into behaviour change systems and to develop AI-enhanced personal health concepts. However, at this time, the Effect-Led Design process does not provide us with a method to evaluate how these systems perform in free-living scenarios. To justify the inclusion of intelligent algorithms into the behaviour change space, we have carried out experiments which place these systems in real-world situations and evaluate their impact. There are two experiments covered in this chapter: an exploratory pilot study of a rule-based Fake Peer in the context of an existing behaviour change service which takes the form of a single behaviour change strategy, and a dedicated device using an intelligent implementation of behaviour change techniques as the key elements of an intervention.

This chapter and it's contained experiment, serve to provide answers to question *SQ3*, and questions *RQ2* and *RQ3* by extension:

- *SQ3*: Do these intelligent interventions have a significant impact on those using them compared to standard approaches?
- *RQ2*: Can a machine learning algorithm function on a mobile device in real-world situations and learn user patterns?
- *RQ3*: Will the two experimental approaches, technique and parameter switching, influence motivation and engagement?

Through the intended outcomes of the experiment. The experimental setup will collect both quantitative data on steps and algorithmic performance, and qualitative data on user motivations and responses to certain techniques and parameters, both of which will aim to resolve the three questions listed.

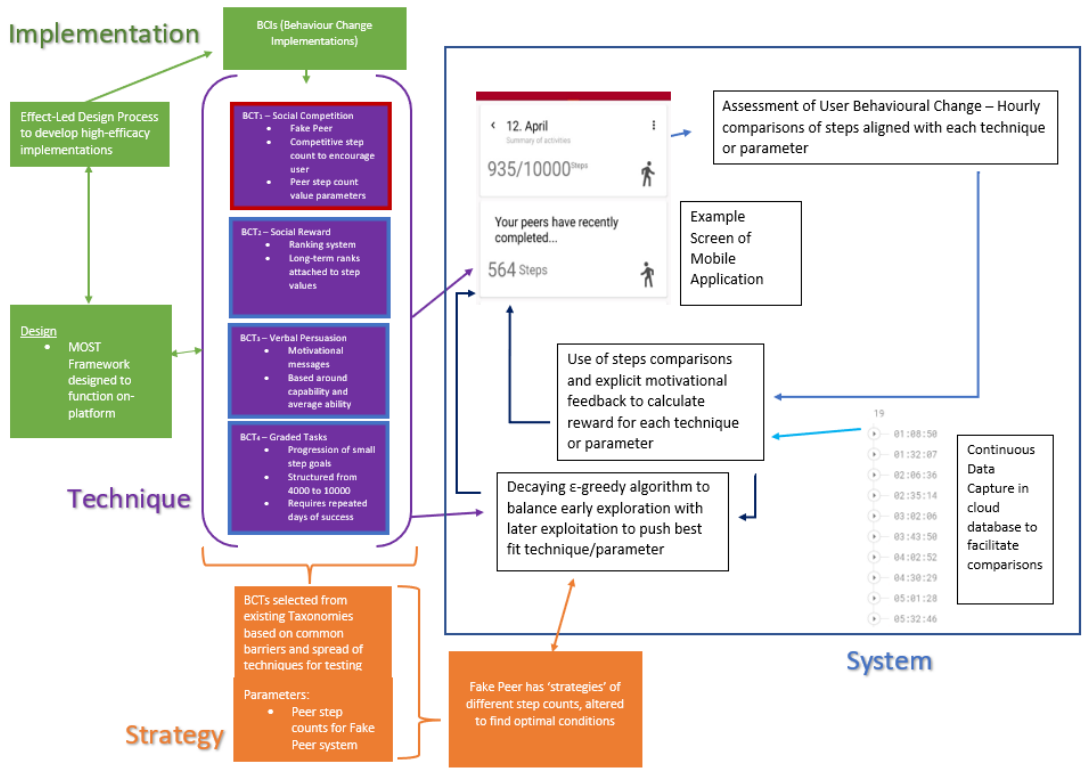


Figure 20: The experimental platform, an instance of the conceptual blueprint that underpins this thesis.

5.1 Experimental Platform & Rationale of Approach

Figure 20 represents the experimental platform that underpins the proposed empirical research of this thesis - an intelligent system that, rather than presenting an amalgamation of techniques and concepts to capture the attention and needs of multiple users, switches out system techniques or technique parameters to best capture the requirements of each user. This experimental platform is separated into four key sections - the technical workings of the digital system, as well as the three key foundational pillars which support the design and delivery of interventions. The content of this experimental platform is matched with the work conducted in this thesis so that this chapter can accurately present the research that will follow. This includes the exact techniques and tenets of design, as well as screenshots of the workings of the system. This chapter will give a general overview of the experimental platform, covering each section, with the specifics being expanded upon in their relevant chapters.

The sections of the experimental platform surrounding the 'System' are pieces of research or design that factor into the final system and ensure it operates with maximum potential efficacy, but are not themselves part of the central loop of the system. These are all considerations that must be made prior to design and implementation, either to determine the exact nature of system components to be implemented or to support their potential for efficacy post-implementation. These sections are named regarding the system element that results from the contained information or actions - The first section returns a **technique**, the second an **implementation**, the third a **strategy**, and finally a **system**.

5.1.1 Strategies & Parameterisation

Michie *et al.* [254] designed a comprehensive list of active techniques in behaviour change, but the composition of a given technique is further open to interpretation. Digital system design also contributes to this as the progression from theoretical technique to technical implementation involves consideration of several parameters. However, many of these decisions may be mostly unconscious and simply deemed the 'correct' way to implement the technique as observed by the designers. To use the example of 'Paradoxical Instructions', the general idea of how to present this contradictory idea is well defined within the taxonomy but the exact nature of the contradictory idea is down to the designer: Does a smoker smoke twice as many cigarettes or three times as many? Does an overweight user overindulge in fatty foods or sweet foods? Does an alcoholic drink until they're drunk or a fixed amount? The interpretation of the user may influence this as well, as an overweight user may not view their weight as an issue, and may have a different interpretation of what constitutes a fatty food, and these factors may heavily influence the applicability and overall effect of technique content. These decisions may in themselves alter the possible outcomes of the intervention. The correct alignment of technique, user and technique implementation may have a major stake in the overall outcomes of the system.

In the scope of this system, specifically the 'Strategy' section, we refer to these decisions as the 'parameters' of the system - small features which can be altered within the grander scope of the technique to impart minor behavioural improvements which may add up to a major effect. These parameters may be broadly applicable to all techniques, such as the saliency of a given technique within the grander scale of the intervention (subtle or promoted strongly) or the tone of the content the particular technique is presenting (is educational content positive? negative? sympathetic? guilt-driving?), to more specific instances such as the exact structuring of goals in a Graded Tasks system. These parameters are effectively the conditions for adaptation; The elements within the implementation of the technique each hold a small part of the potential of behavioural improvement, and aligning these correctly both with each other and with the user in question is key to ensuring this potential is realised. These parameters can be switched out in real-time, and this switching may even extend to whole combinations of techniques and parameters that may be better suited to a given user.

5.1.2 Proposed System Outline

The pre-system design discussed thus far provides the basis for the experimental platform, intended to effectively influence behaviour. The selection of techniques, design of effective technique implementations and development of contained behaviour change technique strategies all create a selection of individual behaviour change components which can contribute to the changing of behaviour. To best achieve this change, the design of that system is important to ensure these behaviours are captured and processed to best assist future decisions regarding the choice of strategies. This system is comprised of a single feedback loop of behaviour, which is supported by algorithms and sensors to contribute to both the delivery of the strategies and to ensuring future strategies are selected based on relevant data and what is calculated to be the most effective approach for the particular user.

Central Feedback Loop

Before discussing the innovative supporting elements of the system, the central loop of the system must be defined. At its core, a feedback loop is the simple approach of providing information about a behaviour or action in real-time to provide an opportunity to acknowledge and change this behaviour [135]. The user may be completely aware of the behaviour they are engaging in, but presenting it for them to actively acknowledge forces them to consider the behaviour. Goetz uses the example of speed cameras which present the speed the driver is travelling at when they pass it - The driver can check their speed at any time through the speedometer on their car, but the act of presenting the speed directly to them in their immediate attention typically reduces instances of speeding and overall encourages safer driving [135]. Feedback loops have been implemented to influence multiple types of behaviour and action. As well as the attention-drawing driver safety intentions of the example from Goetz, Layous *et al.* use positive feedback loops to encourage increased levels of pro-social effort, using the idea of 'do good, feel good' framed more directly in the immediate attention of the user to both improve wellbeing and increase positive actions as a result [209].

This feedback loop is driven by the use of user step counts to determine success. The system compares step counts against different targets or points of comparison based on the behaviour change strategy in play. These goals will be designed to be adaptive and to be selected based on both the actions of the user and the requirements of the technique to best deliver the ideas required. Korinek *et al.* studied adaptive goals within the context of fitness applications and found these goals increased the step counts by over 2000 steps [200]. Another central metric this system is attempting to track as a means to determine strategy efficacy is the level of motivation the strategy gives the user or, to put simply, how well a given strategy encourages the user to improve their behaviours.

There are many possible ways to track the motivation of the user, the most straightforward of which is to ask them directly. A response feature to allow users to report how well the strategy motivated them can be more effective than hard values as this allows for some level of mitigation of human randomness which could influence attempts to estimate motivation through hard outcomes and usage statistics. This does not, however, completely replace such outcomes and statistics; Changes in step values, overall usage numbers and levels of engagement and retention over varying periods of time all give some insight into the motivational potential of a system and may provide greater ideas of this over longer periods of time compared to the direct questioning of each strategy which is mostly limited to the immediate short-term motivational influence of a given approach. The intervention outcome is sent to the user to complete the feedback loop, informing them of their behaviour and presenting a new strategy to explore alternative approaches to changing behaviour or driving known effective approaches to improve and maintain positive behaviours. The relative effectiveness of the strategy is also stored within the system to be used by an intelligent algorithm to define which strategies are more or less effective and drive that same selection of strategies presented to the user based on decisions made and overall intentions.

Machine Learning Algorithm

Adapting goals and strategies to a given user could prove effective in increasing motivation and encouraging improved behaviours. A study by Wang *et al.* examined the general attitudes towards fitness trackers and fitness tracking software and found that for the most part, individuals were positive towards fitness tracking. Those asked found fitness apps were effective in encouraging and assisting their improved activity levels, and provided the necessary extrinsic factor to complement their existing intrinsic motivations. However, criticisms arose around the amount of time and attention required to actively engage with these systems, and the unrealised desire for the application and its internal strategies to match the expectations and requirements of the user [376]. Adaptive goals and strategies represent a promising approach to aligning the application and the user, which is a significant factor in the applicability and acceptability of a strategy due to the ever-changing factors that drive intrinsic motivation and the changes in predictors of success seen in users [287]. Individually tailored, adaptive goals drive increased chances of success by finding what works for the user, developing goals and selecting strategies which best match these needs.

A central feature of the proposed system is the use of machine learning to improve the central effectiveness of the system. As was observed in Chapter 3, machine learning as a component of digital health and behaviour change is an uncommon but highly effective approach which leaves a lot of room for expansion and innovation. Machine learning in behaviour change presents the opportunity for the system to learn what strategies are best fit for the user in question, and use this knowledge to develop further strategies which could prove highly effective. In this specific example, the system proposed here makes use of a reinforcement algorithm [340], which is suited to the purpose at hand by being able to learn and relearn based on repeated intake of data as opposed to being pre-trained on a set of data which could present an inherently-flawed observation or initial assumption. Reinforcement learning is seen as the best-aligned approach to motivating users as reinforcement learning and the general act of fitness tracking are both framed around achieving maximum behavioural reward which allows for a closer alignment of user and algorithm actions and rewards [109]. This reinforcement learning algorithm will be used to calculate adaptive goals and tailor behaviour change strategies based on the content of the feedback loop regarding user motivations and activities, which will improve the potential of a given strategy to impart positive change. The study by Korinek *et al.* that found positive outcomes from adaptive step goals used a similar algorithm which combined reward scores and previous adaptive goals to select the best out of available subsequent goals, which further supports this approach [200].

5.2 Early Pilot Study - Champions for Health

Our work with the Champions for Health project was conducted very early on in this research project and chronologically occurred before any of the work seen in Chapters 3-4. The purpose of this work was to gain an initial insight into how behaviour change strategies may be implemented in a digital intervention, to ground ourselves in the research landscape to gain a greater sense of understanding and to develop an initial piece of research to start us on the right foot. This work provided an initial sense of progression and increased knowledge of the landscape, but it is also important to note that much of this process may have proceeded differently if informed by the findings of the survey and the design tenets of Effect-Led Design.

The exploration of the rule-based fake peer system was implemented as part of the Champions for Health project, an NHS-aligned web service designed to allow self-reported tracking of health behaviours alongside a newly implemented mental health program. The main purpose of this study was to examine the adherence and effect of the Champions for Health service with and without the experimental mental health program attached, but one of the three conditions with the mental health program was granted to us to utilise the collective user base as an early testing ground for theories on behaviour change. The other two conditions were the mental health program alone, and the mental health program with a motivational greeting message on the front page of the website.

The initial Fake Peer framework was developed as a recreation of the implementation by Laut *et al.* to encourage participation in citizen science projects [207]. There was potential to obtain some early inclinations as to whether the fake peer effectively influenced behaviours and increased interest and adherence, but the main purpose of this investigation was to view whether this fake peer system would reliably appear believable and competitive alongside the self-insert figures of the user and whether this had the potential to fabricate social comparison on a large scale through the use of participant data and embedded algorithms. The fake peer system implemented within the Champions for Health service was not intelligent and instead used a fixed position ahead of the user (as found to be most effective by Laut *et al.* [207]) and calculated competition values based on this fixed position.

5.2.1 Fake Peer Implementation

The fake peer system proposed here ideally generates a fake peer value that sits at a pre-determined distance from the performance of the user to encourage competition. This peer should maintain a certain believable distance from the user, able to break from patterns of behaviour where necessary to prevent mimicking the user, but also follow their patterns closer enough to maintain interest. The fake peer operated within a 'closed loop' system, meaning the only data used in the calculation of peer values was data contained within the system, that being the peer values themselves and whatever data the user entered. The peer values, VP, were calculated and adjusted solely using participant data points on desired behaviour, U_n, where n represents the current week of the intervention period. Participant behaviour change, C, was calculated by comparing new behaviours to the previous data point

$$C = U_{n-1} - U_n$$

if the intended behaviour change called for a downward change (e.g. weight loss), or

$$C = U_n - U_{n-1}$$

if the behaviour promoted increasing values (e.g. physical activity).

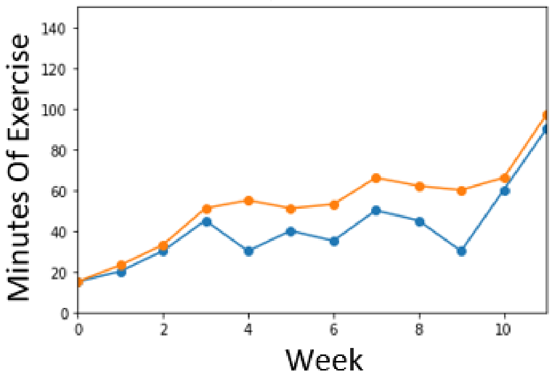


Figure 21: A visual representation of the Fake Peer algorithm (User in blue, peer in orange)

If the behaviour worsens, e.g. $C \leq 0$, the value for the peer VP_n was generated by applying a noise value, α, to the previous peer value. This noise value was randomly selected from a Gaussian distribution with a mean value of 0 to generate both positive and negative noise, and a standard deviation equal to $\sigma/4$ where σ was equal to the standard deviation of $[U_0, U_1, \ldots, U_{t-1}, U_t]$ to ensure that the possible value of $VP + \alpha$ was realistic compared to user behaviour. This was selected as The equation for the peer value in this instance was as follows:

$$VP_n = VP_{n-1} + \alpha$$

If $C > 0$, C was adjusted to provide a behaviour change for the peer, VC. This was calculated by increasing user performance by 50%, such that $VC = 1.5C$. Minor adjustments to peer value adjustment and the noise range given may be necessary to ensure that the difference in performances between the peer and the user does not encourage unhealthy behaviours.

A temporary result, VP_{nT}, was then calculated for the peer. This calculation took the relevant user value, U_n, and adjusted this by the calculated peer change value, VC. Once again, the decision of addition or subtraction was dependent on whether the desired change regards increasing or decreasing values as a positive change. The noise value was applied to prevent peer actions from becoming predictable and suspect. When combined, the equation for calculating the temporary virtual peer data point was as follows:

$$VP_{nT} = (U_n \pm VC) + \alpha$$

This temporary result allowed for the normalisation of the peer data to ensure this was believable as a collective group average. If the temporary result was taken and given to the user for each data point, the resulting progression of data would become predictable and user influence over the presented group data would be clear. The data was normalised using a Weighted Moving Average, where weighted previous data points were used in calculations so that entries from previous weeks had an impact on the newest value, as would arguably be true in the case of real-world behavioural adjustment. By adjusting the data relative to previous

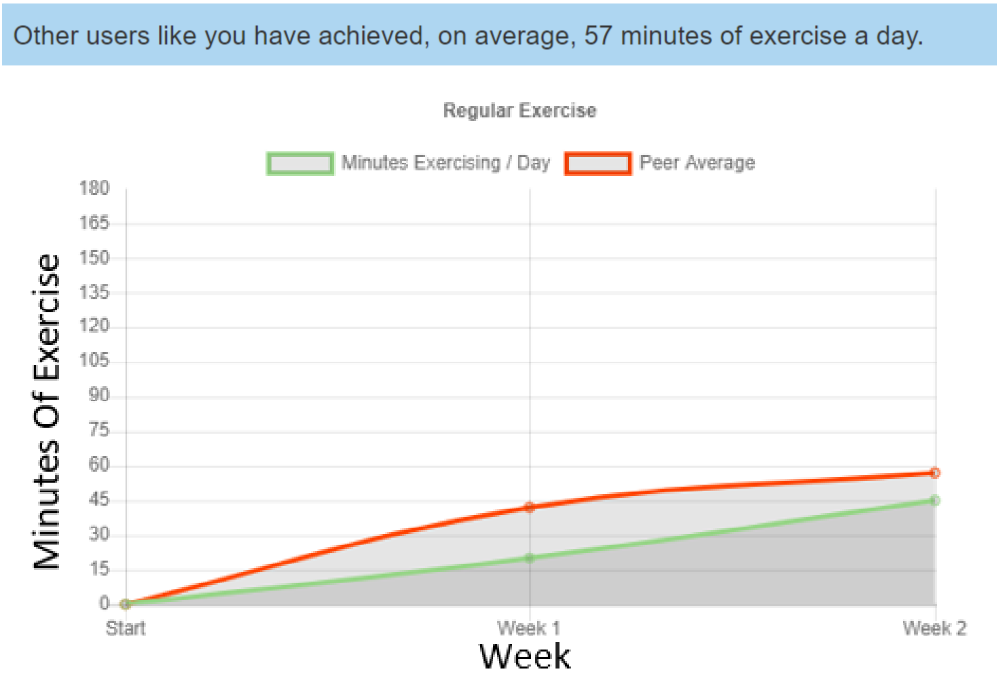


Figure 22: Displayed virtual peer data in both text form (top) and graph form (bottom).

data, the resulting curve more closely replicated the results and progressions of a collective. This Weighted Moving Average was calculated as shown:

$$VP_n = \frac{1}{2}VP_{nT} + \frac{1}{4}VP_{n-1} + \frac{1}{4}VP_{n-2}$$

This value, VP_n, is the peer data point for the desired value of n. In some cases, boundary checks were required, such as preventing values where $VP_n < 0$ or if VP_n results in a value greater than the maximum value obtainable, such as $VP_n > 7$ where VP_n relates to days in a week performing a certain activity. Figure 22 shows how this peer was presented to users, both as a text entry presenting an average amount and a comparative line on personal progress graphs.

5.2.2 Virtual Peer Outcomes

There were no specific behavioural outcomes observed in this study, but the fake peer system encouraged some degree of engagement. Of the 27 individuals who enrolled on the section of the website where the fake peer was implemented, 9 were seen to be 'engaged' with the system (33%). This is compared to 9 of 29 in the condition with attached health information (31%), 0 of 13 in the base intervention condition (0%), and 2 of 5 for the control condition (40%). Overall adherence to the service was poor, but the fake peer performed the best of the three experimental conditions.

The fake peer implemented in this system had several limitations. The first was that the system was tied entirely to the progress of the user, improving when they improved and easing off when they struggled. The result of this connected nature was that over longer periods, the peer became increasingly predictable which then created concerns of users deducing the artificial nature of the peer. An additional issue was that the optimal peer performance required the user to be committed and continuously inputting data. The problems with this were two-fold: Long periods of inactivity would be replicated in the peer which would again make it exceedingly obvious that the comparison was not genuine, and the peer was unable to encourage those who had disengaged from the behaviour as the fake peer would also appear to disengage at the same point in the behaviour change process.

A further issue was that the design of this fake peer, while seemingly effective within the service, reinforced the ergodicity problem discussed in Chapter 3. Laut *et al.* found the superior performance of the peer to be the most effective implementation [207], but applying this as the singular consistent peer state means that any user who found greater influence from other conditions would be unaffected. Hard-coding the performance of the peer to be 150% of what the user was capable of rendered the influence of the system ineffective if the user in question was not motivated by a superior peer.

This test of the fake peer concept provided both positive initial feedback as to the potential impact of the fake peer system, and some considerations to be made. The peer system showed that it could semi-realistically represent a means of social competition, but the implementation was predictable and fixed to a certain relative level of performance. The weekly changes of the fake peer were realistic in terms of their level of change, and there were a mixture of peaks and troughs depending on how the users themselves performed. However, the fact that these peaks and troughs were connected to the change of the user meant changes could be predictable and had the potential to be ineffective if the user performed no activity for a prolonged amount of time. Future implementations would need to be able to partially separate from user performance to be able to continue realistic mimicking of behaviour and would need to include multiple performance levels covering the full scope from under-performing to over-performing. Both of these concerns are alleviated in part by the intelligent algorithms allowing for more independent decision-making, but these considerations are still important for the design of the algorithms and the surrounding system. This work provided practical implementation experience which was both informative and beneficial when considering and forming the typology and Effect-Led Design work in chapters 3 and 4 respectively. With hindsight, we could classify this work as **Rule-Based/Repeated/ Individual**, and the knowledge of the prominence of this and the need to progress towards intelligent systems may have affected the design. However, this work still functioned as a developed behaviour change implementation, and as such allowed us a first real taste of the landscape and what potential positive outcomes could be obtained. This work also established the idea of the 'Fake Peer' as a potential method of behaviour motivation, and raised the question of how this method would operate as a direct competitive value rather than a generalised comparative one - an idea that would form the backbone of the 'Parameter Switching' condition in the experimental setup.

5.3 Main Experimental Framework

This work, which covers the main experimental system and accompanying experiments, was conducted at the end of the research work. This work was conducted after Chapter 3 and Chapter 4, and as such benefits from the findings obtained from this work. This places this as much more developed than the work in the previous section but still utilises some ideas from this section such as the concept of the fake peer. Two experiments were planned to test the proposed approaches to integrating AI into behaviour change. The initial concepts of the exact interactions of techniques and their presentation were discussed there, but further consideration needs to be given to the techniques to be included within these experiments, as well as the platform and exact nature of implementation to give the best chance of consistent data collection with data fit for analysis, as well as allowing for the machine learning algorithms to learn and react to user patterns and provide enhanced behaviour change interventions.

The work presented in this chapter is not presented as a fully functioning prototype that uses highly intelligent AI to drive optimal behaviour change. This is, of course, a challenge for the research community to develop systems like that in Figure 20. However, the purpose of this work is to test key components of the experimental framework expanding upon the conceptual blueprint, the implications of the motivational techniques, and to gain a sense of how these operate in real-world environments. The focus of this work is primarily interested in the interplay of human values and efficacy in behaviour change, specifically motivation and movement, rather than meaningful behaviour change. We focus on testing the individual principles and the structure of the conceptual blueprint, much as the 'Implementation' section of Figure 20 was tested by the evaluation of Effect-Led Design.

5.3.1 Theoretical Design & Selection of Approach

The two experimental conditions, as described previously, are a selection of techniques that can be switched between intelligently, and a single technique with a key technique parameter that can be switched intelligently.

Intelligent Switching of Techniques

The techniques considered for intelligent switching were taken from the BCTTv1 [254] as with Effect-Led Design to give an evidence base to the approaches used. Additionally, the techniques selected were intended to be varied, taking approaches from different taxonomy clusters to mitigate the potential factor of ineffective or unsuitable techniques having a significant impact on uptake and motivation levels. In theory, this is also mitigated by the very nature of the technique switching approach, but selecting all techniques from a single cluster or theoretical background could lead to all techniques having the same amounts of influence and the same limitations of appeal regardless of switching.

The techniques selected (and their placement in the taxonomy) were Social Reward (10.4), Graded Tasks (8.7) and a digital interpretation of Verbal Persuasion about Capability (15.1). These techniques come from different clusters - Reward and Threat, Repetition and Substitution and Self-Belief respectively. Tangible rewards, more attainable goals and reinforcement of capability each target known barriers to physical activity of lacking motivation [159], lack of time to achieve the full step values and the need for confidence and competence for the activity [388].

Intelligent Switching of Parameters

The intelligent switching of parameters required a single base technique structured such that multiple different variants of a central parameter would have their own notable impacts. It was also desirable for the design and listing of these parameters to be simplistic. For example, while Graded Tasks technically has a suitable parameter for switching, this being the tasks themselves, the design and implementation of multiple sets of multiple tasks, each set presenting a different approach to the technique, would add levels of complexity to both the implementation and the algorithmic learning that could have an impact on the overall experiment.

Social Comparison was chosen as the technique in question, with the parameter being the competitor and their relative performance. This social comparison system was approached as an intelligent implementation of the fake peer system explored in the Champions for Health trial study. This was selected as the approach for two key reasons. First, the initial testing of the approach in the Champions for Health study meant that part of the work to integrate this technique was already considered, especially compared to the intelligent selection of real-world users.

Second, and most importantly, the fake peer resolves a concern with the use of real competitors that was initially seen as a concern with the original fake peer implementation. Comparing the user to real individuals is heavily reliant on those same real individuals performing the behaviours consistently over the same period. Additionally, as the intention would be to provide several comparisons within the algorithm, the system would require real-world users to effectively fill a stepped set of conditions around the user which is unfeasible in free-living scenarios of physical activity. By utilising the fake peer system, this stepped set of comparisons could be coded into the algorithm while still presented as real competitors, allowing for a tangible sense of real-world competition without relying on those same competitors to maintain their level of behaviour. This also raises an interesting ethical discussion as to how people feel about competing against the artificial 'optimal' competitor, especially if the artificial nature of said competitor is obscured.

This selection was based on the research seen into the 'virtual peer' device and its impact on user activity. Whereas the work of Laut *et al.* from which most influence is derived established minimal fixed values of just above and just below, the approach considered here is the use of a wide range of potential step values for a given interval which can be swapped based on explicit and implicit user response. Fixed step tiers were used for this initial investigation.

5.3.2 Platform of Implementation

In this experimental setup, these intelligent algorithms to switch techniques or parameters were implemented to additional features of an existing pedometer application. A pedometer application was chosen for this experimental system for three key reasons.

Firstly, a pedometer application is a straightforward digital tool which allows for the majority of implementation time to be focused on the machine learning algorithms and technique/parameter switching functionality. Step counts are an established metric, and there is evidence that step counts influence positive physical behaviour [27, 57]. Sedentary behaviour may be seen as a more prevalent issue in the current health space, and there are emerging algorithms that allow for the intelligent detection and classification of sedentary behaviour [22, 187], but these either require additional physical sensors or are not yet accurate enough for free living scenarios. As such, the established approach with a greater ability to be accurately and effectively tracked in day-to-day situations was chosen as the basis for the experimental system.

Secondly, pedometer applications are ubiquitous in personal health and fitness. Pedometers and pedometer-linked health promotional materials have been around since at least the 1960s and are closely associated with health behaviours. An advantage of pedometers is that they make use of behaviour that is engaged in as standard during daily life and has previously been established as the method of activity most appealing to currently inactive individuals [260]. This, combined with the ability to passively track this behaviour in the background of living situations allowing continuous automated tracking of behaviours [204], makes a pedometer application a straightforward tool for data capture and presentation for both researchers and participants.

Finally, steps as a metric are more effective in this context than metrics such as sedentary behaviour or abstract physical activity, as steps present a quantitative combination of activity data and success criteria. The most common of these success criteria is 10000 steps per day, but this figure comes from the marketing campaign of a Japanese pedometer device named the manpo-kei, or '10000 step meter'. The similarity of the Japanese character for 10000 - 万 - to a running man reinforced this decision and, as a result, this goal in the public mindset [213, 293]. Further research has established step targets of between 4000 and 7000 steps [213], upwards of 7000 steps [279], 8000 to 10000 steps [278] and even as high as 8000 to 12000 steps [317]. These step goals may not be consistent across the research field, but they do present a goal that can be achieved, in that there is a recommended number of steps to achieve such that one has surpassed the required amount to offset any negative impacts of inactivity. Sedentary behaviour can be tracked but lacks such an exact goal to strive for. The inclusion of machine learning algorithms within this experimental framework requires a measure of success for learning to be possible, as the algorithm needs to be able to select and promote certain actions or approaches based on what is deemed most successful. It is technically possible to track this based on absolute step numbers, but this would still require a set of values to be determined as to how successful the given action was. The existence of these target step values gives a starting point for such reward structuring and therefore increases the ability of the reinforcement learning algorithms to learn and more consistently select optimal approaches to behaviour.

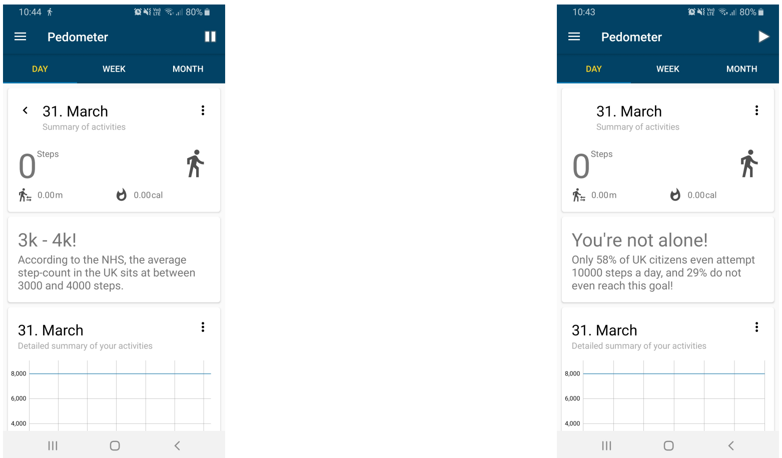


Figure 23: Screenshots of early application prototypes, demonstrating implementation of Verbal Persuasion on Capability, one of the implemented techniques as discussed in Section 5.4

5.4 Experiment Platform

The four behaviour change techniques and associated code were built as additional features to an open-source pedometer application. This pedometer code was developed by the SECUSO Research Group with a focus towards maximum privacy. This focus on privacy presented a good neutral base on which to develop this application, as the existing code contained no external internet connections or device permissions that would need to be adjusted or overridden, instead presenting a blank slate upon which necessary permissions, connections and code could be built up.

The base application provided both hardware-based and accelerometer-based step counting, tracking of steps in both numerical and graphical formats, and multiple periods over which steps could be tracked and presented. This provided several compatibility options to ensure steps could be tracked on any device and presented the means through a variety of display options and time-frames for tracking to allow for most techniques to be integrated into what was already contained within the application with minor adjustments. Minor changes were made to the application to remove certain included features, such as a training service, the ability to alter and learn walking patterns and a built-in motivational alarm system. The ability to switch between daily, weekly and monthly step tracking in a single toolbar was also removed. These were removed to reduce the complexity of implementation and to avoid the possibility of certain features interacting with techniques in such a way that the effectiveness of the technique is significantly altered. Having to include multiple versions of each technique for daily, weekly and monthly intervals would also have increased the number of required conditions and required participants as a result, which would raise necessary recruitment and data capture to unfeasible levels.

Implementation of Techniques

The four techniques were all implemented to easily slot into the existing framework as set up by the pedometer application. This code was written by students as part of their final year projects, specifically by Rajiv Kulkarni (Section 5.4), Noah Mitchell (Section 5.4), David Kajwang' (Section 5.4) and Hadi Jalali-Lak (Section 5.4), and was submitted as part of their dissertations. My contribution to this work was overall mentorship of the work, as well as in-depth guidance on design decisions. These students were also educated on the process of Effect-Led Design to ground their thinking in this experimental space.

Verbal Persuasion on Capability

The 'Verbal Persuasion on Capability' technique is implemented as a set of motivational messages which change upon loading up the application. These messages were selected not to inflate the opinion of the user on their own ability, but rather to accurately re-contextualise their step values and their goals to allow for motivation to be obtained from the steps they are achieving and how these place themselves within the value obtained by wider society.

The three messages all communicate to the user that while they may not consistently achieve ten thousand steps a day, the fact that they are even striving for this is impressive, and if they do achieve a good number of steps or perhaps even achieve their goal, that is a degree of success that is still very impressive in context:

- "Only 58% of UK citizens even attempt 10000 steps a day, and 29% do not even reach this goal!"
- "Most people only reach 10000 steps one or two days a week."
- "According to the NHS, the average step count in the UK sits at between 3000 and 4000 steps."

The selection of these messages cannot be specifically tailored within this implementation, as these would technically classify as parameters, which would mix the two experimental investigations and make it difficult to establish where any potential increases in efficacy come from. As a result, these are selected randomly each day and displayed below the step count, to provide an immediate morale boost and a potential increase in steps each time the steps are viewed by the user.

Graded Tasks

The 'Graded Tasks' technique was implemented as a daily tracking task that tracked the completion of these tasks over numerous days. This was implemented as a very low-complexity presentation of the tasks as the technique itself does not rely on the technology to enhance or support it, so all that was required was the basic presentation of the content. The back end of Graded Tasks required the ability to store goals to be achieved over numerous days, as well as the ability to track which goals were achieved and which needed to be presented.

The goals were set as constants, progressing in stages from 4000 steps for four days to 5000 steps for five days, all the way through to 10000 steps for seven days to represent the week. These were chosen to allow for the final goal of that standard approach, with each stage ensuring the behaviour was manageable over a longer time. The system also stores the previous week's worth of steps, to allow for comparisons to be made between the appropriate step goal and the step logged by the system, ensuring that the system is updated to the appropriate goal. This also allowed for the Graded Tasks process to persist through changes in technique as the combined stored knowledge of the current goal and a week's worth of steps allowed for updating upon use.

Checks were included to identify if the goal was not being achieved. Graded Tasks are intended to allow for the slow increase of step numbers from a number that should be easily obtainable to the desired high value of steps such as the 8000 to 12000 step range, or the classic 10000 steps. The issue with this approach is that while not achieving the full goal can be seen as the fault of an overly ambitious goal, not achieving a more manageable goal may result in the user placing blame upon themselves and negatively impacting their motivation and confidence, which could lead to abandonment. To resolve this, the implementation uses the check of the number of days since the last goal check to observe for how long the goal has not been achieved, and in response, may revert to the previous task if necessary to encourage the progression and perhaps allow for this motivation to be regained and possibly increasing the likelihood of achieving future tasks.

Social Reward

Social Rewards were implemented as an interpretation of social standing, or rewarding action with social praise, which took the form of a ranking system. Rather than an explicit ranking of users based on steps or other subsets of activity, this ranking resembled the system utilised in multiplayer video games such as *Call of Duty* or *Battlefield*, presenting ranks and titles of increasing importance and grandeur as the number of steps achieved by the user also increased.

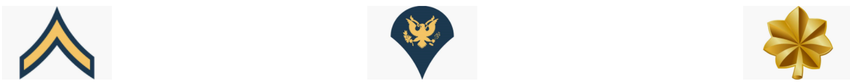


Figure 24: Examples of the ranks for the Social Reward implementation (here pictured the 1^{st}, 5^{th} and 8^{th} ranks

These ranks were presented with a circular progress bar, which was filled as the user performed their steps. Unlike the Verbal Persuasion on Capability and Graded Task implementations, Social Rewards was implemented over a monthly period to allow for the rank functionality to work long term rather than being constrained by the changes in days potentially interrupting progression towards ranks. As the monthly tracker calculates an overall number of steps based on collective daily step counts, this could be used as a continuous step value that would persist through the changing of techniques.

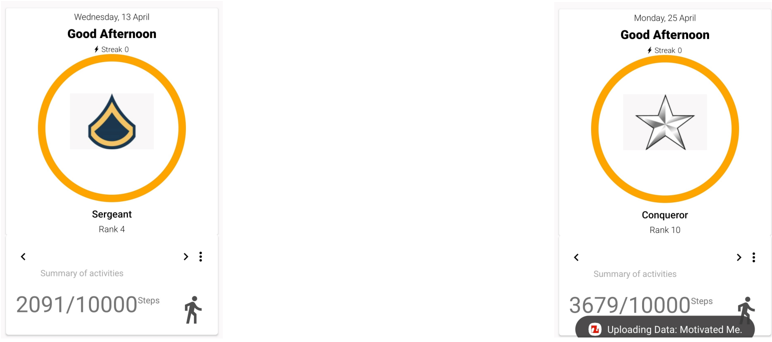


Figure 25: Rewards display with step count, showing two ranks achieved through use

The progression of ranks and badges is calculated by comparing the number of steps achieved by the user within the period to the required steps to increase in rank. This value is calculated by multiplying the badge number, effectively the rank number, by a constant of 12500. This value was determined by calculating the number of steps that would be achieved in a month if the user consistently achieved a realistic value of 5000 steps, and then dividing this by the total number of badges, 12. This effectively presents an equal separation of the total number of steps achieved. If the user can achieve 5000 steps a day for a full month, they will be able to achieve the top rank, which is a realistically obtainable goal that still presents a level of challenge. As the number of total steps does not reset upon a change in rank, it is necessary to multiply the rank value by the badge currently obtained to ensure the required cumulative steps have been achieved.

Fake Peer

The 'Fake Peer' technique implementation, itself an interpretation of the Social Support (6.2) behaviour change technique, was presented as a collective average of individuals similar to the user against which they could compare themselves. The peer steps are calculated mostly by the on-board Python algorithm, with the number of steps calculated using the selected action. An action is equatable to a parameter, with each action representing one of the peer value ranges that can be selected, and these actions are what the system learns in terms of matching parameters and outcomes. The actions available are between 1-19. This action is incremented by one to avoid negative step counts, and then passed through a method to produce the presented step count (between 50-2050):

$i \leftarrow$ random between 50 and -50
$action = action + 1$
$peer = (action * 100) + i$

This follows the concept outlined during the Champions for Health fake peer trial discussed in 5.2, using a fixed action value instead of the user change value and adjusting it through multiplications and noise values to make it believable as a comparable average. Additionally, the noise value is recalculated with each calling of the method to give the impression of a fluid average value changing as the 'users' engage in their activity. This peer steps value is used within the system as a comparative value, presented below the user step value to encourage pairwise comparisons intended to increase activity levels as can be seen in Figure 26:

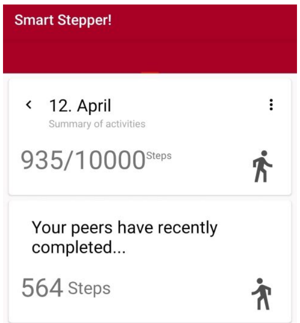


Figure 26: Fake Peer display alongside user step values

5.5 Implementation Details

As well as the techniques themselves, several features were required for the system to effectively perform the requirements of the experiment, as well as record information that would allow for more effective performance and analysis by both the application itself and the associated Python code. This section, as well as the following sections detailing the machine learning algorithm, are written by myself. Whereas the techniques are the individual components of the system, the code here that I have written is the code that directly tests the elements of the conceptual system architecture that underpin the contributions of this thesis.

5.5.1 Application Components

Android App Code

This section is here to give an overview of what components make up the experimental system, their purpose in the overall operation of the system and generation of intervention content, and what data each component collects and processes to allow for the system to operate effectively.

The core application, as described above, functions much like a standard pedometer system. The system records step counts, either through the standard Android step counter functionality or a hardware-based step counter calculation method within the application for use on older devices. These steps are stored at half-hour intervals as dedicated objects within the application called *StepCount* objects. These *StepCount* objects are then uploaded to a cloud-based database to ensure all data is stored together. If uploads are not possible due to poor internet connection, these *StepCount* objects can be buffered and stored in a queue to be uploaded simultaneously.

Functionality is included to capture discrete user feedback on how motivational a given technique or parameter was. An early system issue was the potential for the reinforcement learning algorithm to develop coincidental associations between actions and positive outcomes. This error comes as a result of the way the learning is conducted, which assumes that increased or decreased step counts are entirely dependent on the presented action. This means that if the user engages in a high number of steps for reasons outside of their control such as a particularly high-intensity workday or spending a day out walking from location to location, even if they do not interact with the application a single time during this time, the application will store data with the assumption that this high step count was a direct result of the unseen actions presented during this time. Therefore, it was necessary to implement a system such that the user could assign an exact label of motivation to each action as they were presented, which would then directly influence the weighting of certain step count recordings during the active period of the reinforcement learning algorithm. This manifested as notifications requesting user feedback at the point of technique or parameter change, displaying a screen with four options and asking the user how they felt about either the previous day's technique or the most recent comparative peer step value. The options presented were that the user was motivated, they were demotivated, they were unaffected or they did not see the technique or value at all. Once answered, this response was collected and uploaded to the database alongside the exact intervention to give an image of how motivations aligned.

The system then selects the new action and associated intervention content. In the case of the Technique Switching system, each technique has an implementation within the system that is mapped to one of the three action values. When the system generates an action, this action is read and the respective technique content is loaded up. In the Parameter Switching condition, as described in Section 5.4, the action is selected and put through a calculation to generate a peer step value which is then presented to the user.

Android Learning Code

Two main functions can be called: one that calls functions during the first run of the system that operates before any observations, and another that uses functions including these observations to build upon previous learning periods. In this context, the 'observation' is the knowledge already held by the model in terms of the previous outcomes and current reward assigned to each action. The action, user steps and presented peer steps are stored in the database, with a new step value calculated to be presented to the user. The post-learning code is functionally identical, simply using the observation for the calling of the new action to select one with the best chance of presenting optimal rewards. The next action is selected in one of two ways: either a new action is selected at random, or based on the previous observations made by the system which may allow for selections better aligned with what the user has reacted positively to so far.

Data Storage

The data obtained from the application is uploaded to a cloud-based database, hosted as a Google Firebase service. The storage of the data is scheduled to occur every 30 minutes. As well as collecting the step values and storing them in a format which can be sent with a range of accompanying data, the functionality for calculating the new fake peer values is also contained within this method as they run on the same time scales and as such make functional sense to run as a single method. The steps attained since the last saved file are calculated and presented as a *StepCount* object: If it has been too little time between this current attempt to save and the last save, a time so short that no significant data has been obtained, then the last stored step count is updated rather than creating a new one. This is legacy code from when storing step counts was possible to activate manually, but in the case of an error with the alarm or an accidental firing of the method, it's good to retain this code to avoid excessive creation and storage of near-identical *StepCount* objects:

Once this has been created, and possibly the fake peer information has been calculated depending on the condition, this data is uploaded to the Firebase database. This Firebase method takes in a date from which it calculates the same time difference as searched for in the storage method, to ensure that in the case of error, only one Firebase upload each hour is permitted. An intent is then created that stores all the relevant data, and calls a web service method to upload this information. Any locally-stored *StepCount* objects are loaded in, and the appropriate type of upload is selected depending on which technique was active at the time to ensure all data is captured. These methods are similar but include technique-specific data captures such as the task for Graded Tasks or the rank and progress for Social Reward. The method then iterates through the stored objects uploading them by adding database records for the given date and time under a given username for simple lookup. For this implementation, the usernames were recorded as user phone numbers to allow for easy communication if records stopped saving or the application was seen to no longer be running. The full storage checks and conversion to different objects for storage can be seen in Appendix A.3.

5.5.2 Machine Learning Approach

Rewards	The score used internally in the algorithm to determine how successful an action was at delivering the target outcome
Interval	The period for which a value is compared against (one hour in this implementation)
Episode	A determined number of data points used in learning
User Step Count	The number of steps in a given interval
Feedback Response	Response to the feedback message (positive, negative, neutral, unseen)
Observation	Previous learning, or the weightings currently in place for selecting the optimal action

Table 5.1: Definitions of Machine Learning Terminology

This platform makes use of an on-board machine learning algorithm. The terminology used in this chapter to describe the algorithm and how it operates can be seen in Table 5.1, and the full code can be seen in Appendix A. The algorithm used in this experimental platform is a reinforcement machine learning algorithm. This means that the algorithm is not extensively pre-trained like with supervised models, but rather learns through 'trial and error' by assigning reward or punishment to desirable and undesirable outcomes respectively. To use this experimental platform as an example, reward and punishment would be applied to increases or decreases in physical activity, which would allow the system to learn which actions it takes are more desirable for positive outcomes. The specific type of algorithm used here is a decaying ϵ-greedy algorithm which predicts which technique or parameter will result in the greatest improvement in steps. The benefit of using this type of algorithm is that over time in use, the algorithm will transition from heavily favouring testing all conditions available to heavily favouring selecting conditions based on prior success - The system will go from ensuring all techniques and parameters have been tested to focusing on those which have returned positive step counts. The algorithm predicts this by basing reward scores on the change in steps between one technique/parameter and the next - A greater positive change presents a higher reward score, which then increases the weighting towards that technique or parameter in the next selection. The machine learning algorithm runs once a certain number of data points have been collected. Each episode is equatable to a day to ensure updates are frequent and as close to in-the-moment as possible. The first episode is longer, with more data points; This will be explained in Section 5.5.3. If this threshold has been crossed, the algorithm starts learning using the data collected up to that point, as seen in Algorithm 1:

Algorithm 1 A representation of the code for determining when learning is run through the algorithm

```
if firstLearning then
    if learningPeriod > firstPeriod then
        call firstRunFunction
        saveData
        run firstLearningAlgorithm
    end if
else
    if learningPeriod > shortPeriod then
        call observationRunFunction
        saveData
        run observationLearningAlgorithm
    end if
end if
```

Two reinforcement learning methods are used, designed to learn from the initial set of data and then update the existing observations with new data. The first period threshold was selected following testing of the learning capabilities of the algorithm, and these tests will be discussed further in Section 5.6. Following this, the decision was made to retrain the data each day to repeatedly increase the effectiveness of the algorithm over time with the user's data to reach the optimal level of performance in the shortest amount of time. Technically all historical data is used each time as the observation is repeatedly built upon with the new reward calculations, creating a perception of the space which grows more dense with every period of learning.

The system learning utilises three streams of data: the actions (techniques or parameters), the user step count for the same interval, and the respective feedback value provided by the user. Through system use, these lists of values are accumulated and can be compared to allow for the system to learn. The output once learning is complete is the observation, which is then added to the existing observation to inform the following selection of data. When the system attempts to use its learning, the observation is used to provide a prediction, which is a series of numbers based on the likelihood of returning a positive reward score, with the algorithm picking the action with the highest number as the next action to be presented to the user.

Rewards are assigned by calculating the change in steps between two points and converting this into a percentage value of change, giving an indicator of the influence of a given action. This percentage is then compared to several predetermined states to find which reward will be applied for that given step-action pairing, the process of which can be seen in Algorithm 2.

Algorithm 2 The process through which reward scores are calculated to be awarded to the algorithm - Appendix A.1, Lines 27-45

$change$ = difference between $oldSteps$ and $newSteps$
if $change >= 30\%$ **then**
    $reward = 30$
else if $change = 20\% to 30\%$ **then**
    $reward = 20$
else if $change = 10\% to 20\%$ **then**
    $reward = 15$
else if $change = 5\% to 10\%$ **then**
    $reward = 10$
else if $change = 0\% to 5\%$ **then**
    $reward = 5$
else
    $reward = -50$
end if

Feedback was also stored as an integer value to allow for weighting to be applied to the algorithmic rewards as seen in Algorithm 3.

Algorithm 3 The feedback options and their influence on system learning - Appendix A.2, Lines 75-93

if $noFeedback$ **then**
    $feedbackValue = 1.0$
else
    if $feedback = Positive$ **then**
        $feedbackValue = 2.0$
    else if $feedback = Negative$ **then**
        $feedbackValue = 0.5$
    else if $feedback = Neutral$ **then**
        $feedbackValue = 0.75$
    else if $feedback = Unseen$ **then**
        $feedbackValue = 0$
    end if
end if

This combined value of the reward score multiplied by the feedback value is the final value the system uses to reward a given action.

5.5.3 Edge Conditions

Some minor edge cases will be described here. For the calculation of reward, in instances where either value is 0, the change value is treated as the other value, with the value being negative if the current steps are 0.

A system is included if feedback responses are not provided, to ensure the lists are of equal lengths so the algorithm can correctly work through the lists in parallel. In this instance, a base value of 1.0 is provided to avoid any unwanted major changes.

As described above, the first learning episode is longer. This is to capture more data for the first learning period, as this first observation has no prior basis and as such will benefit from more data to build a more robust observation. This first episode is equatable to six days, the reasoning for which will be described below in section 5.6.

5.6 Off-Platform Algorithm Testing

Initial testing of the algorithm helped to determine the required number of data points for the system to begin to learn and make effective predictions. This testing was done separately from the experimental platform system to try and determine this number before implementation and used simulated step data. This was to reduce the time requirement for algorithm testing and allowed for rapid testing of varied episode lengths, learning lengths and epsilon values. It was felt that repeated implementations to test these different conditions in real-world testing would not have provided sufficiently more useful data that could be obtained through simulated tests.

The learning for this system was conducted as episodes of 60 data points. The system ran the learning algorithm after each set of 60 points, much as the on-app version learns every 24 data points following the initial learning call. The model was tested with different amounts of episodes to find how this affected the score and epsilon value, or how the episodes affected at which point the system could be said to be learning effectively.

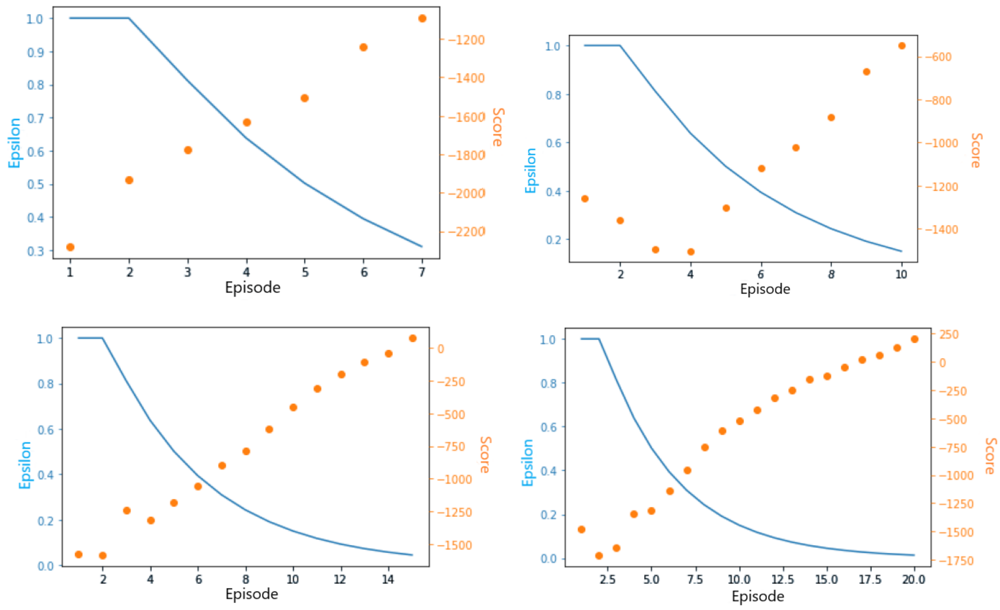


Figure 27: Evaluation of Learning Progression with 7, 10, 15 and 20 episode lengths. Orange dots represent the averaged reward score. The blue line represents the epsilon value, a pre-determined value that determines whether the action of the algorithm is random or based on previous outcomes.

The graphs presented in Figure 27 show four experiments with different numbers of episodes to test the time required for the algorithm to learn effectively. The blue line represents the epsilon value set for the decaying ϵ-greedy algorithm to allow for the transition from frequent exploring to frequent exploiting. This is a consistent, pre-determined decaying value that illustrates in essence a percentage chance that the selection of algorithmic action is random. For example, in the 20-episode graph, at Episode 5 the epsilon value is *0.6*, giving a 60% of the action being random and 40% of the action being selected based on prior observations. At Episode 15, the epsilon value is *0.1*, giving a 10% chance of a random action and a 90% chance of an action based on observations, which is desirable given the additional observations obtained over time. The orange dots each represent the average score across the episode. The scales on each graph are different but illustrate the general region in which the score resides - In the seven-episode graph, the highest obtained score is *-1200*, while in the 20-episode graph, the highest score is *250*, despite beginning at approximately *-1750*, showing the scale of improvement in score over the longer length of time. The important information to be gleaned here is the change in score as the episodes progress as well as where the tests start from, as a lower beginning score is not important in the long run if the score at the end of the test is significantly more positive. Each episode is made up of a series of steps, which in this instance would be the comparisons between step counts as the technique or parameter changes. The desired outcome here is an increase in score, or for the orange dots to increase in score value (seen on the right-hand axis) as this indicates the actions selected by the algorithm are resulting in positive rewards, which in this instance would indicate more positive activity from the user.

This testing indicated that a value equivalent to 2-2.5 games, or episodes, was the point where the epsilon value began to reduce below one, which indicated the ability to exploit knowledge and present actions based on learned patterns rather than for learning purposes. This equated to around 127-129 data points, which is reflected in the value presented in the reinforcement learning algorithm implemented in the experimental platform. These tests also indicated the ability of the model to produce highly effective reward scores with higher amounts of data, indicating that over time the model will produce effective results given adequate amounts of data.

The possibility for prior training of the data was discussed but eventually was not seen as appropriate due to the purpose of the model being a very individualised system. Training the model of each user on a uniform data set would increase the immediate effectiveness for users whose needs aligned with the outcomes of the training data, but for others it would arguably further negatively impact the model, requiring it to not just learn the user but also unlearn the trained associations that prove ineffective.

Original implementations of the machine learning algorithm were subject to the 'Personalisation Paradox' as discussed by Zhu *et al.*, as it was originally defined using a single step goal. The Personalisation Paradox describes the phenomenon that if a behaviour change system is perfectly personalised to a single individual through design, then this personalisation is inherently short-lived as it is specified to the state of that user through complete user modelling. As soon as the user's behaviour is changed by the system, the personalisation is no longer appropriate as their state is technically changed due to their differing outlook and action regarding their behaviour [405]. This is why the application implementation calculates the required reward based on the difference in behaviour to allow for the personalisation to adapt alongside the behaviour of the user and remain relevant at the minor cost of a slightly less specific user model.

Experimental Study Outline

The implementation of this experimental platform was specifically designed to best explore the influence of technique and parameter tailoring without additional features which could influence the clarity of conclusions drawn from these inclusions. This system was built on an existing pedometer application to ensure underlying systems for step tracking and data processing were present, but all other features were removed such that only the required features were present and visible depending on the condition.

The machine learning algorithm was integrated into the necessary conditions, and implemented in such a way as to fully explore conditions and weight based on step count intake and specific comments on motivational impact. This allows for the system to learn effectively based on both implicit and explicit responses and ensures this is consistent for all behaviours. The implementation of this algorithm on the device itself ensured the ability to learn without the need for communication and also allowed for offline devices to still learn, although the lack of database communication made this more difficult to track if this was consistent.

5.7 Experiment Details

The previously described implementation was used in an experimental study to provide answers to questions *RQ2* and *RQ3* as described at the beginning of the chapter. As part of this study, three condition-specific predictions were made:

- Condition **FP** (Fake Peer) and Condition **IS** (Intelligent Switching) would provide the greatest levels of motivation and engagement compared to Condition **US** (Unintelligent Switching) and Condition **C** (Control).
- Condition **US** would outperform Condition **C**.
- Condition **US** would be less effective than Condition **IS** and Condition **FP**.

These predictions outline the expectations of the experimental platform in terms of its benefits over typical approaches. The two intelligent conditions are expected to produce the most positive results, more so than the standard approach or switching approach without intelligent algorithms. However, the unintelligent switching approach is still expected to outperform the standard approach due to the inclusion of multiple behaviour change techniques providing a greater chance of applicability of the technique to the user. The study conducted to test these ideas was made up of four conditions. All four conditions were built from the same base code to avoid any confounding factors relating to application design:

1. A **Control** condition, **C**, with basic step counting and a fixed 10000-step goal, to provide both a baseline set of measurements with which to compare the intelligent approaches, and a set of values to remove the confounding factor of increased step counts due to the inclusion of a step counter of any description into their daily routine.
2. The **Fake Peer** condition, **FP**, with an intelligent peer value presented that is updated at hourly intervals, and supported by intelligent algorithms.
3. The **Intelligent Technique Switching** condition, **IS**, switching between the implementations of Verbal Persuasion on Capability, Graded Tasks and Social Reward at daily intervals, also supported by intelligent algorithms.
4. An **Unintelligent Technique Switching** condition, **US**, which switches between the same three behaviour change techniques as the intelligent system at the same intervals, but does not utilise the intelligent algorithms to learn the patterns of the user over time. This system does not include intelligent algorithms and therefore acts to identify the impact of confounding factors such as novelty on motivation and behaviour when compared to Intelligent Technique Switching.

5.7.1 Qualitative Data Capture

Qualitative questions were also produced to better capture user outcomes and attitudes surrounding system motivation. A full list of the qualitative questions can be found in Appendix C. These questions were asked as part of an interview following the use of the system, to capture opinions in the context of use.

Questions included were specific to differences in content and approach. **Parameter Switching**, specifically in the context of fake social comparison, explores the ethical implications of users competing against a value they believe is a real person but is instead an artificially generated value specifically chosen to best influence their behaviour. This value may give exactly what the user requires to best encourage positive behaviours, but being influenced in this way by a digital device may raise concerns about free will. Furthermore, the knowledge of competing against a device with no stake in the competition may affect motivation and engagement.

Both Technique Switching approaches raise questions about novelty, habit-forming and eventual habituation. In this experiment, the effect of 'novelty' refers to an increase in motivation or interest due to the presence of a new or unfamiliar technique or parameter, regardless of the actual impact of the technique or parameter on the user. The key focus of the Technique Switching approach is combating habituation while introducing an element of novelty to try and keep the user engaged long enough for the habit to form. As discussed by Fritz *et al.* and Pinder *et al.*, the eventual goal of a behaviour change application is to establish the target behaviour as a habit, such that the stimulus is no longer required [119, 289]. The difficulty with this approach is that if a single approach is used, habituation can set in before the habit is formed, which reduces the impact of the stimulus, affecting the ability of the device to encourage the behaviour and in turn, establish the habit. A question arises here, however, whether the regular switching of techniques in itself acts against habit formation. The repeated alteration of goals and targets may disorient users and reduce their ability to engage with the system. Another question is whether improved engagement is solely due to novelty rather than the intelligent switching of techniques, which is the reasoning behind the inclusion of both Intelligent and Unintelligent Technique Switching conditions.

5.7.2 Participants & Recruitment

Recruitment for these studies examining intelligent adaptive fitness trackers was aimed at the age ranges that most frequently utilise such applications. According to statistics captured in 2017, the age group with the largest share of fitness technology users was the 30-39 years age range with 41% of people using such systems, closely followed by 20-29 years at 39% [100]. The difficulty this path of recruitment presented was how to effectively reach out to the individuals in these 40% subsets, and how to encourage them to engage in the use of the application for the required amount of time. These ages were the target focus points for recruitment, but no age groups were excluded from participation.

This study utilised two key methods of recruitment to try to obtain the required user numbers. The first method of recruitment was the recruitment of University students through official University channels. University students filled a wide reach of the 20-29 bracket and presented a wide range of background demographics which gave a variety of insights into system appeal and influence. The second path was approaching individuals in both key age brackets, as well as others, through social media. This was split between individuals known to the research team and social media groups and tags relating to fitness and physical activity. These individuals were less diverse due to being approached through narrower channels but were more likely to be directly connected to either the researchers or the research goals due to this direct approach. This approach also gave a more diverse age range due to exploring outside of the student demographic to all those involved with fitness groups and social media which covered a far wider age range. This recruitment was mostly conducted remotely. Participants recruited through student-focused channels had the potential to be engaged through on-campus meetings to provide a connection between the system and the research team, theoretically promoting engagement. Those recruited through social media were contacted and recruited online.

5.7.3 Study Procedure

The four conditions (**FP, IS, US, C**) were developed as independent applications built on the same underlying code base, and were downloaded as four separate APK files which could then be distributed to participants. As described in Section 5.4, the prototype device was a basic pedometer application with the relevant technique code inserted as the key feature of the main application screen. Other features included in the original application code, such as activity types and graphs, were removed to avoid the potential of these elements encouraging activity and motivation, which could confuse potential outcomes. This application was intended to be run mainly as a background system, with a persistent notification to show the system running and additional push notifications when the technique or parameter changed to encourage engagement with the system. All intervention content was contained within a single application screen to reduce confusion and avoid any chance of participants missing content and therefore not engaging fully with the study.

Upon recruitment, participants were provided with an initial rundown of the study, the details of which were partially obfuscated to not make known the AI aspects of the system which needed to remain hidden for the fake peer system to be effective. Upon agreeing to the details of the study, participants were sent one of the four APK files, along with a short tutorial video developed by the research team which guided participants through installing the APK file on their mobile device. The APK files were provided in the order of Parameter Switching, Unintelligent Technique Switching, Intelligent Technique Switching, and finally Control.

Once the application was installed on the user's device, their activity and usage of the application were able to be tracked passively through the regular Firebase uploads. These uploads not only served to provide the data that would be used to evaluate the application but also acted as a regular confirmation that the application was successfully operating on the device. During their involvement with the study, participants were asked to act as they normally would and to follow the advice and actions of the application where necessary. The only exception to this was an element of encouraged engagement - regular notifications were included as an element of the application, but participants were further asked to open the application regularly both to ensure it was actively running and uploading data, but also to ensure they engaged with the content of the application, be it technique or parameter.

Participants were asked to use the application for four weeks from the initial download, with the research team keeping track of start and end dates for each participant. There was no identifiable data captured from participants - The only form of label used was phone numbers, requested to allow for the research team to contact participants in the instance of lost data to ensure the system is running and to guide the participant to restart the application if not functioning properly.

The data collected was as follows:

- Regular step data from the participant's device was uploaded to a remote Firebase database, which was broken down into half-hour increments to provide a balance between enough data points for the machine learning algorithm and large enough periods to identify the impact of techniques or parameters.
- Qualitative motivational feedback upon the change of a technique or parameter which provided an immediate personal response to the elements of the system. The user provided this qualitative feedback by selecting one of four options on a notification delivered through the mobile device - 'Motivated Me' as a positive response, 'Demotivated Me' as a negative response, 'Didn't Affect Me' as a neutral response, or 'Didn't See It' to attempt to control for high step counts completely unrelated to the application content.
- Qualitative responses from interviews were conducted once the four-week period of use was complete. Questions were asked around motivation, engagement and behaviour change, as well as questions specifically relating to the experimental condition if relevant.

The majority of data analysis was conducted on the interview responses, due to technical issues which will be discussed in Section 5.9.1. Despite this, the available step data was analysed by performing between-groups analysis to view any significant differences generally between the activity levels of different conditions. The motivational feedback was mostly used in conjunction with the analysis of the machine learning outcomes but was also collated to be used as an aide in interviews to examine whether responses around which techniques or parameters were seen as most motivating lined up with the in-moment responses to the notifications.

The interview responses were thematically analysed in a bottom-up fashion, with a loose focus on the key elements of the experiment (e.g. motivation, engagement, behaviour change). The condition-specific questions were analysed in a fully bottom-up fashion to ensure the collective themes were based on the participant attitudes towards elements of the system rather than what the research team perceived would be seen as positive and negative elements. These themes were recorded separately for each condition but analysed between conditions to find any notable differences in response.

5.8 Study Description

There were 61 responses to the recruitment materials. 36 participants downloaded the trial application, with 31 participants finishing the full four-week study period. Of the remaining five that did not finish this period, two encountered technical difficulties during installation which prevented use, and the remaining three encountered technical difficulties during use that prevented the application content from being engaged with to an acceptable level. Each condition contained between six and nine participants (Fake Peer = 9, Unintelligent Switching = 8, Intelligent Switching = 6, Control = 8). Of the 31 participants who finished the four weeks, 28 attended a follow-up interview (Fake Peer = 9, Unintelligent Switching = 6, Intelligent Switching = 6, Control = 7). Participants were recruited primarily through email exchanges, the content of which can be seen in Appendix C.1.

The majority of participants (19/31) were in the 20-29 age bracket, with the next largest being 30-39 (6/31). The gender balance of the participant group was skewed towards males, with a percentage of 76% (n=22). All participants had at least some interest in fitness and fitness tracking, with 28 of the 31 being interested or very interested and the remaining three being somewhat interested. 29 of the 31 participants had previously used a fitness device, with the average rating of experience with previous applications being around a 7/10 (mean average = 6.689). Education levels were high, with only one of the 31 participants not educated to a University level, be this holding an undergraduate degree or currently working towards one. Ten participants were working towards undergraduate degrees, with eight holding this degree, nine holding a Master's degree and three holding a Doctorate-level qualification. All participants provided consent to both take part in the study and for the use of their data for analysis, and this process received full ethical approval from Swansea University.

During recruitment, participants were given an overview of the research goals and the purposes of the study and were asked to fill in both a participant consent form with an attached information sheet, and an online questionnaire which provided demographic data (age, gender, education) from which possible comparisons could be made. Study participants were left to use their application at their own pace, with minimal interaction or interference from the research team. The only instance of researcher influence came when participants had been seen to not upload any data for multiple consecutive days, which suggested the application had closed and therefore the user was not engaging with the system, preventing meaningful interactions. All participants were given the same instructions regardless of condition, which were to use the application as they would any other application of this type, and to try and engage with the content of the application as much as possible.

Following the four weeks of use, participants were sent a questionnaire to capture their feelings on the system, as well as additional factors specific to their condition. All users were asked the same base questions covering usage of the app, influence on behaviour and self-held belief of behavioural improvement. Those in the technique switching condition were also asked about their feelings towards the techniques, in particular, which they found most effective and whether the changing of techniques was beneficial or detracted from the effectiveness. Further questions were asked about the influence of the switching on the appeal of techniques and the ability to form consistent behavioural patterns. Those in the parameter switching condition were given questions about the content of the peer, namely whether the changing of peer values helped and whether higher or lower values were preferred. Participants who engaged with the fake peer also answered questions following the reveal of the peer as fabricated, mainly about the per-

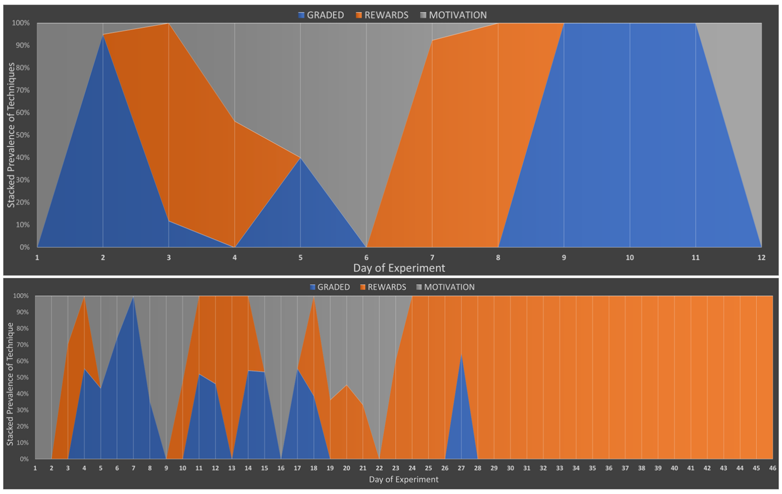


Figure 28: The graphs represent two different users having continuously used the application for 24 (top) and 46 (bottom) days respectively. The actions selected by the machine learning algorithm for two users of the Intelligent Technique Switching condition. Each colour represents a technique, and each vertical line represents a day of use.

ceived believability of the peer, attitudes towards the system through the lens of the newly obtained knowledge, and whether the knowledge of the artificial nature of the peer had significant impacts on the desire to use the system and overall motivational influence provided by the peer when known to be fake. These interviews were then transcribed and thematically analysed. Key themes of the thematic analysis pertained to overall usability, motivation and feelings of engagement, condition-specific information, and the potential impact and performance of the machine learning algorithms as perceived by the users.

5.9 Results

5.9.1 ML Performance and Perception

Intelligent Switching

Figure 28 shows two participants on the Intelligent Switching condition, each continuously using the system and providing data to learn from for different amounts of time. As can be seen from the graphs, while the first user sees balanced occurrences of the techniques, the second heavily favours the Rewards condition late in the process. This may give some indication of learning, although it is equally possible this is a series of random occurrences. There is a high amount of random noise that comes with real-world environments, which heavily limits the algorithm's ability to learn.

Figure 29 shows this lack of consistent growth, presenting the average score across all participants in this condition at each learning cycle. The high level of variation illustrated by the error bars indicates the need to account for factors outside of the simple pairing of action and activity to ensure learning is based on the exact influence of the action. This high level of variation is also an indicator

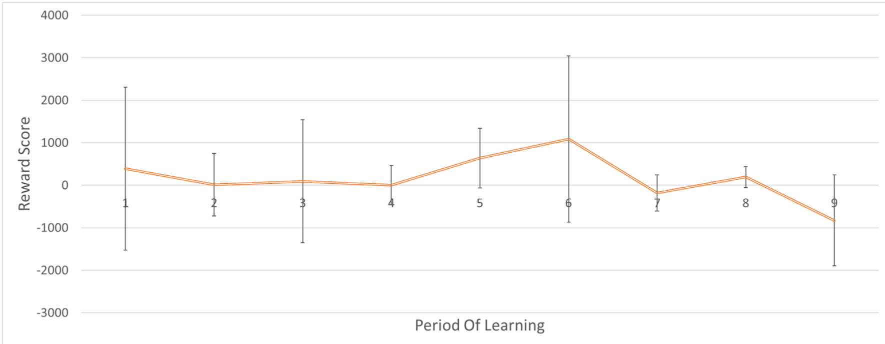


Figure 29: The average score at each update across the users of intelligent switching, where multiple scores were available across users. This is shortened by the long lead-up to learning initially, user drop off and missed data.

of a core issue with the algorithm. As the rewards are mostly based on steps, with only slight steering based on motivation, the overall reward and therefore the ability of the algorithm to learn is heavily dependent on steps being conducted mainly in line with the intervention content. If the steps are conducted for reasons outside of this, the system must take this as a response to the content, which means certain actions may gain some conflicting rewards due to situations outside of its control, or actions may be promoted by the system due to high step counts entirely unrelated to the intervention. These ideas, and potential solutions, will be explored further in Section 6.1.

Parameter Switching

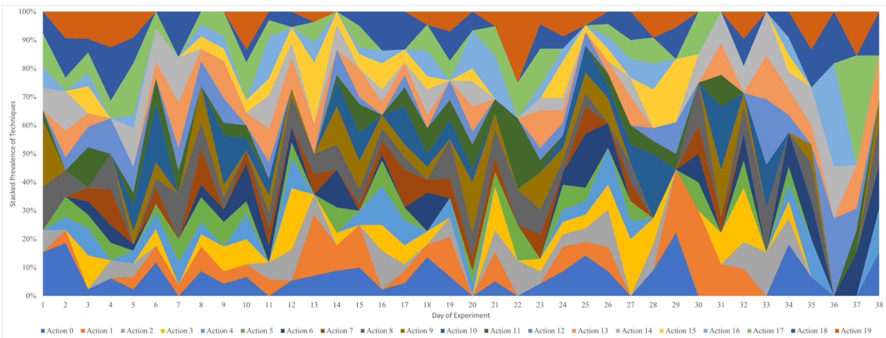


Figure 30: The actions selected by the machine learning algorithm in one instance of the Parameter Switching 'Fake Peer' condition. Each colour represents one of 20 parameters. These parameters were displayed as 100-step windows of fake peer performance e.g. action 5 represented a peer values of 550-650.

Figure 30 shows two examples of parameter selection in use from the Fake Peer application. The main concern of the parameter switching condition is that the selections do not appear to follow a pattern, and do not appear to bear any relation to the parameters picked out by participants as their preferred options for motivational purposes. This is likely due to surrounding contextual factors having a much stronger impact on parameter learning due to the frequent changes

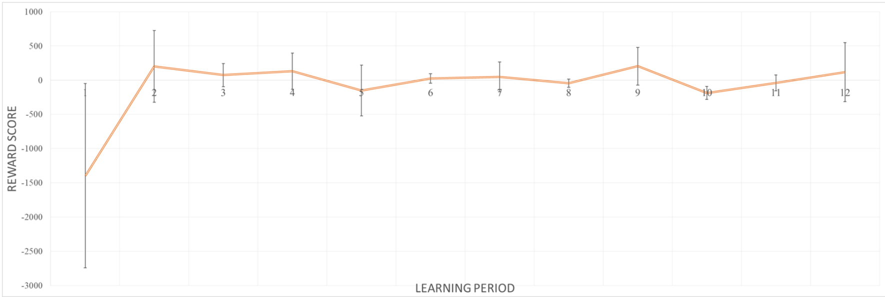


Figure 31: The average score at each update across the users of parameter switching, where multiple scores were available across users. This is shortened by the long lead-up to learning initially, user drop off and missed data.

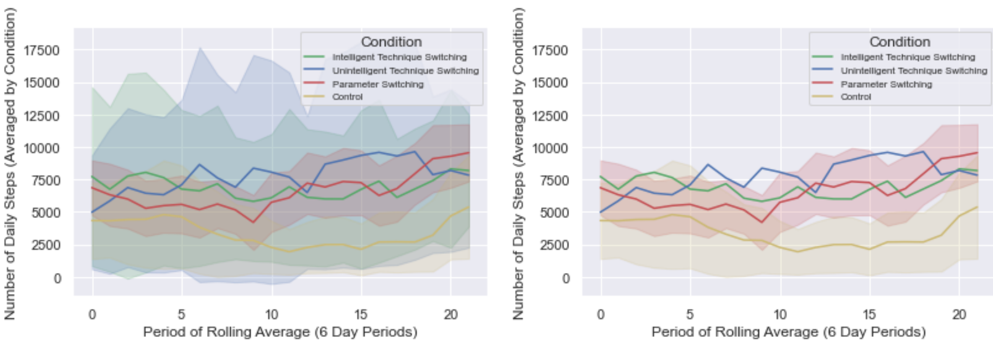


Figure 32: Average step counts from all users grouped by condition. Steps are represented as moving averages. The graph covers the length of the trial period. Shaded regions represent a 95% confidence interval for each condition. The top graph shows all confidence intervals, the bottom graph highlights confidence intervals for Control and Parameter Switching conditions.

in value across a day and the lack of consistency in when parameters appear. The variance in selecting parameters is high, which supports this lack of significant learning.

Figure 31 presents the average reward score for the algorithm across the user base each time the algorithm learns behaviours. Difficulty in presenting significant growth is likely due to the noted issues in parameter presentation and the impact surrounding factors have on this. The inability of the score to vary much past a neutral point coupled with high levels of variance at each learning point indicate that external factors heavily impact the ability of the algorithm to learn rapidly changing parameter responses in free-living situations as discussed above.

5.9.2 System & Behavioural Outcomes

Figure 32 shows the average steps of users across the different conditions, represented as a rolling average from the point where the learning algorithm begins to exert an influence in the intelligent conditions. The top graph shows all four conditions with 95% confidence intervals shaded. The lines on this graph representing the rolling average indicate a difference between the control condition and the three experimental conditions, but this difference is hard to see with the confidence intervals present, especially due to the high level of variance in the Technique Switching conditions. The bottom graph highlights the Parameter Switching and Control conditions to try and identify whether the two conditions with less variance showed any signs of significant difference. There are some instances, between days 10-15 and around day 18 where the two conditions appear to be significantly different, and this may indicate a potential improvement in steps from the Parameter Switching conditions specifically compared to the control. This reflects the qualitative results, which found Parameter Switching had the most positive response in terms of personalisation efficacy and changes in behaviour outcomes.

	Efficacy		Experience		Changed Behaviour?	
	Positive Effect	No Effect	Positive Interaction	Mixed Interaction	Yes	No
Parameter Switching	66.67%	33.33%	77.78%	22.22%	88.89%	11.11%
Unintelligent Switching	33.33%	66.67%	66.67%	33.33%	83.33%	16.67%
Intelligent Switching	50%	50%	83.33%	16.67%	83.33%	16.67%
Control	N/A	N/A	57.14%	42.86%	71.43%	28.57%

Table 5.2: Assessment of the experimental outcomes through the lenses of personalisation efficacy, user experience and self-perceived behaviour change. Fake Peer condition displayed more outright efficacy, while Intelligent Switching had a better user experience. All conditions generally felt their behaviour had improved.

Condition	Positive	Negative
Parameter Switching	Variation in Content Preference in Content Engagement Awareness Behavioural Improvement Motivation	Variation in Content Realism of Peer Presentation of Peer Technical Problems Untracked Behaviours
Unintelligent Switching	Variation in Content Content Switching Awareness Engagement Behavioural Improvement Motivation	Visibility/Ease of Use Technical Problems Untracked Behaviours
Intelligent Switching	Variation in Content Content Switching Preference of Content Awareness Engagement Behavioural Improvement Motivation	Visibility/Ease of Use Technical Problems Untracked Behaviours
Control	Awareness Behavioural Improvement	Lack of Content Engagement Motivation Technical Problems Untracked Behaviours

Table 5.3: The themes used to conduct the thematic analysis, along with whether the overall sentiment of each theme was positive or negative, separated by experimental condition.

5.9.3 Qualitative Outcomes

Qualitative results supported the concept of the experimental conditions, as the regularly changing content of the applications increased behavioural awareness and the likelihood of engaging in behaviours in response. The Control condition with 71% presented the lowest perception of behaviour change. Both Technique Switching conditions saw 83% of users feel their behaviour had changed. The Fake Peer condition was the most successful in this metric with the highest value of 89%.

The themes emerging from the qualitative analysis, as well as their general sentiment, can be seen in Table 5.3. Opinions on usability were generally positive, although some users experienced technical issues. A sense of motivation from the presence of the application alone was seen across conditions. In forthcoming quotations, participants are referred to by condition, for example, participant *C1* would be Participant 1 within the Control Condition.

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Awareness

Numerous participants commented on notable increases in awareness and motivation just from knowing the application was tracking their behaviours: *IS3 - "I think it was just a background thing for me, just having the app on my phone... was more motivation"*. Many users specifically referred to the persistent notification presented by the application: *IS5 - "the persistent notification... whenever I did look at my phone I'd see the app is just running in the background and that in itself would make me remember to move"*. Some in the Control condition did note that any issue that caused the persistent notification to not be presented could lead to overall disengagement: *C1 - "In the first few days, when I saw the little bar in the top of my phone I was like, oh yeah, I can do my steps and... when it went away, probably wasn't as conscious about it"*.

Some used their newfound awareness of their activity as a catalyst to challenge themselves to increase their steps: *C2 - "I'd look at my progress and I'd be like, I can do more than this, I know that for a fact... I just felt I wanted to be more competitive with myself, try and get better"*. Participants felt that even if their activity hadn't increased, the awareness of their behaviours had increased. One participant was unsure if their actual activity had improved, but found themselves more likely to look for opportunities to get up and move: *C6 - "My intent was there and thinking about right, when can I take a little ten-minute break"*.

In some instances, this new-found awareness was obtained from application content intended to more directly drive behaviour change. In the case of the Parameter Switching condition, the peer step value was used by some as a point of curiosity rather than a point of competition: *PS5 - "I think it was, I didn't use the steps to motivate me, I just found it interesting"*. When viewed in this way, being above or below the number was less important, as it was mostly used to see when others were active to align their actions with that of the group: *PS2 - "it will help in that way as well, shows that other people are active at the same time, so it does sort of help"*.

Motivation

Participants in all experimental conditions noted increased motivation from using the application and engaging with its content. Within the Technique Switching condition, motivation was derived not only from the techniques themselves but from the passive knowledge of their continued tracking when other techniques were visible. There was a factor of anticipation for certain techniques, such as days without Social Reward maintaining interest due to wanting to see the increase in rank: *US5 - "it [motivated me] anyway, because I knew [the ranking] will sometimes appear"*. There was also motivation to remain engaged due to wanting to see what technique would be seen, not knowing what options were available within the technique rotation: *IS3 - "Yeah, every day I would open the app, I would look it would come up with the quotes about walking, and I would open it throughout the day"*. Another participant echoed this sentiment but also noted that this motivation dwindled once it became apparent they had seen all the techniques in the rotation: *IS4 - "at first there was the element of that, oh it's changing, I wonder what it'll be today, but after a couple of weeks you've seen everything or you feel like you've seen everything so there's not enough"*.

For the Parameter Switching condition, there were more mixed responses regarding motivation, most centred around the idea of the artificial peer and their competition against it. When perceived as an AI competitor, many users saw the actions of the AI as just picking a number to beat, which removed any personal stake to compete for this and outperform the value given: *PS6 - "when you're seeing a fabricated number of steps higher than your normal number of steps then the app is trying to motivate you, it's like just an algorithm doing that, it's not real people"*. It was seen as less motivating to compete against a number generated by an algorithm, as the belief an actual person performed a certain number of steps gives the incentive to outperform said action: *PS2 - "John down the road has done 20000 steps today when I've only done 8000, where here it's a computer going this person could have done this but you've only done this"*.

Some users, however, felt that the artificial nature of the competitor made no real difference to their desire to engage with the competition. The complaint of the artificial peer being nothing more than a value picked by the system as a feasibly achievable value was seen as a positive point by one user. The fact that this value was selected by the app was seen as motivational as this was effectively the 'ideal' value for that given user, which was then motivational as beating this value meant you were outperforming what was seen as your requirement: *PS7 - "I think it would still motivate me in a way to still do exercise because it would still kind of push me to do more"*. The fake peer was seen as a positive in terms of its ability to match up to an optimal competitor value, rather than hoping a random user is hitting those values: *PS3 - "having something that is a little more reflexive and interactive whether you know it or not could definitely be more useful than relying on, hoping that someone is doing something you want to shoot for"*. This same user described losing motivation due to the disengagement of another competitor, which again supports the reasoning behind the fake peer system: *PS3 - "It was very useful to have someone to directly compete with, but when they stopped, or if they had an off-day, that then gave me nothing to shoot for"*.

There was also the perspective that, artificial or otherwise, the motivating factor was the general experience of being challenged: *PS4 - "some competition, I don't mind... it pushes me, you know?*. The AI was seen as a benefit to this as it was able to more directly tailor this challenge, being seen as a learned benchmark to compete against which only enhanced the feeling of beating it. The general sense of challenge was also presented as a negative element of the artificial peer, as the nature of the peer not being another user's steps meant their personal step counts were also not being presented to other users, which reduced the desire to maintain a strong level of activity: *PS1 - "I think, it being tangible, as opposed to being... like, the notion of having my steps on my peer's phones is quite motivating"*.

Behavioural Improvement

All conditions suggested some form of behavioural improvement, with users engaging in more short-form physical activity: *PS8 - "I usually take the bus down the road... but instead, I thought I'll take a walk down there instead.* The presence of the app also increased the likelihood of choosing walking over public transport, increasing activity in these split-decision scenarios: *C4 - "I think without the app, I would've been a lot less motivated to walk into town instead of taking the bus"*.

Behavioural improvement was also positively linked to increased awareness of the behaviour, even if this improvement was only minor: *PS3 - "I would say I did increase my awareness of the behaviour, and, yeah it was definitely slightly more present in my mind... a small increase potentially in the actual behaviour"*.

Variance & Preference in Content

A key benefit of the experimental conditions was the ability for the content to change, which could capture motivations and promote engagement since there was a reasonable chance at least one of the techniques or parameters on offer would be at least slightly motivating.

Diversity of technique preference supported the Technique Switching approach, as each technique was heavily favoured or unfavoured depending on motivational requirements, which the system could then account for and adapt to through extended use. Technique Switching participants typically found the changing of techniques interesting, and most participants found a technique that they preferred compared to the others included. Participants expressed preferring each of the three techniques, be this Graded Tasks: *US1 - "the initial four days where it tried to get you to have more than, I think, 4000 steps four days in a row actually kind of made me feel bad when I lost my streak one day"*, Verbal Persuasion on Capability: *US2 - "Um, I would say that notifications with the comparisons was best"* or Social Reward: *IS4 - "So I think possibly the most motivating one was where I was getting ranked, and the first time I saw that I was like, oh I wonder what happens, I wonder what the higher ranks are and how high I can get"*. There were also negative statements on each from participants who found them least helpful of the options - Graded Tasks was frustrating when goals changed once they were grasped: *IS4 - "it says like, can you meet that target for four or five days, and it was four thousand steps, and I did four thousand steps... it had changed to can you do 5000 steps and I was like... that's not fair*, Verbal Persuasion was not immediately helpful upon viewing: *IS2 - "I understand the concept of percentage of people in terms of quantity of it, and I think some people might struggle to grasp what, if it says only 50% of the population try it, I don't think they can quantify that number"*, and Social Reward was obtuse without a grander sense of scale: *US2 - "I'm not super aware of what it means, so I guess you need some sort of awareness of the rankings to full understand, oh yes, I'm now higher, even though it says rank 5, 5 of what? Of 10? Of 100?"* or required longer to be productive as a means of motivation: *IS1 - "after all I've only had the app for a small period of time so it's not like I can become emotionally invested into that, the rankings or whatnot"*.

One participant expressed the benefit of switching for different sources of motivation: *IS2 - "you struck a chord with me with one of them, you're going to do* *something else with somebody else I imagine, nobody is the same... you have to keep the cycle changing"*. This ability to address differences in individuals was also visible in terms of certain techniques or approaches being unfeasible due to external factors. For example, one participant had sustained a minor injury that reduced their ability to engage in high levels of activity for the early stages of the study. This participant was drawn to the Graded Tasks technique in the rotation, as it was a reduced target that only the single participant was competing for: *US1 - "a community ranking... but then they're of course going to walk thousands of steps more than me so it doesn't mean anything to me, where this one is just me so it does make me feel better"*. This uncovers another positive effect of the Technique Switching condition, which is the ability to adjust technique selection in the case of injury or sudden changes in conditions which limit the ability to engage with learned positive techniques.

The continuous switching of techniques was met with mixed reception. The switching of techniques was generally seen as a positive factor, with participants saying it provided a sense of change within the system: *US5 - "I think it's more interesting for the user... it's more encouraging to see something else rather than one view for the whole thing"*. On the other hand, some participants found the changes of technique difficult to follow, especially without any cohesive connections between techniques: *US4 - "I was a little bit confused... it went from military-style rankings then to one app that seemed to just be a number ranking?... I was just not sure how they married up"*, and without an understanding of why techniques were changing: *US4 - "if I understood why they changed and what the difference was, what the point of the difference was, that might have helped"*.

The continuous switching of techniques was viewed more negatively by participants who had engaged heavily with a single technique. For some, the switching of techniques to those less interesting meant they effectively viewed days with those techniques as lost motivation: *IS2 - "you're waiting like, obviously, I think it was the last one I didn't really engage with... I would be waiting for it to move on"*. For others, the moving of a given technique to the background made it difficult to continuously engage with that technique, be it the inability to view progress in a set of Graded Tasks: *US1 - "I was more focused on getting my streak and knowing that I did it and that was it"* or difficulties in visualising progression in ranks in Social Reward: *IS4 - "wanting that consistency of wanting something like the ranking where you want to see yourself moving up through the ranking, where I found it difficult to get a clear picture of whether I was moving up because I might have seen that one day and then not seen it for a few days"*.

Users in the Parameter Switching condition differed in whether they wanted to be ahead of the peer or behind them in terms of step numbers. Some users found being outperformed by the peer motivational as they were behind what was perceived to be the societal norm, so felt the desire to match the output: *PS1 - "you felt as if, if you were underneath what your peers are doing, you'd want to increase it to what I'm meant to be doing, this is how many steps I'm meant to be taking because it's just what everyone else is doing"*. Some users found a sense of motivation in being ahead as they enjoyed being in lead and were motivated by others seeing their high values, so felt the desire to push further ahead to avoid being caught by users in the opposite position of chasing the peer ahead of them: *PS1 - "being higher helped me, like I'd strive to be higher than everyone else... the* *days I was ahead, I would try to get further ahead, or try and maintain staying ahead".* However, some users felt complacent if they were ahead of the value presented and would do less activity, since they felt already being ahead of the peer average gave them space to be inactive and still be level with the general user group: *PS6 - "if the value was lower and I had already had higher steps than the other peers, I didn't then feel like that encouragement I had before to walk more".*

Presentation of Peer

The presentation of the peer was a key point in discussions on the Parameter Switching condition, especially concerning clarity of what exactly the peer represented. The presentation of the steps implied an updated average within a window of time, and those that perceived the steps as such were generally motivated: *PS7 - "I saw, oh the peers are doing a little bit more... I can just pop down to the gym, do a little treadmill, that sort of stuff* . Other users who misinterpreted the 'recent' step counts as a rolling daily value were less motivated as they would quickly outperform the step counts and therefore lose motivation: *PS9 - "perhaps within the last half an hour someone has completed 386 steps or if it's been a full day or anything like that, so wasn't quite sure where those figures were coming from so I ignored them in a way".* These same users often saw the peer value as a day's worth of steps and often found the values to be far too low for what would be expected: *PS4 - "I walk a lot and usually I do at least ten thousand, fifteen thousand steps a day, and my peers were mostly one thousand, two thousand, it didn't give the competition of things".* One user even explicitly outlined this question of timings: *PS3 - "3000 steps across a whole day might be quite low but 3000 steps within the last hour is obviously relatively high".*

All users responded neutrally or positively to the information of the peer being an AI construct, with some even stating they had wondered at times if the comparisons were made up due to inconsistencies or step counts which created a disconnect with the belief of normal step patterns: *PS8 - "I thought that the numbers, it's either these are randomly picked... or it's the person with the most or the least average sort of things, I thought if this is like an average or a highest number, this is... people aren't moving that much.* Some users were able to see issues with the peer values due to how they were generated, and these issues increased the chance of them working out the fabricated nature of the competitor: *PS1 - "I'll be honest, I did suspect a little bit... like it was generated".*

Realism of Peer

The randomness of the peer values in Parameter Switching impacted the believability as a 'peer average'. One user felt the high level of step count fluctuation caused doubt as the nature of the study meant this average would consist of a small number of users, and as such wouldn't change much: *PS6 - "I'm pretty sure if it was showing the real results of a group of people, the other testers, then it should be pretty steady across different days, you know? People have habits and they walk more or less, and I think they do it quite regularly... in the app, it was different every day and very different sometimes".* However, another user felt this fluctuation increased how believable the values were, as the multi-week nature of the study would naturally increase variation in step counts: *PS3 - "I know on* *certain days, it's like exam season and that sort of thing, I'd get very very few steps in, so it didn't seem unrealistic at all* ".

The semi-random generation of peer step counts meant that these values did not always reflect expected time-appropriate step values. For example, one user who worked nights found that the values did not follow the expected patterns of step counts that one would see in a rolling average: *PS2 - "12 o'clock it's saying other people around you have done like, 200 steps, I'm thinking if other people are usually out then, it should be a lot more"*, and another who often engaged in running sessions in the early hours of the morning found they often started these sessions to find the app reporting the average had already done thousands of steps that morning: *PS1 - "like four in the morning when it has two, three thousand steps I would think...* ".

This perception of issues with the presented values correlated well with existing levels of active behaviours. Users who were active outside of the influence of the application had a stronger understanding of what step counts would be reasonable for a given time of day and situation, which would lead to suspicions when the steps did not align with this understanding: *PS9 - "your peers have recently completed 356 steps, I suppose I do that when I walk to the toilet and back, you know what I mean"*.

Visibility

A major problem with the implementation of the Technique Switching condition was a lack of convenient visibility of application content. Some participants found that their engagement with the techniques was negatively impacted by the lack of immediate visibility, as the only means of seeing the content was by going into the application. All three techniques provided visual tracking of progress, be it checked boxes for tasks, a circular progress bar for ranks or specific statistics to motivate users, so opening the application was required to fully engage with these techniques: *US4 - "it was a case of having to go out of my way to open it to see the step count sort of slowed it down a bit"*. One participant, in particular, noted that the purpose of a system built around tailored, challenging content to motivate users is undercut by having to rely on internal motivation to open the app in the first place to view this content: *IS1 - "If there are challenges, they should come in your notification bar... It should be like some nudge towards it, but if it's going to challenge you, you shouldn't have to go in to ask for your challenge"*.

Lack of Content

Within the Control condition, a common issue was the lack of specific content on offer outside of the step counter itself. Participants found a lack of application content or drive to engage led to a lack of improvement: *C7 - "At the start, I wanted to try and hit the goal, but that definitely waned very quickly"*. This differed from the experimental conditions as these at least gave some incentive to check the specific technique or parameter, while the Control condition system could easily be forgotten about: *C3 - "it's easy to just have it on the background and not think about it at all, and that doesn't really push you to keep going"*.

5.10 Discussion

The initial predictions:

- Condition **FP** (Fake Peer) and Condition **IS** (Intelligent Switching) would provide the greatest levels of motivation and engagement compared to Condition **US** (Unintelligent Switching) and Condition **C** (Control).
- Condition **US** would outperform Condition **C**.
- Condition **US** would not perform as well as Condition **IS** and Condition **FP**.

were supported by the results obtained from the experimental study. The qualitative responses by participants within the scope of the study indicated that the two conditions that utilised machine learning were most effective, followed by the Unintelligent Switching condition and finally the Control condition. There was a 16% difference in positive responses between the Fake Peer and Control conditions and a 12% difference in positive responses between the two Technique Switching conditions and Control. This initially suggests no difference between Intelligent and Unintelligent Switching in terms of changing behaviours, but Intelligent Switching performed more positively in both Personalisation Efficacy and Interaction Experience, with Interaction Experience also more positive than the Fake Peer condition. This raises interesting questions regarding machine learning, as there is a difference between the conditions even without any evidence of the machine learning performing effectively.

The themes drawn from the qualitative analysis indicated the experimental systems were generally engaging and motivating, with positive and negative comments on all conditions regarding their approaches to behaviour change. All conditions also generally felt their behaviour improved (as indicated by Table 5.2, although the thematic analysis indicates Control participants may have only improved their awareness of their behaviour while the experimental conditions improved their motivation and engagement in changing behaviours. Technique switching participants praised the ability to focus on specific sources of motivation with all three techniques being preferred by at least one participant, although there were some comments on the potential for confusion and disruption of interest due to the switching mechanism. Parameter Switching participants were positive about the system and the peer comparisons, with competition found engaging whether the user desired to be ahead of the peer or behind the peer. However, some issues with the presentation and the believability of the peer reduced the potential impact. There is some evidence that the Parameter Switching condition promoted a significant change in steps against the Control condition (as visible in Figure 32), but high levels of variation in the Intelligent and Unintelligent Switching conditions make it difficult to make any claims on the step counts in these conditions.

The machine learning was unsuccessful in learning user behaviours, with no clear evidence of successful learning presented in either intelligent condition. A more in-depth discussion of the model and how these issues may be resolved is presented in Chapter 6.

5.10.1 Literature & Previous Work

The findings here align with some of the initial insights from the literature in Chapter 2, helping to situate this new intervention approach within the wider space. Section 2.4.1 outlined the sources of motivation, and found there were a wide range of determinants including age, gender, background and economic status which could impact how well the content of a system influenced positive behaviours. There is potential for the adaptable nature of the experimental conditions to be able to align their content with the specific elements of each determinant which alter the impact of a given technique or parameter. Whereas current research may find differing outcomes in different demographics due to the alignment of content and individual (similar to the comments of De Roos & Brennan [87]), the systems presented here can overcome that issue to potentially provide a more uniform level of positive behavioural impact. It is true to say that this issue could be overcome in the current design space by utilising a more hands-on approach to intervention design and deployment, working with the user to align the content with their needs. However, this would go against the concept of the 'minimal contact intervention' which was seen as highly effective. The experimental conditions presented here combine these concepts, able to tailor intervention content to the continuously changing state of the user without sacrificing the passive nature of the intervention which allows it to operate effectively in real-world conditions.

Shin *et al.* named the "interrelationship between people and their information needs" as one of the key elements to better serve user needs and improve overall system adherence. There is the potential for the system presented here to begin to explore this relationship, especially as more techniques begin to be included within the Technique Switching condition - there are Behaviour Change Techniques such as 'Monitoring of emotional consequences' and 'Framing/re-framing' which could find what information needs are possessed by a given individual and utilise parameters or alternative techniques to best serve and address these. This also highlights a potentially interesting issue with the current approach to intervention evaluation, specifically in the area of certain demographics responding more or less strongly to a given technique. Certain ages, genders and backgrounds not finding success with these applications may be due to poor alignment between technique and user, and the ability to shift and change content in use may help a wider range of users find the same long-term system success.

There is also an interesting parallel in play to the outputs of the Effect-Led Design work presented in Chapter 4. In the exploratory study, a concern raised around one of the design concepts presented was fairness and reliability, specifically in the context of a system which compared activity numbers without any concern for health conditions or contextual factors impacting how much activity an individual can perform. Related to this is a comment from one participant in the Technique Switching condition, who praised the Graded Tasks technique as it allowed them to engage with activity despite having sustained an injury which limited their ability to engage with a typical leaderboard-based health system. This ability to change techniques and parameters to address external factors which may leave certain techniques temporarily ineffective helps to address these concerns around fairness and reliability in AI systems.

5.10.2 Limitations

Some limitations in this study may have impacted potential outcomes. Technical issues with the application resulted in losses of data. A lack of measures in place to ensure users continuously used the application meant some instances of the Fake Peer and Intelligent Switching conditions were not as effective as a limited introduction to these conditions confused or did not engage users. Additionally, the time scale of the study means that there may have been instances where the intelligent algorithms were not able to effectively adapt to user behaviours, especially if data was missed due to the previously discussed limitations.

5.11 Chapter Summary

The experiments described in this chapter explored the approaches of Intelligent Parameter Switching and Intelligent Technique Switching in real-world environments compared to a standard step-counter system. These experiments returned positive qualitative results, indicating that these approaches can provide high levels of motivation and behavioural impact, with users praising the novel approaches of each system for their ability to encourage behaviour. There were some minor issues, although these were mostly due to the exact nature of implementation - Parameter Switching presented issues with content presentation influencing the degree of impact on user engagement, and Technique Switching saw issues with limited technique numbers eventually leading to reduced interest in the switching content. The machine learning algorithms were initially unsuccessful in performing any meaningful degree of learning, with the outcomes presented showing no clear evidence of trending towards intelligent selection of techniques and parameters. This experiment explored the system presented in both the conceptual blueprint and the more specific experimental platform outlined at the beginning of this chapter.

With the positive qualitative outcomes explored in this chapter, the next chapter, Chapter 6, examines the negative outcomes of the machine learning algorithms in this experiment. The algorithm itself is explored through a small number of data sets and focused examinations, before going on to explore possible changes to the algorithm and its implementation that could lead to more effective learning and system outcomes for users in future.

CHAPTER 6

ANALYSIS OF ML FAILURES & ALGORITHM REDESIGN

6.1 Analysis of Machine Learning Failure

The outcomes of the deployed experiment indicate clear issues with the machine learning algorithms failing to learn from real-world data. Here we present a series of post-experiment tests, using the ML model on the real data captured during the live experiment, and trialed a range of conditions and changes in an attempt to understand why the ML failed to learn.

6.1.1 Current State of the Model

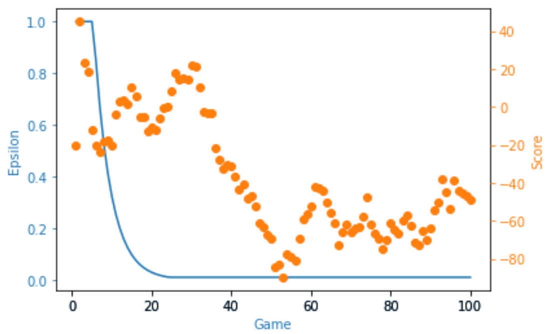


Figure 33: The performance of the application machine learning algorithm when presented with random values, without controls such as motivational preferences or feedback modifiers. There are some instances of growth and decline, which come as a natural outcome of the structure of rewards.

Figure 33 presents a baseline for machine learning performance - the input of random numbers to view the ability of the model without any confounding factors. These graphs are similar to those seen in Section 6.1: The blue line represents the epsilon value and indicates the point in exploration or exploitation, and the orange dots represent the averaged score from each episode, with dots higher on the graph showing a higher reward and therefore more evidence of learning. These graphs show a lack of consistent improvement in score, with the dots either decreasing or remaining relatively stable in terms of their score. This lack of learning is to be expected, as there is no connection between step values and actions, which means no actions are going to emerge as high reward options due to no consistent behavioural response. This graph tells us the expected outcome that highly noisy inputs, or inputs without any sort of relation to the algorithmic actions, prevent the system from learning. The next step of understanding the model is seeing what happens when trends are introduced, to show the algorithm can learn trends that are present and to understand what may influence this learning.

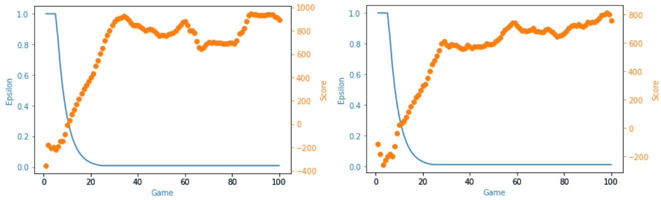


Figure 34: The performance of the application machine learning algorithm in two conditions: Left shows step preference towards actions, right shows feedback preference.

Figure 34 shows two variations on this same experiment, expanding upon whether the rewards structure operates more effectively when certain actions are actively promoted. The left-hand image shows skewed steps, with 100 steps for actions 0-6, 5000 steps for actions 7-14 and 10000 steps for actions 15-19. The right-hand image shows skewed rewards, with a negative response modifier (x0.5) to actions 0-6, a neutral modifier (x0.75) to actions 7-14, and a positive modifier (x2) to actions 15-19. These graphs demonstrate a strong incline, which demonstrates the system is learning from the trends that have been introduced. This learning is expected from the left-hand graph which has tailored its step outcomes to the actions, but the right-hand graph demonstrates a more interesting outcome in that the noisy step values were still able to learn when supported by another more stable metric. This shows that the model is capable of learning when the user's actions directly relate to the actions of the model, or when noisy behaviour data is effectively supported by other user measures. This understanding of the model can be used to identify where issues arose in real-world studies.

6.1.2 Model Performance with Real Data

The noise of real data combined with inconsistent feedback modifiers limits the ability of the model to learn in free-living environments. The tests with random data show that learning from solely noisy activity values is not possible and that the inclusion of consistent feedback responses or trends in steps can help correct for these values. The examples found in real-world data show feedback and trending behaviour shape the model slightly, but not enough is given to allow for a strong positive progression of learning.

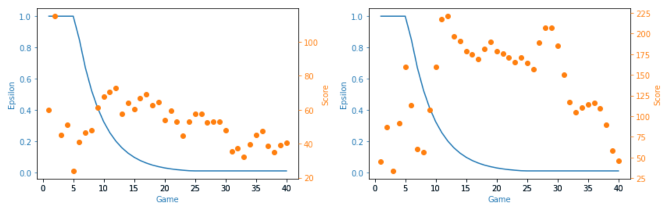


Figure 35: The performance of the application machine learning algorithm with real data from a Technique Switching participant. The left shows the performance from solely captured step values, while the right shows the performance with feedback modifiers.

Figure 35 shows the outcome of the learning algorithm for a participant in the Technique Switching condition. The left-hand image shows the outcomes without the feedback modifiers, while the right-hand image shows the experimental set-up, with the feedback modifiers included and the score adjusted accordingly. The difference shows both the benefits provided by the reward modifiers, as well as where these still may fail to adequately guide the model.

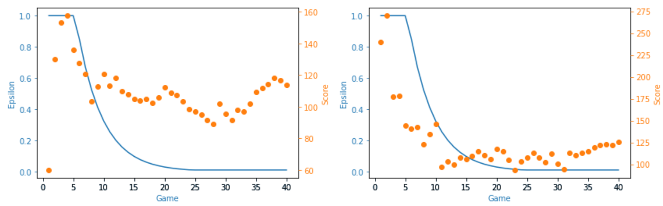


Figure 36: The performance of the application machine learning algorithm with real data from a Parameter Switching participant. The left shows the performance from solely captured step values, while the right shows the performance with feedback modifiers.

Figure 36 shows the same comparison being made with Parameter Switching data. These graphs are much more similar in shape than the graphs in Figure 35. The reward scores also appear to be similar, indicating that the feedback modifiers in the Parameter Switching condition may serve as corrections rather than enhancements.

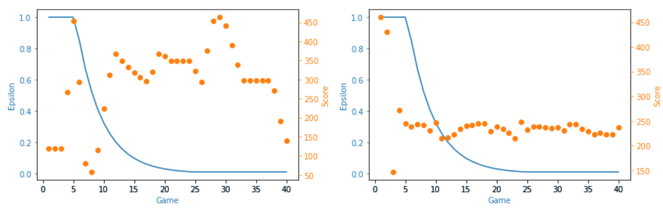


Figure 37: Graphs showing the scores produced when just the reward scores are read in and used to make decisions. In these examples, the left-hand side shows the Technique Switching condition while the right-hand side shows the Parameter Switching condition.

To try and ascertain the isolated impact of the feedback modifiers, Figure 37 shows scores based solely on the feedback modifiers, with positive responses

Action	Motivated Me	Didn't Affect Me	Demotivated Me
0	76.74%	11.63%	11.63%
1	37.50%	12.50%	50.00%
2	0.00%	80.00%	20.00%
3	50.00%	25.00%	25.00%
4	75.00%	25.00%	0.00%
5	66.67%	16.67%	16.67%
6	75.00%	25.00%	0.00%
7	0.00%	25.00%	75.00%
8	33.33%	0.00%	66.67%
9	25.00%	25.00%	50.00%
10	75.00%	25.00%	0.00%
11	66.67%	0.00%	33.33%
12	60.00%	40.00%	0.00%
13	81.82%	18.18%	0.00%
14	33.33%	33.33%	33.33%
15	75.00%	0.00%	25.00%
16	100.00%	0.00%	0.00%
17	11.11%	55.56%	33.33%
18	10.00%	20.00%	70.00%
19	60.00%	0.00%	40.00%

Table 6.1: Balance of feedback responses for each parameter from one participant, excluding Didn't See or non-response to indicate meaningful balance of parameters.

giving positive rewards and negative responses giving negative rewards. Technique Switching shows extreme changes, seen between games 10-15 and games 25-30. On the other hand, the Parameter Switching example is much more stable.

6.2 Proposed Refinement of Learning Algorithm

If the user continuously does not engage with the feedback system in place and their steps do not strongly trend towards certain actions, then the system will not have enough rewards to learn from to provide optimal parameter actions. Table 6.1 shows the responses from a single participant for the Parameter Switching condition for each feedback request. Parameters such as Action 0, Action 13, Action 16 or Action 19 all returned highly positive levels of response when feedback when given, but the overall lack of feedback meant these trends could not be exploited.

Further tests were conducted using three participants who were encouraged directly to answer all feedback prompts to aid algorithmic learning. As this was an exploratory piece of work, participants were known to the research team to allow for repeated contact and were selected to be more likely to respond to both the system prompts and further encouragement. Participants were contacted every two to three hours, as well as when feedback was seen to be missing, to ensure prompts were being answered.

The initial outcomes of this second run visible in Figure 38 are once again

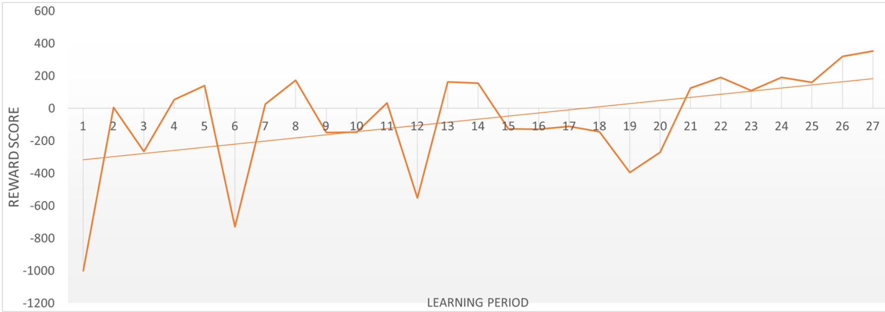


Figure 38: Average score from the second run with high response rate.

unsuccessful, although there is some evidence from the positive trend line and growth later in the process that some learning is in progress. The lack of success even with full utilisation of the feedback process suggests that a fundamental change is needed in how the scores are calculated. Feedback scores were a step towards this change, but the feedback scores are unable to act effectively due to how they are implemented - their use as a modifier to the change in steps means these values are heavily constricted in what impact they can offer. Therefore, these feedback responses may be better utilised as a standalone influence, balanced with the absolute activity change to best guide the system to what is preferred. The proposed solution treats both steps and motivation as key metrics in the decision of optimal actions. Another inclusion is the ability to shift the focus of the algorithm between activity and motivation, depending on which is required. Below is the proposed solution:

$$R_I = (\alpha)M + (1 - \alpha)A$$

Where R_I represents the reward score for that interval, M represents the feedback score, A represents the level of activity, and α represents a constant between 0 and 1 which can be altered to shift the balance of learning entirely activity-based or entirely feedback-based.

6.3 Experimental Testing of New Algorithm

The new process of reward calculation was tested with the Technique Switching and Parameter Switching conditions. Both conditions were tested to ensure any potential benefits applied to both conditions - For example, a solution that provided better reward selection for Technique Switching may provide no benefit to Parameter Switching, which could complicate the inclusion of such an algorithm within the identical underlying system framework. Additionally, in the case of the algorithm described above where a key element is the alterable constant, there may be notable differences in the optimal position of this constant which are worth analysing to better tune the algorithm in future.

6.3.1 Testing Methods

The first experiment with this new algorithm was conducted as a desk study, using the data captured to conduct the initial investigation presented in Figure 38. The step data, respective system action and motivational response were presented as continuous lists which a computer-based simulation of the application could take in as the hourly values. Once all lists were depleted, the system selected random step values within the range of the values within the list (the upper and lower bounds being the upper and lower bounds of the recorded data) and the motivational values aligning with what was previously seen.

The second experiment was run on mobile devices in a real-world setting with the balancing system implemented, with a setting of $\alpha = 1$. The same individuals were used as in the previous study, once again due to ease of contact and trustworthiness in providing consistent, usable data.

6.3.2 Testing Results

Figure 39 shows that calculating a score solely on feedback returns very successful learning outcomes for the Parameter Switching condition, while solely activity response returns mixed-to-negative outcomes. However, the learning algorithm returns increasingly positive scores from as low as $\alpha = 0.4$, which suggests that the influence of feedback is highly beneficial, and was mainly hindered by the need to be attached to the steps rather than seen as their necessary impact on the direction of system actions.

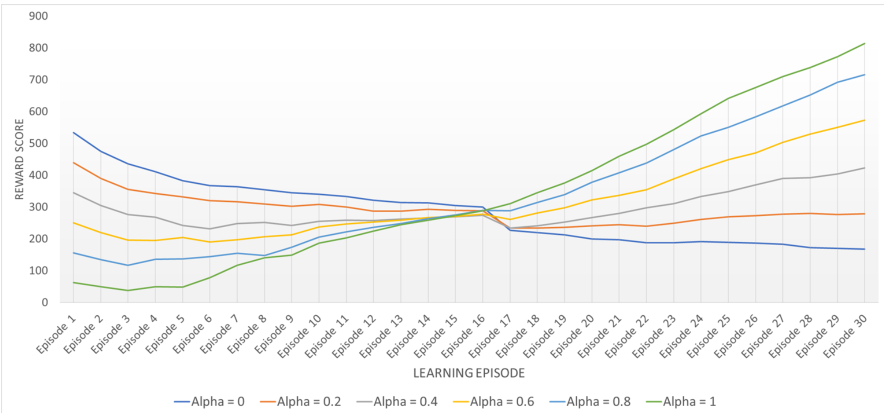


Figure 39: Average score from the second run of the Parameter Switching condition with high response rate, with multiple lines representing different values for α. Low α values (activity-based) return poor learning, while high α values (feedback-focused) perform well.

Figure 40 shows this process with the Technique Switching condition. This shows positive growth of reward score and subsequent tests with adjusted α values generating progressively worse outcomes. The early downward trend of this graph is due to the reduced number of actions available. The higher number of actions in parameter switching systems means that while there are more demotivating actions that can be chosen, these each only contribute a single negative point. The daily nature of technique switching means that a demotivating action generates 24 negative points, even if the overall odds of this being chosen during algorithmic exploration are theoretically lower. This is similar to what is seen in Figure 37, with the influence of a single technique leading to potential huge shifts in reward each day. Figure 40 indicates, however, that despite the potential for large shifts in score due to days with demotivating techniques, the overall learning afforded by the focus on motivational feedback is not significantly impacted. There is also an interesting plateau in the learning graph between episodes 13 and 19 - This plateau is visible in all variations of α which may indicate a user-based drop-off or complication as opposed to the algorithm itself experiencing difficulties, indicated by the subsequent increase from episode 19 onward.

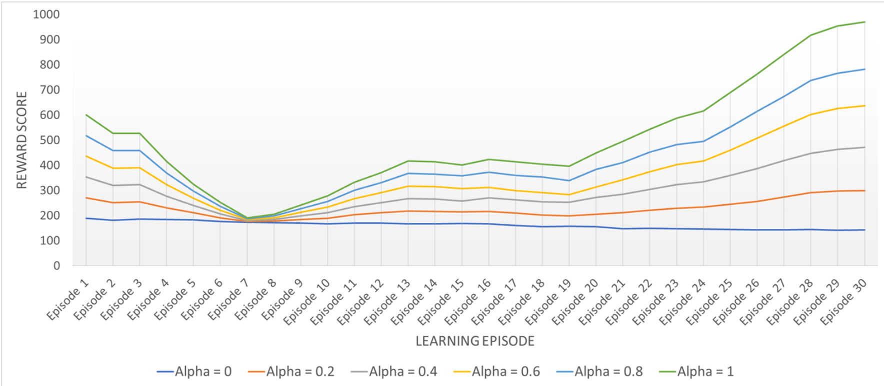


Figure 40: Data captured from an experimental run of the Technique Switching system using the new reward calculation method, with alpha shown here once again from 0 to 1.

6.4 Chapter Summary

Investigations were conducted into how the model operates with different levels of steps and the specific impact of feedback itself upon the model. Much as the literature highlighted a concern around over-tuning to performance metrics creating problematic AI deployments, the use of physical activity as a core driving metric with motivational feedback used only to scaffold this metric led to a system which was unable to effectively learn what best drove user behaviour and encouraged continued motivation and engagement. A theory was formed around the need to consider activity and motivation equally rather than one supporting the other, and subsequent tests showed the ability of this new approach to learn behaviours much more successfully. This is not presented as a key contribution of the thesis, as more experiments are required to identify how this new approach operates in real-time on the system, especially in instances of long-term system engagement.

The next chapter, Chapter 7, serves to conclude the thesis as a whole. The chapter will provide:

- High-level discussions on the thesis narrative as a whole, exploring the balance between activity outcomes and user engagement and motivation which pervades the thesis throughout.
- Resolution to the research questions established in Chapter 1, with specific discussions on how chapter content links to each question.
- Links between thesis work and the overall research landscape, using current literature to establish the place of this work within the wider space.

- Future work suggestions for where the emerging ideas in this thesis could be taken forward to explore avenues to greater behaviour outcomes

CHAPTER 7

CONCLUSIONS

7.1 Thesis Discussion

This thesis set out with the goal of provoking designs for AI-enabled personalised digital health and behaviour interventions that are grounded in scientific evidence and based on established behavioural change techniques. The focus on evidence-based approaches was intended to promote an increased level of efficacy from the resulting systems, facilitated by the timely inclusion of AI which could enable greater levels of effective personalisation. This intuition in the potential AI afforded to this space was evidenced by the outcomes of the digital personalisation survey, which found that **Intelligent** systems (as defined in the survey) often present positive outcomes. From this survey, two key sides of personalisation emerged - the physical lived experience and mechanical actions of system efficacy, and the mental internal experience of values and motivations that both impact the ability of personalised content to present a significant impact. In this work, we have witnessed and explored the interplay and importance of both components on personalised digital behaviour change systems powered by data-driven algorithms at several stages: Literature meta-analysis; design process; and the implementations of embedding this interplay into experimental learning objectives tailored to a specific behaviour change intervention.

The Effect-Led Design process is designed to explore this interplay between physical and mental elements of personalisation, with both playing a key role in the process. In this process, initial conceptualisation flouted the mental side of this interplay by driving maximum efficacy. The values of the user, representative of the mental side, were used as a means of correction to evolve concepts to designs, taking systems with little-to-no consideration for values and reinserting values into the concepts generated to try and create a balance between the outcomes of the system and the feelings of the user towards the system. These interactions were seen as ‘trade-offs’, exchanging system efficacy for better value consideration or vice versa. Users within the Effect-Led Design process did show some instances of changing their attitudes towards systems, and these users were often less intent on some user values which would often be fore-fronted in intervention design. However, there were still some values which were seen as highly important, and these were seen as central to the user and their interactions with the system, acting as their most 'true' values within the intervention space. Effect-Led Design presented the need for balance: While the process was structured around encouraging maximum efficacy in the initial conceptualisation phase and used values to taper these concepts, the final designs that emerged were built up through a nuanced combination of efficacy and values, a specific balance of these physical and mental elements.

The experimental platform, and in particular the design of the AI algorithm, was approached initially in much the same way as the Effect-Led Design process, with a heavy focus on these physical elements by using physical activity as the core goal and structuring algorithmic rewards around the change in activity, with the mental elements of motivation used as a secondary method to try and steer the learning once the reward was calculated. This heavy dependence on activity-based efficacy in the algorithm rewards shows this imbalance, but the specific experimental research questions of learning potential and changes in motivation gave some hint as to the solution to see them separately, as these questions were structured around what were seen to be the core principles of the experimental framework, and focused on the performance of the algorithm (physical) and the ability to encourage motivation and engagement (mental). Qualitative motivation was high in the experimental conditions, but the learning struggled due to the noisy nature of the physical activity metric. Steps as a performance metric are heavily influenced by external factors, which means the learning is also heavily affected by these factors. Although motivation was included in the reward algorithm, it was secondary in its effect compared to steps and therefore the system was less responsive in its learning from motivational feedback. Much like the strongest held user values in Effect-Led Design were unaffected by the high-efficacy solutions presented, motivational feedback represented a 'true' representation of the attitudes towards a technique - A technique or parameter is likely to be motivating or demotivating to an individual regardless of factors like weather, time or other commitments. The subsequent simulated experiments on real-world data illustrated this, and once again presented the need for nuance. The algorithm was able to learn when the reward structure was balanced around these physical and mental elements in the pursuit of behaviour, rather than using the more stable mental elements to scaffold the unpredictable nature of the physical elements more closely related to system efficacy.

This clear thread throughout the work and contributions in this thesis has highlighted the need to re-evaluate the relationship between the physical and mental elements of personalisation and behaviour change. Effect-Led Design used the term 'trade-offs' to discuss this relationship, which placed these physical and mental elements as adversarial in that one actively detracted from the other - values needed to be infringed upon to promote efficacy, and efficacy needed to be infringed upon to promote user values. However, the findings from the testing of the experimental platform seem to indicate that this is more of a nuanced 'interplay' between the two elements that persist throughout the landscape of behaviour change. The survey revealed Behaviours and Attitudes to be the two key data types that drove behaviour change, and this is again apparent here with their mutual benefit to personalisation clearer following the simulated studies of the machine learning algorithm. The nature of this interplay is also potentially specific to each intervention, and each technique and parameter within these interventions, with different approaches requiring different balances between the physical and mental elements of behaviour change and personalisation.

7.2 Research Questions & Findings

The content of this thesis was structured around a set of research questions established in Section 1.1. The initial overarching research question, as reiterated below:

How can AI be designed and utilised in the personalised physical activity intervention landscape, and what alternative approaches to designing such systems best harness the potential of intelligent algorithms?

Has been answered through a combination of the key research contributions - The literature survey, Effect-Led Design, and the experimental platform and subsequent experiment. To guide the overall question, and to better divide the grander investigation into its contributions, the following sub-questions, or *SQs*, were established:

1. *SQ1*: What AI implementations exist currently in the landscape of health and behaviour change, and where exists scope for AI innovation?
2. *SQ2*: How can current intervention approaches be redesigned to best harness the potential for innovation afforded by machine learning?
3. *SQ3*: Do these intelligent interventions have a significant impact on those using them compared to standard approaches?

Chapter 3 answered Q1 through the development and subsequent use of a classification system for the wide space of digital personalisation. This classification showed the current space focuses on rule-based approaches to personalisation, using updates at regular intervals to tune personalisation content mostly based on the problem behaviours and self-reported attitudes to them. Currently, existing intelligent innovations are individual-focused and often focus on the generation of user models, although there is scope for intelligent systems to better provide the services offered by current rule-based approaches. Potential spaces for innovation were an increase in intelligent, real-time systems, and an increase in the use of certain data types which can be more effectively utilised by intelligent systems such as context and in-the-moment behaviours. These findings were used to build a conceptual blueprint for intelligent personalised behaviour change, which positions itself to challenge the current perception of the space and drive more innovative behaviour change solutions.

Recent papers attempting to provide some form of an overview on the progression of the intervention space such as Alslaity *et al,* [12] are able to outline the increasing prevalence of intelligent systems in this space and broadly discuss these systems in terms of their theories and goals, but are less able to discuss the concrete mechanisms of these applications and how they approach changing behaviour. Similarly, the limitations described in the literature review of context-aware digital interventions by Craig *et al.* show major issues with reporting interventions and methodologies, and the nature of these systems makes it difficult to perform head-to-head comparisons of intervention efficacy [353]. We hope that the classification structure presented within Chapter 3 provides a more concrete structure to classify and report such systems, one that could be used to facilitate such head-to-head comparisons in future based on elements such as personalisation specificity relative to efficacy. This will hopefully also provide a clearer picture of both how intelligent digital interventions are progressing within this emerging space and where recommendations such as those presented by Alslaity *et al.* are beginning to be fulfilled within state-of-the-art designs.

SQ2 and *SQ3* were re-framed as refined research questions to better structure the upcoming contributions:

1. *RQ1*: Will the approach of pre-design in the focus space of behaviour change theory result in more effective technique designs, and will these present patterns in desired techniques and approaches to using these techniques that work within the scope of the system?
2. *RQ2*: Can a machine learning algorithm function on a mobile device in real-world situations and learn user patterns?
3. *RQ3*: Will the two experimental approaches, technique and parameter switching, influence motivation and engagement?

RQ1 was explored in Chapter 4 which developed and trialled **Effect-Led Design**, a process placing immediate design focus on AI algorithms and established behaviour change techniques by first intentionally removing any consideration for the user from the space. Afterwards, Effect-Led Design provided a phase for end-users to reclaim only the values they deem important by making changes which specifically targeted their most closely held values. The focus on behaviour change techniques and AI, coupled with the high-effect focus, resulted in designs built around efficacy and saw a departure from the techniques and approaches commonly seen in the space.

Effect-Led Design places itself at a nexus in the design research landscape by aiming to address the concerns of both design methods which build their entire process around the perceived needs of the potential user base and design methods which are solely focused on maximum-efficacy outcomes. Regarding the former, we return to French *et al.'s* four steps which consider best practice to be derived from theory and evidence rather than pragmatic solutions. Effect-Led Design fully bases itself within this stance, with all initial concepts built up from behaviour change theory and using this foundation to ground all concepts in evidence-based approaches. However, this stance is fairly countered by the comments of Carvalho *et al.* that placing too much focus on the rigid and evidence-driven implementation of theory-based techniques may undermine the ability of the system to influence behaviour. Carvalho *et al.* further highlight the importance of not silencing qualitative methods which serve to understand the reception of such evidence-driven implementations [48], a concept which Effect-Led Design serves through the user-centred second and third stages of the process. The combination approach utilised by Effect-Led Design aligns the process with the comments of John *et al.* ensuring that optimised efficacy is not the sole focus of the process, and the inclusion of users attempts to drive more effective and engaging system design.

To ensure user attitudes are properly included alongside the heavy focus on efficacy, Effect-Led Design takes an approach similar to the concept of 'embedded ethics' as presented by McLennan *et al.*, integrating those with a strong understanding of ethics throughout the process to ensure design decisions don't lead to ethical shortcomings [246]. Where Effect-Led Design takes a different approach is that these individuals are the users themselves, who are introduced at a slightly later stage once initial design decisions regarding conceptualisation have been made. A problem with the 'embedded ethics' concepts is that it may fall into the same pitfalls as the designer who believes they know what users want from their system - Allowing the users to act as ethical experts of systems within their own sphere of interest ensures the systems are properly aligned with the potential userbase without sacrificing potential efficacy.

Overall, the approach of Effect-Led Design is best aligned with the statement by Rothman in 2004 that theory and intervention are separate [314]. The theory in this case is handled by the designer's usage of behaviour change techniques and designing concepts based solely around these techniques and their proper usage to drive behaviour change. The intervention is the input of the user, ensuring that the approaches built from these techniques are able to be altered and tuned based on user requirements to be truly effective as a user-focused intervention. The third stage where both parties are joined together ensures these two elements are both able to be properly integrated, and avoids either party making decisions to undermine the other - Designers aren't able to make decisions based on their own perceptions of user needs, and users aren't able to make decisions on efficacy which don't align with the present theory and evidence.

The development of Effect-Led Design and subsequent tests of the design process partially answered *RQ1* as the high focus on behaviour change techniques and behavioural outcomes in the design phase resulted in designs that differed significantly from commonly available systems which were deemed ineffective. The comments of users and experts following the initial exploratory study also highlighted this difference to the parties involved in the design, which places Effect-Led Design as a potential driver of designs which adhere more accurately to the actual desires of users regarding efficacy and acceptability. The encouragement of absurd and exaggerated concepts within Effect-Led Design makes it difficult to state with certainty that these designs would be more 'effective' in strictly behavioural terms, and further research is required both by utilising the method with multiple disciplines and specialities to find where differences emerge and by taking some of these concepts forward to be designed and real-world tested.

Chapter 5 sought to address *RQ2* and *RQ3* by testing a system that promoted increased step counts in free-living scenarios. We aimed to examine both the learning capabilities of the reinforcement learning algorithm in highly unregulated spaces and the impact of technique and parameter switching both comparatively to each other and a basic pedometer alternative.

The ideas presented in Chapter 5 hold an interesting place in the literature space as it currently stands, as more recent publications attempting to direct the future of the space seem to suggest concepts that can be seen in the design ideas presented within this thesis, and particularly within the experimental system. Two publications of note here are the work of Mamykina *et al.*, looking at grand challenges for including AI in personal informatics systems, and the work of Alslaity *et al.* establishing a 'panoramic view' of the personalisation research landscape. In particular, as originally highlighted in Chapter 2:

1. "Integrating a combination of personalisation techniques... to increase effectiveness for motivating behaviour change [12]" - This is the core concept of the experimental platform in action, that being the utilisation of multiple techniques and parameters to help align the content of the system with any potential user regardless of needs. Where the suggestion by Alslaity *et al.* may be referring to multiple techniques in parallel, an approach which is also potentially effective if the techniques are properly aligned, the system here suggests individual techniques selected based on the user to help ensure continuous motivation.

2. "Continuously monitor the user so that the system is kept up-to-date about the user's habits and motivation [12]" - The tracking of both user behaviour in near-real-time and user motivation upon the changing of a technique or parameter serve this idea of monitoring the user's habits and motivation, and in fact monitoring user motivation is the core tenet of the entire design, in that the learning of the algorithm and the selection of techniques and parameters is intended to maintain user motivation by selecting the intervention content which maintains this motivation.

3. "Difficulties with passive tracking of behaviour that may result in noisy datasets, and the suggestion of triangulating between passively and actively captured data to get closer to what is deemed 'correct' by the user and their circumstance [235]" - The first of these two challenges is, in fact, a reflection on the very circumstances that caused the initial algorithmic design to be less effective in real-world settings. The noisy activity data meant techniques and behavioural outcomes did not accurately align, and the inclusion of motivational feedback only served to slightly correct a learning process which was already beyond repair. The concept of 'triangulating' between active and passive data to find the 'correct' situation for the user and circumstance is what the initial algorithmic design tried and the subsequent re-design succeeded in accomplishing by utilising both passive activity data and active motivational feedback to drive learning and find techniques or parameters which were the actual best fit for the user and their motivational needs.

4. "What opportunities exist for personalisation such as timing, form and tone of intervention content and, in the specific context of 'human-in-the-loop' systems, what different user actions could enhance the functioning of the algorithms contained within these systems? [235]" - The idea of the 'behaviour change strategy' as defined in the conceptual blueprint and experimental platform, and the concept of parameters as included (in a limited fashion) in the experimental platform gives an emerging answer to this concept of personalising timings, form and tone of content by placing these are parameters which could be actively changed by the system based on user response.

> The inclusion of user response more generally through the use of explicit motivational feedback also answers the question of user actions to enhance the functioning of the algorithm; As seen in both the initial implementation and the subsequent re-evaluation of the approach seen in Chapter 6, the use of this explicit feedback can help provide much more accurate and effective learning that would be seen from solely relying on the activity levels observed alongside a given technique or parameter.

Regarding *RQ2*, we were unable to conclusively show evidence of learning behaviour in the experimental study. This was due to the high levels of noise in passively collected activity data (as alluded to in the challenges presented by Mamykina *et al.* [235]) which left the learning process unable to find consistent outcomes on which to base recommendations of techniques and parameters. However, subsequent tests using altered versions of the algorithm (as seen in Chapter 6) presented evidence that learning in such an environment is possible when behaviours and attitudes are considered as balanced factors in learning, echoing their status as the primary data types in Chapter 3. This demonstrates that there is potential for the intelligent personalisation proposed in this system to be effective with sufficient data intake, and more research is required to identify whether this is successful in a full-scale experiment. The outcomes of *RQ3* were far more positive - The two approaches both returned more positive outcomes than simply counting steps without additional feedback or a predefined behaviour change intervention, with key differences between the two. This shows the benefit of increased numbers of techniques and technique parameters and establishes the positive influence on motivation from these new approaches to intervention design.

7.3 Impact on the Research Landscape

These studies demonstrate the potential of real-time tailoring of behavioural interventions to better attract and maintain user engagement and motivation. Digital AI-enhanced intervention research in recent years, such as intelligent calendar-based recommendations [83] or AI-enhanced conversational systems to support health care [205], typically follows something akin to the parameter switching approach, where a single approach decided upon in design is enhanced with AI. Where these systems look for patterns that have been pre-determined, the parameter switching approach takes this a step further by learning the patterns of use within the normal flow of behaviour, and can potentially learn an individualised set of patterns to account for with the user in question, leading to more closely tailored behavioural adjustments. The technique switching concept takes this a step further still by exploring how this can be expanded from just adapting to behaviour to adapting and personalising to full value sets as determined for each user within the free-living setting of their day-to-day activities. Current approaches tend to utilise a single approach, and usage of AI in these systems is limited. By taking this further and using the AI as a foundation rather than a scaffold, higher levels of personalisation can be obtained from previously seen tailored variables to whole techniques and even learned patterns of behaviour and required adjustments, and this in turn can lead to more behavioural impact and overall engagement as the full system is built to the needs and preferences of any given user.

Swann *et al.* have criticised the established SMART goal system, presenting several issues within this formula for setting goals and establishing approaches to better behaviours [341]. The issues raised included a lack of grounding in scientific research and empirical evidence, insufficient details in time frames and conditions, and the possibility of harmful effects when goals do not align with user needs. It is arguable that the work presented in this thesis provides means to overcome these criticisms and gives a better process of designing effective goals and overall effective behaviour change. The explicit use of behaviour change techniques in building the foundation of design both in the Effect-Led Design process and in the development of switchable approaches within the application grounds these processes in theory and in empirical research on effective techniques. The requirement of time frames and conditions which are not explored in the SMART process are avoided entirely due to the intelligent nature of the technique and parameter switching systems, which could adapt optimal arrangements of details such as time frames and conditions in real-time. This same ability to adjust conditions in real time may avoid the concern of harmful effects when the design of the intervention does not align with the user. The ability to adapt conditions in real time only mostly avoids concerns around harm to users as there is still the potential for detrimental outcomes in the initial instances of use where the system is still learning what exactly is required for the specific user, but real-time tailoring also presents the ability to progress to potentially more positive outcomes once this alignment is achieved. The process of intelligent technique and parameter switching not only presents positive outcomes over basic intervention design but also over these established processes of designing goals which have formed the foundation of effective behaviour change.

There are several pieces of closely related work: Taj *et al.* present a theoretical system for exploring the mechanisms of action for specific behaviour change techniques through user motivation, personalising and adapting the content of techniques based on generating and maintaining motivation [343]. This explores a similar space to the research of this thesis, with a focus on behaviour change techniques, user motivation and personalisation. This thesis differs in the scale of personalisation - Our system uses motivation as a measure of success and uses behaviour change techniques as a factor to which motivation can be applied, but our research applies this motivational impact to a full value set, a grander scale of technique and parameter options which can be more finely tuned than just the options available and their specific interactions. Chew *et al.* explore the potential of artificial intelligence in weight loss interventions, with improvements in perceiving actions, predicting behaviour or learning prediction models for behavioural lapse and presenting adaptive nudges to combat potential lapses in behaviour [62]. Chew *et al.'s* final approach most closely aligns with what we present, and the ability to learn signs of behavioural lapse even presents a means through which our research could be improved, but their work also lacks the scope of personalisation ability.

Aonghusa & Michie present an adjacent piece of recent research which serves as a partial follow-up to the lessons of the Human Behaviour Change Project [255], allowing an AI system to effectively predict the outcomes of interventions provided they have been checked and annotated by behavioural scientists [231]. Our processes of technique and parameter switching do not require the annotations and intervention of behavioural scientists, as the system actively records behavioural outcomes and motivational information provided by the user to assess the success of a given technique in the system. Where these two align is the potential for the active prediction of future success - Where the work of Aonghusa & Michie explores the potential for success or failure before deployment to avoid ineffective interventions, the intelligent technique and parameter switching systems could make these assessments of prospective success during use based on the prior success of techniques or parameters deemed similar and align its selection of content based on these predictions - For example, the Fake Peer system upon finding a successful peer value could raise the weighting of parameters immediately adjacent to this, or technique switching could favour other techniques which use reward-based approaches if Social Reward was seen to be the preferred technique of that user. This is a topic for future work and may require further development of the machine learning algorithms to realise this potential.

What this research presents is the potential for intelligent algorithms to drive more complex approaches to personalisation and changing behaviour than what is currently being explored. Current research into this space either ground their research in behaviour change techniques and immediate user response to drive low-level personalisation [343], use AI to identify lapses in behaviour to be immediately combated with adaptive nudges [62], or use AI in the design phase to predict the potential success or failure of an intervention before the work is put into making it a reality [231]. The research proposed here acts as a progression of many of these points, building intervention content from a foundation of behaviour change techniques using user motivation and response as a key driving force, identifying user behaviours in real time to ascertain the impact of a given technique or parameter, and using AI to build the selection of intervention content around this impact. What our proposed approach does differently from current examples in the research landscape is allow for the changing of entire value sets of techniques and parameters in free-living, real-time situations, rather than simple low-level personalisation of nudges or numerical goals. This method enables a cohesive system to be built containing many techniques which can then learn natural behaviour patterns and determine the effectiveness of a given technique. This method also avoids the potential influence of personally delivered experiments artificially impacting the perceived impact of behaviour, the idea of which was voiced by certain participants during the experimental study. The contributions of this system to live solely with the user, adapt to their natural behaviours to best influence their behaviour through desired routes of technique and parameter, and alter entire interventions as opposed to minor variables are what present the greatest potential and most novel source of findings within this thesis.

7.4 Future Research

The presented research provides a number of potential benefits over what is currently seen in the design space and opens up new avenues of intelligent intervention design. The experiment outlined in Chapter 5 was limited by poor uptake and issues with the ML algorithm, but this should not detract from the potential afforded by these approaches to the personalised behaviour change landscape. Below are three areas that are seen as key progressions of the presented exploratory work.

7.4.1 Full Range of Techniques and Parameters

One of the key benefits of the proposed conceptual blueprint (Figure 15 was a wide array of behaviour change techniques and behaviour change strategies which cover the full scope of motivational requirements and individual behavioural needs. Each of these would be refined through processes such as Effect-Led Design to develop high-efficacy technique implementations with multiple internal parameters to be adjusted depending on the user and their context. Further research must be conducted on the performance of this system when integrating much higher numbers of both techniques and parameters, as well as implementing both of these in a single cohesive system.

Combining these personalisation options would also possibly require more exploration into how best to measure the impact of an intervention both on the whole and as a single element in a wider free-living space. This is where the ideas put forth by Aonghusa & Michie may become highly desirable [231], as well as a more robust approach to measuring impact other than simple hourly parameter-behaviour pairings which are highly subject to external influences. Better integration of Effect-Led Design into the overall cycle may also help identify how techniques and parameters could be presented as larger combinations, as the Effect-Led Design process uncovered interesting approaches to combining techniques which could be utilised by an intelligent system to combine effective individual techniques into a single cohesive intervention.

7.4.2 Dynamic Behaviour

The complex nature of human behaviour means that digital interventions need to evolve dynamically to ensure the needs of the user are captured and responded to within the period of optimal influence. Current research shows that there is a disconnect between the static theory of behaviour change research and the dynamic behaviours of users and the overall physical activity landscape, which limits the ability to integrate this theory effectively [266]. The research in this thesis attempts to resolve this issue by allowing for both the intelligent switching of techniques based on immediate behavioural response, and by utilising segmented intelligent parameters to tune these techniques, aligning dynamic adjustments with theoretical foundations. However, there is still space for this to progress, increasing the granularity of parameters and frequency of ability to alter content such that behavioural responses can be delivered as close to real-time as possible. This is not to say that real-time change should be the absolute end goal for all techniques and parameters, as responses from participants indicated the frequent changing of long-term techniques was disorientating. However, there may be some instances, such as techniques based around adverse stimuli or parameters based on external context, that would benefit from the ability to update at the point of need rather than at the next fixed update time.

The proposed reason for the difficulties faced by the Fake Peer condition in appearing believable was the inability to reflect what was seen as human behaviour, due to both a lack of learned knowledge on what exactly constituted 'human behaviour', and on the surrounding context which would impact how many steps would be expected in a given window of time. The key requirement to progress this emerging avenue of research and fully exploring the potential of intelligent parameter and technique switching systems is aligning the dynamic nature of these intelligent switching systems with the dynamic fluctuation of human behaviour, and providing exact responses when required to bolster behavioural efforts and engage with user behaviours at every opportunity to maintain engagement.

7.4.3 External Influencing Factors

There are several external factors which influence the ability to engage in active behaviours and respond to intervention content which either need to be addressed outside of the application or need the algorithm to be able to account for to better drive behavioural improvement. There may be factors in play such as societal expectations regarding availability to engage in behaviours and larger psychological barriers that are not currently explored. These factors are typically explored in non-digital interventions, as the researcher in place can engage in discussion and draw out these barriers, which can then be resolved to allow for greater behavioural engagement. The algorithm within the application could potentially pick up on markers of barriers, and work to adjust to combat these. This also applies to contextual data, such as external influences like weather and work commitments which may affect the ability to engage. This is something that research such as that by Damen *et al.* has begun to explore [83], and intelligently accounting for these factors in the selection of techniques and parameters may provide the means to establish these habits and behavioural satisfaction and overcome the concerns of Ghelani *et al.* and Valcarce-Torrente *et al.* [131, 360].

The ability to identify personality-based barriers to engagement may also allow for a degree of 'pre-learning' for new users. If the system can identify user personality types and factors and can align these with certain effective techniques or parameters, then new users can have these same connections made earlier in the process of behaviour change by aligning their personality type with that of other users. Further research would be required into whether these links exist between personality types and techniques, and whether the AI can make these connections and subsequently use them to drive earlier effective change for new users of the intervention.

7.5 Closing Remarks

Sedentary behaviour and physical activity are woven throughout this thesis as health concerns that must be addressed. The emergence of the COVID-19 pandemic and subsequent lock-downs across the globe since this thesis was first proposed have only strengthened the call for more effective, evidence-driven approaches to behaviour change on an individual level, without the massive investment of funds and man-hours required to deliver these interventions directly.

This research demonstrates how to expand upon the existing capabilities of physical activity applications to allow for highly individualised content, and how to intelligently deliver them such that every user can receive their personalised intervention driven only by their actions and habits. The findings of this thesis illustrate that this new approach proves effective in motivating and engaging users, and while the intelligent algorithms were not successful in the experiment itself, the subsequent testing and analysis indicate that there is potential for these algorithms to carry out this personalisation effectively. This research presents an exciting step towards encouraging and maintaining effective long-term behaviours.

BIBLIOGRAPHY

[1] Examining the role of conversational ai in personal informatics systems for collaborative health work and care. *CHI Conference on Human Factors in Computing Systems (CHI '22')* (2022).

[2] Abraham, C., Michie, S., and Psychology, H. A Taxonomy of Behavior Change Techniques Used in Interventions. *Psychological Association 27*, 3 (2008), 379–387.

[3] Adams, M. A., Sallis, J. F., Norman, G. J., Hovell, M. F., Hekler, E. B., and Perata, E. An adaptive physical activity intervention for overweight adults: A randomized controlled trial. *PLoS ONE 8*, 12 (dec 2013).

[4] Admiraal, J. M., van der Velden, A. W., Geerling, J. I., Burgerhof, J. G., Bouma, G., Walenkamp, A. M., de Vries, E. G., Schröder, C. P., and Reyners, A. K. Web-Based Tailored Psychoeducation for Breast Cancer Patients at the Onset of the Survivorship Phase: A Multicenter Randomized Controlled Trial. *Journal of Pain and Symptom Management 54*, 4 (oct 2017), 466–475.

[5] Aguilera, A., Figueroa, C. A., Hernandez-Ramos, R., Sarkar, U., Cemballi, A., Gomez-Pathak, L., Miramontes, J., Yom-Tov, E., Chakraborty, B., Yan, X., Xu, J., Modiri, A., Aggarwal, J., Jay Williams, J., and Lyles, C. R. MHealth app using machine learning to increase physical activity in diabetes and depression: Clinical trial protocol for the DIAMANTE Study. *BMJ Open 10*, 8 (aug 2020), e034723.

[6] Ahsan, G. M., Addo, I. D., Ahamed, S. I., Petereit, D., Kanekar, S., Burhansstipanov, L., and Krebs, L. U. Toward an mHealth intervention for smoking cessation. In *Proceedings - International Computer Software and Applications Conference* (2013), pp. 345–350.

[7] Ahsan, G. M. T., Tumpa, J. F., Adib, R., Ahamed, S. I., Petereit, D., Burhansstipanov, L., Krebs, L. U., and Dignan, M. A Culturally Tailored Intervention System for Cancer Survivors to Motivate Physical

Activity. In *Proceedings - International Computer Software and Applications Conference* (jun 2018), vol. 1, IEEE Computer Society, pp. 875–880.

[8] Alharthi, R., Albalawi, R., Abdo, M., and El Saddik, A. A context-aware e-health framework for students with moderate intellectual and learning disabilities. In *Proceedings - IEEE International Conference on Multimedia and Expo* (2011).

[9] Ali, R., Afzal, M., Hussain, M., Ali, M., Siddiqi, M. H., Lee, S., and Ho Kang, B. Multimodal hybrid reasoning methodology for personalized wellbeing services. *Computers in Biology and Medicine 69* (feb 2016), 10–28.

[10] Allen, M. S., Walter, E. E., and Swann, C. Sedentary behaviour and risk of anxiety: A systematic review and meta-analysis. *Journal of affective disorders 242* (jan 2019), 5–13.

[11] Alley, S., Jennings, C., Plotnikoff, R. C., and Vandelanotte, C. Web-based video-coaching to assist an automated computer-tailored physical activity intervention for inactive adults: A randomized controlled trial. *Journal of Medical Internet Research 18*, 8 (aug 2016).

[12] Alslaity, A., Chan, G., and Orji, R. A panoramic view of personalization based on individual differences in persuasive and behavior change interventions. *Frontiers in Artificial Intelligence 6* (2023).

[13] American College of Sports Medicine. *Guidelines for graded exercise testing and exercise prescription.* Lea & Febiger, 1980.

[14] American College of Sports Medicine. *ACSM's Guidelines for Exercise Testing and Prescription.* Wolters Kluwer, 2021.

[15] Ammann, R., Vandelanotte, C., de Vries, H., and Mummery, W. K. Can a Website-Delivered Computer-Tailored Physical Activity Intervention Be Acceptable, Usable, and Effective for Older People? *Health Education & Behavior 40*, 2 (apr 2013), 160–170.

[16] Amodei, D., Olah, C., Steinhardt, J., Christiano, P., Schulman, J., and Mané, D. Concrete problems in ai safety.

[17] Anand, S. S., Samaan, Z., Middleton, C., Irvine, J., Desai, D., Schulze, K. M., Sothiratnam, S., Hussain, F., Shah, B. R., Pare, G., Beyene, J., Lear, S. A., Mente, A., Punthakee, Z., Islam, S., and Joseph, P. A digital health intervention to lower cardiovascular risk: A randomized clinical trial. *JAMA Cardiology 1*, 5 (aug 2016), 601–606.

[18] Antypas, K., and Wangberg, S. C. An internet- and mobile-based tailored intervention to enhance maintenance of physical activity after cardiac rehabilitation: Short-term results of a randomized controlled trial. *Journal of Medical Internet Research 16*, 3 (2014).

[19] Armstrong, S., Bostrom, N., and Shulman, C. Racing to the Precipice: a Model of Artificial Intelligence Development. Tech. rep., Future of Humanity Institute, Oxford University, 2013.

[20] Attig, C., and Franke, T. Abandonment of personal quantification: A review and empirical study investigating reasons for wearable activity tracking attrition. *Computers in Human Behavior 102* (jan 2020), 223–237.

[21] Attwood, S., Parke, H., Larsen, J., and Morton, K. L. Using a mobile health application to reduce alcohol consumption: a mixed-methods evaluation of the drinkaware track & calculate units application. *BMC Public Health 17*, 1 (may 2017).

[22] Bach, K., Kongsvold, A., Bårdstu, H., Bardal, E. M., Kjærnli, H. S., Herland, S., Logacjov, A., and Mork, P. J. A Machine Learning Classifier for Detection of Physical Activity Types and Postures During Free-Living. *Journal for the Measurement of Physical Behaviour 5*, 1 (dec 2021), 24–31.

[23] Bakker, D., Kazantzis, N., Rickwood, D., and Rickard, N. Development and Pilot Evaluation of Smartphone-Delivered Cognitive Behavior Therapy Strategies for Mood- and Anxiety-Related Problems: MoodMission. *Cognitive and Behavioral Practice 25*, 4 (nov 2018), 496–514.

[24] Bandura, A. Social foundations of thought and action: A social cognitive theory., 1986.

[25] Bannink, R., Broeren, S., Joosten-Van Zwanenburg, E., Van As, E., Van De Looij-Jansen, P., and Raat, H. Effectiveness of a web-based tailored intervention (E-health4Uth) and consultation to promote adolescents' health: Randomized controlled trial. *Journal of Medical Internet Research 16*, 5 (2014).

[26] Barker, F., Mackenzie, E., and de Lusignan, S. Current process in hearing-aid fitting appointments: An analysis of audiologists' use of behaviour change techniques using the behaviour change technique taxonomy (v1). *http://dx.doi.org/10.1080/14992027.2016.1197425 55*, 11 (nov 2016), 643–652.

[27] Bassett, D. R., Toth, L. P., LaMunion, S. R., and Crouter, S. E. Step Counting: A Review of Measurement Considerations and Health-Related Applications. *Sports Medicine (Auckland, N.z.) 47*, 7 (jul 2017), 1303.

[28] Bastiaansen, J. A., Meurs, M., Stelwagen, R., Wunderink, L., Schoevers, R. A., Wichers, M., and Oldehinkel, A. J. Self-monitoring and personalized feedback based on the experiencing sampling method as a tool to boost depression treatment: A protocol of a pragmatic randomized controlled trial (ZELF-i). *BMC Psychiatry 18*, 1 (sep 2018), 276.

[29] Bauermeister, J. A., Golinkoff, J. M., Horvath, K. J., Hightow-Weidman, L. B., Sullivan, P. S., and Stephenson, R. A Multilevel Tailored Web App-Based Intervention for Linking Young Men Who Have Sex With Men to Quality Care (Get Connected): Protocol for a Randomized Controlled Trial. *JMIR research protocols 7*, 8 (aug 2018), e10444.

[30] Bell, S. L., Audrey, S., Gunnell, D., Cooper, A., and Campbell, R. The relationship between physical activity, mental wellbeing and symptoms of mental health disorder in adolescents: A cohort study. *International Journal of Behavioral Nutrition and Physical Activity 16*, 1 (dec 2019), 1–12.

[31] Bénabou, R., and Tirole, J. Intrinsic and extrinsic motivation. *The review of economic studies 70*, 3 (2003), 489–520.

[32] Bhattacharya, S., Reddy Maddikunta, P. K., Pham, Q. V., Gadekallu, T. R., Krishnan S, S. R., Chowdhary, C. L., Alazab, M., and Jalil Piran, M. Deep learning and medical image processing for coronavirus (COVID-19) pandemic: A survey. *Sustainable Cities and Society 65* (feb 2021), 102589.

[33] Bjögvinsson, E., Ehn, P., and Hillgren, P.-A. Design Things and Design Thinking: Contemporary Participatory Design Challenges. *Design Issues 28*, 3 (jul 2012), 101–116.

[34] Blair, S. N., LaMonte, M. J., and Nichaman, M. Z. The evolution of physical activity recommendations: how much is enough? *The American journal of clinical nutrition 79*, 5 (may 2004), 913S–920S.

[35] Bødker, S. When Second Wave HCI meets Third Wave Challenges. In *Proceedings of the 4th Nordic conference on Human-computer interaction changing roles - NordiCHI '06* (New York, New York, USA, 2006), ACM Press.

[36] Bohlen, L. C., DPhil, S. M., de Bruin, M., Rothman, A. J., Kelly, M. P., Groarke, H. N., Carey, R. N., Hale, J., and Johnston, M. Do Combinations of Behavior Change Techniques That Occur Frequently in Interventions Reflect Underlying Theory? *Annals of Behavioral Medicine 54*, 11 (nov 2020), 827–842.

[37] Bohr, A., and Memarzadeh, K. The rise of artificial intelligence in healthcare applications., 2020.

[38] Bommelé, J., Schoenmakers, T. M., Kleinjan, M., Peters, G. J. Y., Dijkstra, A., and van de Mheen, D. Targeting hardcore smokers: The effects of an online tailored intervention, based on motivational interviewing techniques. *British Journal of Health Psychology 22*, 3 (sep 2017), 644–660.

[39] Boudreau, F., Walthouwer, M. J. L., De Vries, H., Dagenais, G. R., Turbide, G., Bourlaud, A. S., Moreau, M., Côté, J., and Poirier, P. Rationale, design and baseline characteristics of a randomized

controlled trial of a web-based computer-tailored physical activity intervention for adults from Quebec City. *BMC Public Health 15*, 1 (oct 2015), 1038.

[40] Brand, R., and Cheval, B. Theories to Explain Exercise Motivation and Physical Inactivity: Ways of Expanding Our Current Theoretical Perspective. *Frontiers in Psychology 10* (2019).

[41] Bratteteig, T., and Verne, G. Does AI make PD obsolete?: Exploring challenges from artificial intelligence to participatory design. In *ACM International Conference Proceeding Series* (New York, New York, USA, sep 2018), vol. 2, Association for Computing Machinery, pp. 1–5.

[42] Brickwood, K. J., Watson, G., O'brien, J., and Williams, A. D. Consumer-Based Wearable Activity Trackers Increase Physical Activity Participation: Systematic Review and Meta-Analysis. *JMIR mHealth and uHealth 7*, 4 (2019).

[43] Bull, F. C., Al-Ansari, S. S., Biddle, S., Borodulin, K., Buman, M. P., Cardon, G., Carty, C., Chaput, J.-P., Chastin, S., Chou, R., Friedenreich, C. M., Garcia, L., Gichu, M., Jago, R., Katzmarzyk, P. T., Lambert, E., Leitzmann, M., Milton, K., Ortega, F. B., Ranasinghe, C., Stamatakis, E., Tiedemann, A., Troiano, R. P., Van Der Ploeg, H. P., Wari, V., and Willumsen, J. F. World Health Organization 2020 guidelines on physical activity and sedentary behaviour. *Br J Sports Med 54* (2020), 20.

[44] Burford, K., Golaszewski, N. M., and Bartholomew, J. " I shy away from them because they are very identifiable": A qualitative study exploring user and non-user's perceptions of wearable activity trackers. *Digital health 7* (2021).

[45] Burns, M. N., Begale, M., Duffecy, J., Gergle, D., Karr, C. J., Giangrande, E., and Mohr, D. C. Harnessing context sensing to develop a mobile intervention for depression. *Journal of Medical Internet Research 13*, 3 (jul 2011).

[46] Cahill, N. E., Murch, L., Cook, D., and Heyland, D. K. Implementing a multifaceted tailored intervention to improve nutrition adequacy in critically ill patients: Results of a multicenter feasibility study. *Critical Care 18*, 3 (may 2014), R96.

[47] Career Foundry. 10 Classic UX Design Fails That Teach Us How Not To Do UX, 2019.

[48] Carvalho, F., Jun, G. T., and Mitchell, V. Participatory design for behaviour change: An integrative approach to healthcare quality improvement.

[49] Castro, R., Ribeiro-Alves, M., Oliveira, C., Romero, C. P., Perazzo, H., Simjanoski, M., Kapciznki, F., Balanzá-Martínez, V.,

and De Boni, R. B. What Are We Measuring When We Evaluate Digital Interventions for Improving Lifestyle? A Scoping Meta-Review. *Frontiers in Public Health 9* (jan 2022), 735624.

[50] Cave, S., Coughlan, K., and Dihal, K. "Scary robots" examining public responses to AI. In *AIES 2019 - Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society* (jan 2019), Association for Computing Machinery, Inc, pp. 331–337.

[51] Celis-Morales, C., Livingstone, K. M., Marsaux, C. F. M., Macready, A. L., Fallaize, R., O'Donovan, C. B., Woolhead, C., Forster, H., Walsh, M. C., Navas-Carretero, S., San-Cristobal, R., Tsirigoti, L., Lambrinou, C. P., Mavrogianni, C., Moschonis, G., Kolossa, S., Hallmann, J., Godlewska, M., Surwiłło, A., Traczyk, I., Drevon, C. A., Bouwman, J., van Ommen, B., Grimaldi, K., Parnell, L. D., Matthews, J. N. S., Manios, Y., Daniel, H., Martinez, J. A., Lovegrove, J. A., Gibney, E. R., Brennan, L., Saris, W. H. M., Gibney, M., and Mathers;, J. C. Effect of personalized nutrition on health-related behaviour change: evidence from the food4me european randomized controlled trial. *Int. J. Epidemiol.* (Aug. 2016), dyw186.

[52] Chan, H. P., Samala, R. K., and Hadjiiski, L. M. CAD and AI for breast cancer—recent development and challenges. *The British Journal of Radiology 93*, 1108 (apr 2020).

[53] Chandler, J., Sox, L., Kellam, K., Feder, L., Nemeth, L., and Treiber, F. Impact of a Culturally Tailored mHealth Medication Regimen Self-Management Program upon Blood Pressure among Hypertensive Hispanic Adults. *International Journal of Environmental Research and Public Health 16*, 7 (apr 2019), 1226.

[54] Chaput, J. P., Olds, T., and Tremblay, M. S. Public health guidelines on sedentary behaviour are important and needed: A provisional benchmark is better than no benchmark at all, mar 2020.

[55] Charoensiriwath, S. SizeThailand e-Health: A personalised health monitoring and diagnosis system using 3D body scanning technology - IEEE Conference Publication, 2010.

[56] Chatzitofis, A., Zarpalas, D., Filos, D., Triantafyllidis, A., Chouvarda, I., Maglaveras, N., and Daras, P. Technological Module for Unsupervised, Personalized Cardiac Rehabilitation Exercising. In *Proceedings - International Computer Software and Applications Conference* (sep 2017), vol. 2, IEEE Computer Society, pp. 125–130.

[57] Chaudhry, U. A., Wahlich, C., Fortescue, R., Cook, D. G., Knightly, R., and Harris, T. The effects of step-count monitoring interventions on physical activity: Systematic review and meta-analysis of community-based randomised controlled trials in adults. *International Journal of Behavioral Nutrition and Physical Activity 17*, 1 (oct 2020), 1–16.

[58] Cheatham, S. W., Stul, K. R., Fantigrassi, M., and Motel, I. The efficacy of wearable activity tracking technology as part of a weight loss program: a systematic review. *The Journal of sports medicine and physical fitness 58*, 4 (apr 2018), 534–548.

[59] Cheung, K. L., Schwabe, I., Walthouwer, M. J., Oenema, A., Lechner, L., and De Vries, H. Effectiveness of a video-versus text-based computer-tailored intervention for obesity prevention after one year: A randomized controlled trial. *International Journal of Environmental Research and Public Health 14*, 10 (oct 2017).

[60] Cheval, B., and Boisgontier, M. P. The Theory of Effort Minimization in Physical Activity. *Exercise and Sport Sciences Reviews 49*, 3 (jul 2021), 168–178.

[61] Chew, H. S. J., and Achananuparp, P. Perceptions and Needs of Artificial Intelligence in Health Care to Increase Adoption: Scoping Review. *J Med Internet Res 2022;24(1):e32939 https://www.jmir.org/2022/1/e32939 24*, 1 (jan 2022), e32939.

[62] Chew, H. S. J., Ang, W. H. D., and Lau, Y. The potential of artificial intelligence in enhancing adult weight loss: a scoping review. *Public health nutrition 24*, 8 (jun 2021), 1993–2020.

[63] Chiang, P. H., and Dey, S. Personalized effect of health behavior on blood pressure: Machine learning based prediction and recommendation. In *2018 IEEE 20th International Conference on e-Health Networking, Applications and Services, Healthcom 2018* (nov 2018), Institute of Electrical and Electronics Engineers Inc.

[64] Chung, A., Wallace, B., Stanton-Koko, M., Seixas, A., and Jean-Louis, G. Feasibility and acceptability of a culturally tailored website to increase fruit and vegetable intake and physical activity levels in african American mother-child dyads: Observational study. *Journal of Medical Internet Research 21*, 3 (mar 2019).

[65] Church, T. S., Thomas, D. M., Tudor-Locke, C., Katzmarzyk, P. T., Earnest, C. P., Rodarte, R. Q., Martin, C. K., Blair, S. N., and Bouchard, C. Trends over 5 decades in U.S. occupation-related physical activity and their associations with obesity. *PLoS ONE 6*, 5 (2011).

[66] Codreanu, I. A., and Florea, A. M. A Proposed Serious Game Architecture to Self-Management HealthCare for Older Adults. In *Proceedings - 17th International Symposium on Symbolic and Numeric Algorithms for Scientific Computing, SYNASC 2015* (mar 2016), Institute of Electrical and Electronics Engineers Inc., pp. 437–440.

[67] Collins, C. E., Morgan, P. J., Hutchesson, M. J., Oldmeadow, C., Barker, D., and Callister, R. Efficacy of web-based weight loss maintenance programs: A randomized controlled trial comparing standard features versus the addition of enhanced personalized feedback over 12 months. *Behavioral Sciences 7*, 4 (dec 2017).

[68] Collins, L. M., Murphy, S. A., and Strecher, V. The Multiphase Optimization Strategy (MOST) and the Sequential Multiple Assignment Randomized Trial (SMART): New Methods for More Potent eHealth Interventions. *American Journal of Preventive Medicine 32*, 5 (may 2007), S112–S118.

[69] Compernolle, S., Vandelanotte, C., Cardon, G., De Bourdeaudhuij, I., and De Cocker, K. Effectiveness of a web-based, computer-tailored, pedometer-based physical activity intervention for adults: A cluster randomized controlled trial. *Journal of Medical Internet Research 17*, 2 (feb 2015).

[70] Conroy, D. E., Yang, C.-H., and Maher, J. P. Behavior Change Techniques in Top-Ranked Mobile Apps for Physical Activity. *American Journal of Preventive Medicine 46*, 6 (jun 2014), 649–652.

[71] Cook, T. L., De Bourdeaudhuij, I., Maes, L., Haerens, L., Grammatikaki, E., Widhalm, K., Kwak, L., Plada, M., Moreno, L. A., Zampelas, A., Tountas, Y., and Manios, Y. Moderators of the Effectiveness of a Web-Based Tailored Intervention Promoting Physical Activity in Adolescents: The HELENA Activ-O-Meter. *Journal of School Health 84*, 4 (apr 2014), 256–266.

[72] Cook, W. The effect of personalised weight feedback on weight loss and health behaviours: Evidence from a regression discontinuity design. *Health Economics 28*, 1 (jan 2019), 161–172.

[73] Coolbaugh, C. L., Raymond Jr, S. C., and Hawkins, D. A. Feasibility of a Dynamic Web Guidance Approach for Personalized Physical Activity Prescription Based on Daily Information From Wearable Technology. *JMIR Research Protocols 4*, 2 (jun 2015), e67.

[74] Cordova, D., Mendoza Lua, F., Muñoz-Velázquez, J., Street, K., Bauermeister, J. A., Fessler, K., Adelman, N., Neilands, T. B., and Boyer, C. B. A multilevel mHealth drug abuse and STI/HIV preventive intervention for clinic settings in the United States: A feasibility and acceptability study. *PLOS ONE 14*, 8 (aug 2019), e0221508.

[75] Coughlin, S. S., and Stewart, J. USE OF CONSUMER WEARABLE DEVICES TO PROMOTE PHYSICAL ACTIVITY: A REVIEW OF HEALTH INTERVENTION STUDIES. *Journal of Environment and Health Science 2*, 6 (2016), 1–6.

[76] Coumans, J. M., Bolman, C. A., Friederichs, S. A., Oenema, A., and Lechner, L. Development and testing of a personalized web-based diet and physical activity intervention based on motivational interviewing and the self-determination theory: Protocol for the mylifestylecoach randomized controlled trial. *JMIR Research Protocols 9*, 2 (feb 2020).

[77] Cozza, M., Angeli, A. D., and Tonolli, L. Ubiquitous technologies for older people. *Personal and Ubiquitous Computing 21* (6 2017), 607–619.

[78] Cristi-Montero, C., and Rodríguez R., F. Paradoja: "activo físicamente pero sedentario, sedentario pero active físicamente". nuevos antecedentes, implicaciones en la salud y recomendaciones, 2014.

[79] Cushing, C. C., Fedele, D. A., Patton, S. R., McQuaid, E. L., Smyth, J. M., Prabhakaran, S., Gierer, S., Koskela-Staples, N., Ortega, A., Fleming, K. K., and Nezu, A. M. Responsive Asthma Care for Teens (ReACT): Development protocol for an adaptive mobile health intervention for adolescents with asthma. *BMJ Open 9*, 8 (aug 2019), e030029.

[80] D'Alfonso, S., Santesteban-Echarri, O., Rice, S., Wadley, G., Lederman, R., Miles, C., Gleeson, J., and Alvarez-Jimenez, M. Artificial intelligence-assisted online social therapy for youth mental health. *Frontiers in Psychology 8*, JUN (jun 2017), 796.

[81] Dallal, C. M., Brinton, L. A., Matthews, C. E., Lissowska, J., Peplonska, B., Hartman, T. J., and Gierach, G. L. Accelerometer-based measures of active and sedentary behavior in relation to breast cancer risk. *Breast Cancer Research and Treatment 134*, 3 (aug 2012), 1279–1290.

[82] Dam, R. F., and Siang, T. Y. 5 Stages in the Design Thinking Process, 2020.

[83] Damen, I., van den Heuvel, R., Brankaert, R., and Vos, S. Advancing digital behavior change interventions by exploring a calendar-based suggestion system. In *European Conference on Cognitive Ergonomics 2021* (New York, NY, USA, 2021), ECCE 2021, Association for Computing Machinery.

[84] Daowd, A., Faizan, S., Abidi, S., Abusharekh, A., Shehzad, A., and Abidi, S. S. R. Towards personalized lifetime health: A platform for early multimorbid chronic disease risk assessment and mitigation. In *Studies in Health Technology and Informatics* (aug 2019), vol. 264, IOS Press, pp. 935–939.

[85] De Cocker, K., Cardon, G., Bennie, J. A., Kolbe-Alexander, T., De Meester, F., and Vandelanotte, C. From evidence-based research to practice-based evidence: Disseminating a web-based computer-tailored workplace sitting intervention through a health promotion organisation. *International Journal of Environmental Research and Public Health 15*, 5 (may 2018).

[86] De Lyon, A. T. C., Neville, R. D., and Armour, K. M. The Role of Fitness Professionals in Public Health: A Review of the Literature. *Quest 69*, 3 (jul 2017), 313–330.

[87] de Roos, B., and Brennan, L. Personalised Interventions-A Precision Approach for the Next Generation of Dietary Intervention Studies. *Nutrients 9*, 8 (aug 2017).

[88] Dempsey, A. F., Maertens, J., Sevick, C., Jimenez-Zambrano, A., and Juarez-Colunga, E. A randomized, controlled, pragmatic trial of an iPad-based, tailored messaging intervention to increase human papillomavirus vaccination among Latinos. *Human Vaccines and Immunotherapeutics 15*, 7-8 (aug 2019), 1577–1584.

[89] Dharia, S., Jain, V., Patel, J., Vora, J., Yamauchi, R., Eirinaki, M., and Varlamis, I. PRO-Fit: Exercise with friends. In *Proceedings of the 2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, ASONAM 2016* (nov 2016), Institute of Electrical and Electronics Engineers Inc., pp. 1430–1433.

[90] Dijkstra, A. Working mechanisms of computer-tailored health education: Evidence from smoking cessation. *Health Education Research 20*, 5 (oct 2005), 527–539.

[91] Dobrican, R. A., and Zampunieris, D. A Proactive Solution, using Wearable and Mobile Applications, for Closing the Gap between the Rehabilitation Team and Cardiac Patients. In *Proceedings - 2016 IEEE International Conference on Healthcare Informatics, ICHI 2016* (dec 2016), Institute of Electrical and Electronics Engineers Inc., pp. 146–155.

[92] Dohrn, I. M., Welmer, A. K., and Hagströmer, M. Accelerometry-assessed physical activity and sedentary time and associations with chronic disease and hospital visits - A prospective cohort study with 15 years follow-up. *International Journal of Behavioral Nutrition and Physical Activity 16*, 1 (dec 2019).

[93] Dombrowski, S. U., Sniehotta, F. F., Avenell, A., Johnston, M., MacLennan, G., and Araújo-Soares, V. Identifying active ingredients in complex behavioural interventions for obese adults with obesity-related co-morbidities or additional risk factors for co-morbidities: a systematic review. *https://doi.org/10.1080/17437199.2010.513298 6*, 1 (mar 2010), 7–32.

[94] Downs, D. S., Savage, J. S., Rivera, D. E., Smyth, J. M., Rolls, B. J., Hohman, E. E., McNitt, K. M., Kunselman, A. R., Stetter, C., Pauley, A. M., Leonard, K. S., and Guo, P. Individually tailored, adaptive intervention to manage gestational weight gain: Protocol for a randomized controlled trial in women with overweight and obesity. *Journal of Medical Internet Research 20*, 6 (jun 2018).

[95] Dugdale, S., Ward, J., Hernen, J., Elison, S., Davies, G., and Donkor, D. Using the Behavior Change Technique Taxonomy v1 to conceptualize the clinical content of Breaking Free Online: A computer-assisted therapy program for substance use disorders. *Substance Abuse: Treatment, Prevention, and Policy 11*, 1 (jul 2016), 1–14.

[96] Duncan, M. J., Brown, W. J., Burrows, T. L., Collins, C. E., Fenton, S., Glozier, N., Kolt, G. S., Morgan, P. J., Hensley, M., Holliday, E. G., Murawski, B., Plotnikoff, R. C., Rayward,

A. T., Stamatakis, E., and Vandelanotte, C. Examining the efficacy of a multicomponent m-Health physical activity, diet and sleep intervention for weight loss in overweight and obese adults: Randomised controlled trial protocol. *BMJ Open 8*, 10 (oct 2018), 26179.

[97] Ekelund, U., Tarp, J., Fagerland, M. W., Johannessen, J. S., Hansen, B. H., Jefferis, B. J., Whincup, P. H., Diaz, K. M., Hooker, S., Howard, V. J., Chernofsky, A., Larson, M. G., Spartano, N., Vasan, R. S., Dohrn, I. M., Hagströmer, M., Edwardson, C., Yates, T., Shiroma, E. J., Dempsey, P., Wijndaele, K., Anderssen, S. A., and Lee, I. M. Joint associations of accelero-meter measured physical activity and sedentary time with all-cause mortality: A harmonised meta-analysis in more than 44 000 middle-aged and older individuals. *British Journal of Sports Medicine 54*, 24 (dec 2020), 1499–1506.

[98] Ekstedt, M., Schildmeijer, K., Wennerberg, C., Nilsson, L., Wannheden, C., and Hellström, A. Enhanced patient activation in cancer care transitions: protocol for a randomized controlled trial of a tailored electronic health intervention for men with prostate cancer. *Journal of Medical Internet Research 21*, 3 (mar 2019).

[99] El Hassouni, A., Hoogendoorn, M., Eiben, A. E., Van Otterlo, M., and Muhonen, V. End-to-end personalization of digital health interventions using raw sensor data with deep reinforcement learning: A comparative study in digital health interventions for behavior change. In *Proceedings - 2019 IEEE/WIC/ACM International Conference on Web Intelligence, WI 2019* (oct 2019), Association for Computing Machinery, Inc, pp. 258–264.

[100] Elflein, J. Percentage of people that used technology to track their fitness by age 2016 | Statista.

[101] Ellingson, L. D., Meyer, J. D., Shook, R. P., Dixon, P. M., Hand, G. A., Wirth, M. D., Paluch, A. E., Burgess, S., Hebert, J. R., and Blair, S. N. Changes in sedentary time are associated with changes in mental wellbeing over 1 year in young adults. *Preventive Medicine Reports 11* (sep 2018), 274.

[102] Endrighi, R., Steptoe, A., and Hamer, M. The effect of experimentally induced sedentariness on mood and psychobiological responses to mental stress. *The British Journal of Psychiatry 208*, 3 (mar 2016), 245.

[103] Epstein, D. A., Caraway, M., Johnston, C., Ping, A., Fogarty, J., and Munson, S. A. Beyond abandonment to next steps: Understanding and designing for life after personal informatics tool use. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (New York, NY, USA, 2016), CHI '16, Association for Computing Machinery, p. 1109–1113.

[104] Etter, J. F. Comparing the efficacy of two internet-based, computer-tailored smoking cessation programs: A randomized trial. *Journal of Medical Internet Research 7*, 1 (jan 2005).

[105] Everett, E., Kane, B., Yoo, A., Dobs, A., and Mathioudakis, N. A Novel Approach for Fully Automated, Personalized Health Coaching for Adults with Prediabetes: Pilot Clinical Trial. *Journal of medical Internet research 20*, 2 (feb 2018), e72.

[106] Everhart, R. S., Heron, K. E., Leibach, G. G., and Miadich, S. A. Developing a Mobile Health Intervention for Low-Income, Urban Caregivers of Children with Asthma: A Pilot Study. *Pediatric, Allergy, Immunology, and Pulmonology 30*, 4 (dec 2017), 252–256.

[107] Fahim, M., Idris, M., Ali, R., Nugent, C., Kang, B., Huh, E. N., and Lee, S. ATHENA: A personalized platform to promote an active lifestyle and wellbeing based on physical, mental and social health primitives. *Sensors (Switzerland) 14*, 5 (may 2014), 9313–9329.

[108] Fanning, J., Brooks, A. K., Ip, E., Nicklas, B. J., and Jack Rejeski, W. A mobile health intervention to reduce pain and improve health (MORPH) in older adults with obesity: Protocol for the MORPH trial. *Journal of Medical Internet Research 20*, 5 (may 2018).

[109] Farrokhi, A., Farahbakhsh, R., Rezazadeh, J., and Minerva, R. Application of Internet of Things and artificial intelligence for smart fitness: A survey. *Computer Networks 189* (2021), 107859.

[110] Fast, E., and Horvitz, E. Long-Term Trends in the Public Perception of Artificial Intelligence. *31st AAAI Conference on Artificial Intelligence, AAAI 2017* (sep 2016), 963–969.

[111] Fico, G., Fioravanti, A., Arredondo, M. T., Gorman, J., Diazzi, C., Arcuri, G., Conti, C., and Pirini, G. Integration of personalized healthcare pathways in an ICT platform for diabetes managements: A small-scale exploratory study. *IEEE Journal of Biomedical and Health Informatics 20*, 1 (jan 2016), 29–38.

[112] Filice, R. W., and Ratwani, R. M. The Case for User-Centered Artificial Intelligence in Radiology. *Radiology: Artificial intelligence 2*, 3 (may 2020), e190095.

[113] Finkelstein, J., Bedra, M., Li, X., Wood, J., and Ouyang, P. Mobile App to Reduce Inactivity in Sedentary Overweight Women. In *Studies in Health Technology and Informatics* (2015), vol. 216, IOS Press, pp. 89–92.

[114] Forastiere, M., De Pietro, G., and Sannino, G. An mHealth application for a personalized monitoring of one's own wellness: Design and development. In *Smart Innovation, Systems and Technologies* (2016), vol. 60, Springer Science and Business Media Deutschland GmbH, pp. 269–278.

[115] Freigoun, M. T., Martin, C. A., Magann, A. B., Rivera, D. E., Phatak, S. S., Korinek, E. V., and Hekler, E. B. System identification of Just Walk: A behavioral mHealth intervention for promoting physical activity. In *Proceedings of the American Control Conference* (jun 2017), Institute of Electrical and Electronics Engineers Inc., pp. 116–121.

[116] French, S. D., Green, S. E., O'Connor, D. A., McKenzie, J. E., Francis, J. J., Michie, S., Buchbinder, R., Schattner, P., Spike, N., and Grimshaw, J. M. Developing theory-informed behaviour change interventions to implement evidence into practice: a systematic approach using the Theoretical Domains Framework. *Implementation Science : IS 7*, 1 (apr 2012), 38.

[117] Friederichs, S. A., Oenema, A., Bolman, C., Guyaux, J., Van Keulen, H. M., and Lechner, L. Motivational interviewing in a web-based physical activity intervention: Questions and reflections. *Health Promotion International 30*, 3 (sep 2015), 803–815.

[118] Friedman, B., Kahn, P. H., Borning, A., and Huldtgren, A. Value Sensitive Design and Information Systems. Springer, Dordrecht, 2013, pp. 55–95.

[119] Fritz, T., Huang, E. M., Murphy, G. C., and Zimmermann, T. Persuasive technology in the real world: A study of long-term use of activity sensing devices for fitness. *Conference on Human Factors in Computing Systems - Proceedings* (2014), 487–496.

[120] Fylan, B., Tomlinson, J., Raynor, D. K., and Silcock, J. Using experience-based co-design with patients, carers and healthcare professionals to develop theory-based interventions for safer medicines use. *Research in Social and Administrative Pharmacy 17*, 12 (dec 2021), 2127–2135.

[121] G. Mitchell, E., M. Heitkemper, E., Burgermaster, M., E. Levine, M., Miao, Y., L. Hwang, M., M. Desai, P., Cassells, A., N. Tobin, J., G. Tabak, E., J. Albers, D., M. Smaldone, A., and Mamykina, L. From reflection to action: Combining machine learning with expert knowledge for nutrition goal recommendations. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (New York, NY, USA, 2021), CHI '21, Association for Computing Machinery.

[122] Ganapathy, K. Artificial Intelligence and Healthcare Regulatory and Legal Concerns. *Telehealth and Medicine Today 6*, 2 (apr 2021).

[123] Gance-Cleveland, B., Leiferman, J., Aldrich, H., Nodine, P., Anderson, J., Nacht, A., Martin, J., Carrington, S., and Ozkaynak, M. Using the Technology Acceptance Model to Develop StartSmart: mHealth for Screening, Brief Intervention, and Referral for Risk and Protective Factors in Pregnancy. *Journal of Midwifery & Women's Health 64*, 5 (sep 2019), 630–640.

[124] Gannod, G. C., Abbott, K. M., Van Haitsma, K., Martindale, N., and Heppner, A. A Machine Learning Recommender System to Tailor Preference Assessments to Enhance Person-Centered Care among Nursing Home Residents. *Gerontologist 59*, 1 (jan 2019), 167–176.

[125] Garnett, C. V., Crane, D., Brown, J., Kaner, E. F. S., Beyer, F. R., Muirhead, C. R., Hickman, M., Beard, E., Redmore, J.,

de Vocht, F., and Michie, S. Behavior Change Techniques Used in Digital Behavior Change Interventions to Reduce Excessive Alcohol Consumption: A Meta-regression. *Annals of Behavioral Medicine 52*, 6 (may 2018), 530–543.

[126] Gasparetti, F., Maria Aiello, L., and Quercia, D. Evaluating the Efficacy of Traditional Fitness Tracker Recommendations. *IUI '19: Proceedings of the 24th International Conference on Intelligent User Interfaces: Companion* (mar 2019), 15–16.

[127] Gatwood, J., Shuvo, S., Ross, A., Riordan, C., Smith, P., Gutierrez, M. L., Coday, M., and Bailey, J. The Management of Diabetes in Everyday Life (MODEL) program: Development of a tailored text message intervention to improve diabetes self-care activities among underserved African-American adults. *Translational Behavioral Medicine 10*, 1 (dec 2018), 204–212.

[128] Gautam, A., Shrestha, C., Kulak, A., Harrison, S., and Tatar, D. Participatory tensions in working with a vulnerable population. In *ACM International Conference Proceeding Series* (New York, New York, USA, sep 2018), vol. 2, Association for Computing Machinery, pp. 1–5.

[129] Gaynor, M., Schneider, D., Seltzer, M., Crannage, E., Barron, M. L., Waterman, J., and Oberle, A. A user-centered, learning asthma smartphone application for patients and providers. *Learning Health Systems 4*, 3 (jul 2020), e10217.

[130] Gerke, S., Minssen, T., and Cohen, G. Ethical and legal challenges of artificial intelligence-driven healthcare. *Artificial Intelligence in Healthcare* (jan 2020), 295.

[131] Ghelani, D. P., Moran, L. J., Johnson, C., Mousa, A., and Naderpoor, N. Mobile Apps for Weight Management: A Review of the Latest Evidence to Inform Practice. *Frontiers in Endocrinology 11* (jun 2020), 412.

[132] Gingele, A. J., Ramaekers, B., Brunner-La Rocca, H. P., De Weerd, G., Kragten, J., van Empel, V., van der Weg, K., Vrijhoef, H. J. M., Gorgels, A., Cleuren, G., Boyne, J. J. J., and Knackstedt, C. Effects of tailored telemonitoring on functional status and health-related quality of life in patients with heart failure. *Netherlands Heart Journal 27*, 11 (nov 2019), 565–574.

[133] Girgis, A., Delaney, G. P., Arnold, A., Miller, A. A., Levesque, J. V., Kaadan, N., Carolan, M. G., Cook, N., Masters, K., Tran, T. T., Sandell, T., Durcinoska, I., Gerges, M., Avery, S., Ng, W., Della-Fiorentina, S., Dhillon, H. M., and Maher, A. Development and Feasibility Testing of PROMPT-Care, an eHealth System for Collection and Use of Patient-Reported Outcome Measures for Personalized Treatment and Care: A Study Protocol. *JMIR Research Protocols 5*, 4 (nov 2016), e227.

[134] Godino, J. G., Merchant, G., Norman, G. J., Donohue, M. C., Marshall, S. J., Fowler, J. H., Calfas, K. J., Huang, J. S., Rock, C. L., Griswold, W. G., Gupta, A., Raab, F., Fogg, B. J., Robinson, T. N., and Patrick, K. Using social and mobile tools for weight loss in overweight and obese young adults (Project SMART): a 2 year, parallel-group, randomised, controlled trial. *The Lancet Diabetes and Endocrinology 4*, 9 (sep 2016), 747–755.

[135] Goetz, T. Harnessing the Power of Feedback Loops, jun 2011.

[136] Goldstein, S. P., Thomas, J. G., Foster, G. D., Turner-McGrievy, G., Butryn, M. L., Herbert, J. D., Martin, G. J., and Forman, E. M. Refining an algorithm-powered just-in-time adaptive weight control intervention: A randomized controlled trial evaluating model performance and behavioral outcomes. *Health Informatics Journal* (2020).

[137] Golsteijn, R. H. J., Bolman, C., Peels, D. A., Volders, E., De Vries, H., and Lechner, L. A Web-based and print-based computer-tailored physical activity intervention for prostate and colorectal cancer survivors: A comparison of user characteristics and intervention use. *Journal of Medical Internet Research 19*, 8 (aug 2017).

[138] Guidotti, R., Monreale, A., Ruggieri, S., Turini, F., Pedreschi, D., and Giannotti, F. A Survey Of Methods For Explaining Black Box Models.

[139] Gupta, S., Kamboj, S., and Bag, S. Role of Risks in the Development of Responsible Artificial Intelligence in the Digital Healthcare Domain. *Information Systems Frontiers* (aug 2021), 1–18.

[140] Guszcza, J. AI Needs Human-Centered Design | WIRED.

[141] Guthold, R., Stevens, G. A., Riley, L. M., and Bull, F. C. Global trends in insufficient physical activity among adolescents: a pooled analysis of 298 population-based surveys with 1·6 million participants. *The Lancet Child and Adolescent Health 4*, 1 (jan 2020), 23–35.

[142] Hadgraft, N. T., Winkler, E., Climie, R. E., Grace, M. S., Romero, L., Owen, N., Dunstan, D., Healy, G., and Dempsey, P. C. Effects of sedentary behaviour interventions on biomarkers of cardiometabolic risk in adults: Systematic review with meta-analyses, feb 2021.

[143] Haerens, L., Deforche, B., Maes, L., Cardon, G., Stevens, V., and De Bourdeaudhuij, I. Evaluation of a 2-year physical activity and healthy eating intervention in middle school children. *Health Education Research 21*, 6 (dec 2006), 911–921.

[144] Hagendorff, T. The Ethics of AI Ethics: An Evaluation of Guidelines. *Minds and Machines 30*, 1 (mar 2020), 99–120.

[145] Hajna, S., Sharp, S. J., Cooper, A. J., Williams, K. M., van Sluijs, E. M., Brage, S., Griffin, S. J., and Sutton, S. Effectiveness of Minimal Contact Interventions: An RCT. *American Journal of Preventive Medicine 60*, 3 (mar 2021), e111.

[146] Haller, N., Lorenz, S., Pfirrmann, D., Koch, C., Lieb, K., Dettweiler, U., Simon, P., and Jung, P. Individualized web-Based exercise for the treatment of depression: Randomized controlled trial. *Journal of Medical Internet Research 20*, 10 (oct 2018).

[147] Hallgren, M., Dunstan, D. W., and Owen, N. Passive Versus Mentally Active Sedentary Behaviors and Depression. *Exercise and Sport Sciences Reviews 48*, 1 (jan 2020), 20–27.

[148] Halse, R. E., Shoneye, C. L., Pollard, C. M., Jancey, J., Scott, J. A., Pratt, I. S., Dhaliwal, S. S., Norman, R., Straker, L. M., Boushey, C. J., Delp, E. J., Zhu, F., Harray, A. J., Szybiak, M. A., Finch, A., McVeigh, J. A., Mullan, B., Collins, C. E., Mukhtar, S. A., Edwards, K. N., Healy, J. D., and Kerr, D. A. Improving nutrition and activity behaviors using digital technology and tailored feedback: Protocol for the Livelighter Tailored Diet and Activity (TODAY) randomized controlled trial. *Journal of Medical Internet Research 21*, 2 (feb 2019).

[149] Hannah, J. 10 Classic UX Design Fails That Teach Us How Not To Do UX, may 2019.

[150] Hardeman, W., Houghton, J., Lane, K., Jones, A., and Naughton, F. A systematic review of just-in-time adaptive interventions (JITAIs) to promote physical activity. *International Journal of Behavioral Nutrition and Physical Activity 16*, 1 (2019), 31.

[151] Hartzler, A. L., Venkatakrishnan, A., Mohan, S., Silva, M., Lozano, P., Ralston, J. D., Ludman, E., Rosenberg, D., Newton, K. M., Nelson, L., and Pirolli, P. Acceptability of a team-based mobile health (mHealth) application for lifestyle self-management in individuals with chronic illnesses. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS* (oct 2016), vol. 2016-October, Institute of Electrical and Electronics Engineers Inc., pp. 3277–3281.

[152] Haslam, J. Exclusive health tracker installs and retention data | Adjust, 2019.

[153] Haslam, R. L., Pezdirc, K., Truby, H., Attia, J., Hutchesson, M., Burrows, T., Callister, R., Hides, L., Bonevski, B., Kerr, D. A., Lubans, D., Kirkpatrick, S., Rollo, M., McCaffrey, T., and Collins, C. E. Investigating the efficacy and cost-effectiveness of technology-delivered personalized feedback on dietary patterns in young Australian adults in the advice, ideas, and motivation for my

eating (Aim4Me) study: Protocol for a randomized controlled trial. *JMIR Research Protocols 9*, 5 (may 2020).

[154] Hawley-Hague, H., Horne, M., Skelton, D. A., and Todd, C. Review of how we should define (and measure) adherence in studies examining older adults' participation in exercise classes. *BMJ Open 6*, 6 (jun 2016), e011560.

[155] Hayman, M., Reaburn, P., Browne, M., Vandelanotte, C., Alley, S., and Short, C. E. Feasibility, acceptability and efficacy of a web-based computer-tailored physical activity intervention for pregnant women - the Fit4Two randomised controlled trial. *BMC pregnancy and childbirth 17*, 1 (mar 2017), 96.

[156] Heffernan, K. J., Chang, S., MacLean, S. T., Callegari, E. T., Garland, S. M., Reavley, N. J., Varigos, G. A., and Wark, J. D. Guidelines and recommendations for developing interactive ehealth apps for complex messaging in health promotion, mar 2016.

[157] Heisler, M., Choi, H., Mase, R., Long, J. A., and Reeves, P. J. Effectiveness of Technologically Enhanced Peer Support in Improving Glycemic Management Among Predominantly African American, Low-Income Adults With Diabetes. *Diabetes Educator 45*, 3 (jun 2019), 260–271.

[158] Henriksen, A., Sand, A. S., Deraas, T., Grimsgaard, S., Hartvigsen, G., and Hopstock, L. Succeeding with prolonged usage of consumer-based activity trackers in clinical studies: a mixed methods approach. *BMC Public Health 20*, 1 (aug 2020).

[159] Herazo-Beltrán, Y., Pinillos, Y., Vidarte, J., Crissien, E., Suarez, D., and García, R. Predictors of perceived barriers to physical activity in the general adult population: a cross-sectional study. *Brazilian Journal of Physical Therapy 21*, 1 (jan 2017), 44.

[160] Hermens, H., op den Akker, H., Tabak, M., Wijsman, J., and Vollenbroek, M. Personalized Coaching Systems to support healthy behavior in people with chronic conditions, dec 2014.

[161] Hermsen, S., Moons, J., Kerkhof, P., Wiekens, C., and De Groot, M. Determinants for Sustained Use of an Activity Tracker: Observational Study. *JMIR Mhealth Uhealth 2017;5(10):e164 https://mhealth.jmir.org/2017/10/e164 5*, 10 (oct 2017), e7311.

[162] Höchsmann, C., Infanger, D., Klenk, C., Königstein, K., Walz, S. P., and Schmidt-Trucksäss, A. Effectiveness of a behavior change technique–based smartphone game to improve intrinsic motivation and physical activity adherence in patients with type 2 diabetes: Randomized controlled trial. *Journal of Medical Internet Research 21*, 2 (feb 2019).

[163] Hochstatter, K. R., Gustafson, D. H., Landucci, G., Pe-Romashko, K., Maus, A., Shah, D. V., Taylor, Q. A., Gill, E. K.,

Miller, R., Krechel, S., and Westergaard, R. P. A Mobile Health Intervention to Improve Hepatitis C Outcomes Among People With Opioid Use Disorder: Protocol for a Randomized Controlled Trial. *JMIR research protocols 8*, 8 (aug 2019), e12620.

[164] Holder, C. Artificial Intelligence: Public perception, attitude and trust. Tech. rep., Bristows, sep 2018.

[165] Holtermann, A., and Stamatakis, E. Do all daily metabolic equivalent task units (METs) bring the same health benefits? *British Journal of Sports Medicine 53*, 16 (aug 2019), 991.

[166] Hors-Fraile, S., Schneider, F., Fernandez-Luque, L., Luna-Perejon, F., Civit, A., Spachos, D., Bamidis, P., and De Vries, H. Tailoring motivational health messages for smoking cessation using an mHealth recommender system integrated with an electronic health record: A study protocol. *BMC Public Health 18*, 1 (jun 2018).

[167] Hribernik, K. A., Ghrairi, Z., Hans, C., and Thoben, K. Co-creating the internet of things — first experiences in the participatory design of intelligent products with arduino. In *2011 17th International Conference on Concurrent Enterprising* (2011), pp. 1–9.

[168] Hsieh, W. T., Su, Y. C., Han, H. L., and Huang, M. Y. A novel mHealth approach for a patient-centered medication and health management system in Taiwan: Pilot study. *JMIR mHealth and uHealth 6*, 7 (jul 2018).

[169] Huang, Y., Li, L., Gan, Y., Wang, C., Jiang, H., Cao, S., and Lu, Z. Sedentary behaviors and risk of depression: a meta-analysis of prospective studies. *Translational Psychiatry 2020 10:1 10*, 1 (jan 2020), 1–10.

[170] Hutchesson, M., Callister, R., Morgan, P., Pranata, I., Clarke, E., Skinner, G., Ashton, L., Whatnall, M., Jones, M., Oldmeadow, C., and Collins, C. A Targeted and Tailored eHealth Weight Loss Program for Young Women: The Be Positive Be Healthe Randomized Controlled Trial. *Healthcare 6*, 2 (may 2018), 39.

[171] IBM. What is Deep Learning?, 2020.

[172] Ingersoll, K., Dillingham, R., Reynolds, G., Hettema, J., Freeman, J., Hosseinbor, S., and Winstead-Derlega, C. Development of a personalized bidirectional text messaging tool for HIV adherence assessment and intervention among substance abusers. *Journal of Substance Abuse Treatment 46*, 1 (jan 2014), 66–73.

[173] Iorfino, F., Cross, S. P., Davenport, T., Carpenter, J. S., Scott, E., Shiran, S., and Hickie, I. B. A Digital Platform Designed for Youth Mental Health Services to Deliver Personalized and Measurement-Based Care. *Frontiers in Psychiatry 10* (aug 2019), 595.

[174] Jakicic, J. M., Davis, K. K., Rogers, R. J., King, W. C., Marcus, M. D., Helsel, D., Rickman, A. D., Wahed, A. S., and Belle, S. H. Effect of Wearable Technology Combined with a Lifestyle Intervention on Long-Term Weight Loss: the IDEA Randomized Clinical Trial. *JAMA 316*, 11 (sep 2016), 1161.

[175] Jander, A., Crutzen, R., Mercken, L., and De Vries, H. A Web-based computer-tailored game to reduce binge drinking among 16 to 18 year old Dutch adolescents: Development and study protocol. *BMC Public Health 14*, 1 (dec 2014), 1054.

[176] Jankovič, A., Kolenik, T., and Pejović, V. Can personalization persuade? study of notification adaptation in mobile behavior change intervention application. *Behavioral Sciences 12*, 5 (2022).

[177] Janols, R., and Lindgren, H. A Method for Co-Designing Theory-Based Behaviour Change Systems for Health Promotion. *Studies in Health Technology and Informatics 235* (2017), 368–372.

[178] Janols, R., Sandlund, M., Lindgren, H., and Pettersson, B. Older adults as designers of behavior change strategies to increase physical activity—report of a participatory design process. vol. 10.

[179] Jetté, M., Sidney, K., and Blümchen, G. Metabolic equivalents (METS) in exercise testing, exercise prescription, and evaluation of functional capacity. *Clinical cardiology 13*, 8 (aug 1990), 555–65.

[180] Jo, A., Coronel, B. D., Coakes, C. E., and Mainous, A. G. Is There a Benefit to Patients Using Wearable Devices Such as Fitbit or Health Apps on Mobiles? A Systematic Review. *The American journal of medicine 132*, 12 (dec 2019), 1394–1400.e1.

[181] Jobin, A., Ienca, M., and Vayena, E. The global landscape of AI ethics guidelines. *Nature Machine Intelligence 1*, 9 (sep 2019), 389–399.

[182] John, K., Flynn, D., and Armstrong, M. Co-designing Behaviour Change in Healthcare. *DRS2018: Catalyst 5* (jun 2018).

[183] Johnson, S. S., Levesque, D. A., Broderick, L. E., Bailey, D. G., and Kerns, R. D. Pain Self-Management for Veterans: Development and Pilot Test of a Stage-Based Mobile-Optimized Intervention. *JMIR Medical Informatics 5*, 4 (oct 2017), e40.

[184] Kamal, A. K., Shaikh, Q., Pasha, O., Azam, I., Islam, M., Memon, A. A., Rehman, H., Akram, M. A., Affan, M., Nazir, S., Aziz, S., Jan, M., Andani, A., Muqeet, A., Ahmed, B., and Khoja, S. A randomized controlled behavioral intervention trial to improve medication adherence in adult stroke patients with prescription tailored Short Messaging Service (SMS)-SMS4Stroke study. *BMC Neurology 15*, 1 (dec 2015), 212.

[185] Kandola, A. A., del Pozo Cruz, B., Osborn, D. P., Stubbs, B., Choi, K. W., and Hayes, J. F. Impact of replacing sedentary behaviour with other movement behaviours on depression and anxiety symptoms: a prospective cohort study in the UK Biobank. *BMC Medicine 19*, 1 (dec 2021).

[186] Kanera, I. M., Willems, R. A., Bolman, C. A., Mesters, I., Zambon, V., Gijsen, B. C., and Lechner, L. Use and appreciation of a tailored self-management ehealth intervention for early cancer survivors: Process evaluation of a randomized controlled trial. *Journal of Medical Internet Research 18*, 8 (aug 2016).

[187] Kańtoch, E. Recognition of Sedentary Behavior by Machine Learning Analysis of Wearable Sensors during Activities of Daily Living for Telemedical Assessment of Cardiovascular Risk. *Sensors (Basel, Switzerland) 18*, 10 (oct 2018).

[188] Karanam, Y., Filko, L., Kaser, L., Alotaibi, H., Makhsoom, E., and Voida, S. Motivational affordances and personality types in personal informatics. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication* (New York, NY, USA, 2014), UbiComp '14 Adjunct, Association for Computing Machinery, p. 79–82.

[189] Kattelmann, K. K., Bredbenner, C. B., White, A. A., Greene, G. W., Hoerr, S. L., Kidd, T., Colby, S., Horacek, T. M., Phillips, B. W., Koenings, M. M., Brown, O. N., Olfert, M. D., Shelnutt, K. P., and Morrell, J. S. The Effects of Young Adults Eating and Active for Health (YEAH): A Theory-Based Web-Delivered Intervention. *Journal of Nutrition Education and Behavior 46*, 6 (nov 2014), S27–S41.

[190] Katzmarzyk, P. T., Ross, R., Blair, S. N., and Després, J. P. Should we target increased physical activity or less sedentary behavior in the battle against cardiovascular disease risk development?, oct 2020.

[191] Kelly, C. J., Karthikesalingam, A., Suleyman, M., Corrado, G., and King, D. Key challenges for delivering clinical impact with artificial intelligence, oct 2019.

[192] Kim, Y., Seo, J., An, S. Y., Sinn, D. H., and Hwang, J. H. Efficacy and safety of an mHealth app and wearable device in physical performance for patients with hepatocellular carcinoma: Development and usability study. *JMIR mHealth and uHealth 8*, 3 (mar 2020), e14435.

[193] King, A. Health risks of physical inactivity similar to smoking. *Nature Reviews Cardiology 9*, 9 (sep 2012), 492–492.

[194] King, G., Currie, M., and Petersen, P. Child and parent engagement in the mental health intervention process: A motivational framework. *Child and Adolescent Mental Health 19*, 1 (feb 2014), 2–8.

[195] Kitsiou, S., Thomas, M., Marai, G. E., Maglaveras, N., Kondos, G., Arena, R., and Gerber, B. Development of an innovative mHealth platform for remote physical activity monitoring and health coaching of cardiac rehabilitation patients. In *2017 IEEE EMBS International Conference on Biomedical and Health Informatics, BHI 2017* (apr 2017), Institute of Electrical and Electronics Engineers Inc., pp. 133–136.

[196] Klasnja, P., Smith, S., Seewald, N. J., Lee, A., Hall, K., Luers, B., Hekler, E. B., and Murphy, S. A. Efficacy of contextually tailored suggestions for physical activity: A micro-randomized optimization trial of heart steps. *Annals of Behavioral Medicine 53*, 6 (2019), 573–582.

[197] Klausen, S. H., Andersen, L. L., Søndergaard, L., Jakobsen, J. C., Zoffmann, V., Dideriksen, K., Kruse, A., Mikkelsen, U. R., and Wetterslev, J. Effects of eHealth physical activity encouragement in adolescents with complex congenital heart disease: The PReVaiL randomized clinical trial. *International Journal of Cardiology 221* (oct 2016), 1100–1106.

[198] Klein, M. C., Manzoor, A., and Mollee, J. S. Active2Gether: A personalized m-health intervention to encourage physical activity. *Sensors (Switzerland) 17*, 6 (jun 2017), 1–16.

[199] Klepac Pogrmilovic, B., Ramirez Varela, A., Pratt, M., Milton, K., Bauman, A., Biddle, S. J., and Pedisic, Z. National physical activity and sedentary behaviour policies in 76 countries: Availability, comprehensiveness, implementation, and effectiveness. *International Journal of Behavioral Nutrition and Physical Activity 17*, 1 (sep 2020).

[200] Korinek, E. V., Phatak, S. S., Martin, C. A., Freigoun, M. T., Rivera, D. E., Adams, M. A., Klasnja, P., Buman, M. P., and Hekler, E. B. Adaptive step goals and rewards: a longitudinal growth model of daily steps for a smartphone-based walking intervention. *Journal of Behavioral Medicine 41*, 1 (feb 2018), 74–86.

[201] Kreiner, K., Welte, S., Modre-Osprian, R., Fetz, B., Heidt, A., Kropf, M., Ammenwerth, E., Pölzl, G., and Kastner, P. A Personalized Feedback System for Supporting Behavior Change for Patients after an Acute Myocardial Infarction. In *Studies in Health Technology and Informatics* (2015), vol. 212, IOS Press, pp. 50–56.

[202] Kyriazakos, S., Valentini, V., Cesario, A., and Zachariae, R. FORECAST – A cloud-based personalized intelligent virtual coaching platform for the well-being of cancer patients, jan 2018.

[203] Laï, M. C., Brian, M., and Mamzer, M. F. Perceptions of artificial intelligence in healthcare: findings from a qualitative survey study among actors in France. *Journal of Translational Medicine 18*, 1 (jan 2020), 14.

[204] Laranjo, L., DIng, D., Heleno, B., Kocaballi, B., Quiroz, J. C., Tong, H. L., Chahwan, B., Neves, A. L., Gabarron, E., Dao, K. P.,

Rodrigues, D., Neves, G. C., Antunes, M. L., Coiera, E., and Bates, D. W. Do smartphone applications and activity trackers increase physical activity in adults? Systematic review, meta-analysis and metaregression. *British Journal of Sports Medicine 55*, 8 (apr 2021), 422–432.

[205] Laranjo, L., Shaw, T., Trivedi, R., Thomas, S., Charlston, E., Klimis, H., Thiagalingam, A., Kumar, S., Tan, T., Nguyen, T., Marschner, S., and Chow, C. Coordinating Health Care With Artificial Intelligence–Supported Technology for Patients With Atrial Fibrillation: Protocol for a Randomized Controlled Trial. *JMIR Res Protoc 2022;11(4):e34470 https://www.researchprotocols.org/2022/4/e34470 11*, 4 (apr 2022), e34470.

[206] Larsen, B., Benitez, T., Cano, M., Dunsiger, S. S., Marcus, B. H., Mendoza-Vasconez, A., Sallis, J. F., and Zive, M. Web-based physical activity intervention for latina adolescents: Feasibility, acceptability, and potential efficacy of the niñas saludables study. *Journal of Medical Internet Research 20*, 5 (may 2018).

[207] Laut, J., Cappa, F., Nov, O., and Porfiri, M. Increasing citizen science contribution using a virtual peer. *Journal of the Association for Information Science and Technology 68*, 3 (mar 2017), 583–593.

[208] Lavigne, M., Mussa, F., Creatore, M. I., Hoffman, S. J., and Buckeridge, D. L. A population health perspective on artificial intelligence. *Healthcare Management Forum 32*, 4 (jul 2019), 173.

[209] Layous, K., Nelson, S. K., Kurtz, J. L., and Lyubomirsky, S. What triggers prosocial effort? A positive feedback loop between positive activities, kindness, and well-being. *The Journal of Positive Psychology 12*, 4 (jul 2016), 385–398.

[210] Lazar, A., Koehler, C., Tanenbaum, T. J., and Nguyen, D. H. Why we use and abandon smart devices. *UbiComp 2015 - Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (sep 2015), 635–646.

[211] Lee, H., Ghebre, R., Le, C., Jang, Y. J., Sharratt, M., and Yee, D. Mobile phone multilevel and multimedia messaging intervention for breast cancer screening: Pilot randomized controlled trial. *JMIR mHealth and uHealth 5*, 11 (nov 2017).

[212] Lee, H. H., Emerson, J. A., and Williams, D. M. The exercise-affect-adherence pathway: An evolutionary perspective. *Frontiers in Psychology 7*, AUG (aug 2016), 1285.

[213] Lee, I.-M., Shiroma, E. J., Kamada, M., Bassett, D. R., Matthews, C. E., and Buring, J. E. Association of Step Volume and Intensity With All-Cause Mortality in Older Women. *JAMA Internal Medicine 179*, 8 (aug 2019), 1105.

[214] Lee, I.-M., Shiroma, E. J., Lobelo, F., Puska, P., Blair, S. N., Katzmarzyk, P. T., and Lancet Physical Activity Series Working Group. Effect of physical inactivity on major non-communicable diseases worldwide: an analysis of burden of disease and life expectancy. *Lancet (London, England) 380*, 9838 (jul 2012), 219–29.

[215] Legler, S., Celano, C. M., Amador, A., Novis, A., Ebrahim, S., and Huffman, J. C. Development and theoretical approach to an adaptive text message program to promote well-being and health behaviors in primary care patients. *Primary Care Companion to the Journal of Clinical Psychiatry 20*, 5 (2018).

[216] Levin, M. E., Haeger, J., and Cruz, R. A. Tailoring Acceptance and Commitment Therapy Skill Coaching in the Moment Through Smartphones: Results from a Randomized Controlled Trial. *Mindfulness 10*, 4 (apr 2019), 689–699.

[217] Li, C., Chen, X., and Bi, X. Wearable activity trackers for promoting physical activity: A systematic meta-analytic review. *International Journal of Medical Informatics 152* (aug 2021), 104487.

[218] Li, I., Dey, A., and Forlizzi, J. A stage-based model of personal informatics systems. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (New York, NY, USA, 2010), CHI '10, Association for Computing Machinery, p. 557–566.

[219] Li, J., Hodgson, N., Lyons, M. M., Chen, K. C., Yu, F., and Gooneratne, N. S. A personalized behavioral intervention implementing mHealth technologies for older adults: A pilot feasibility study. *Geriatric Nursing 41*, 3 (may 2020), 313–319.

[220] Li, L., Peng, W., Kononova, A., Kamp, K., and Cotten, S. Rethinking wearable activity trackers as assistive technologies: A qualitative study on long-term use. *Proceedings of the Annual Hawaii International Conference on System Sciences 2020-January* (2021), 3923–3931.

[221] Liao, Q. V., and Muller, M. Enabling Value Sensitive AI Systems through Participatory Design Fictions.

[222] Lim, C. G., Kim, Z. M., and Choi, H. J. Developing a mobile wellness management system for healthy lifestyle by analyzing daily living activities. In *Studies in Health Technology and Informatics* (2017), vol. 245, IOS Press, pp. 146–150.

[223] Linke, S. E., Dunsiger, S. I., Gans, K. M., Hartman, S. J., Pekmezi, D., Larsen, B. A., Mendoza-Vasconez, A. S., and Marcus, B. H. Association between physical activity intervention website use and physical activity levels among Spanish-speaking latinas: Randomized controlled trial. *Journal of Medical Internet Research 21*, 7 (jul 2019).

[224] Little, P., Stuart, B., Andreou, P., Mcdermott, L., Joseph, J., Mullee, M., Moore, M., Broomfield, S., Thomas, T., and Yardley, L. Primary care randomised controlled trial of a tailored interactive website for the self-management of respiratory infections (Internet Doctor). *BMJ Open 6*, 4 (apr 2016), 9769.

[225] Lowie, W. M., and Verspoor, M. H. Individual Differences and the Ergodicity Problem. *Language Learning 69* (mar 2019), 184–206.

[226] Lugones-Sanchez, C., Sanchez-Calavera, M. A., Repiso-Gento, I., Adalia, E. G., Ignacio Ramirez-Manent, J., Agudo-Conde, C., Rodriguez-Sanchez, E., Gomez-Marcos, M. A., Recio-Rodriguez, J. I., Garcia-Ortiz, L., Ortiz, L. G., Recio Rodriguez, J. I., Lugones-Sanchez, C., Gomez-Marcos, M. A., Agudo-Conde, C., Alonso-Dominguez, R., Sanchez-Aguadero, N., de Cabo-Laso, A., Rodriguez-Martin, C., Castaño-Sanchez, C., Sanchez-Salgado, B., Rodriguez-Sanchez, E., Gonzalez-Sanchez, S., Gonzalez-Sanchez, J., Patino-Alonso, M. C., Maderuelo-Fernandez, J. A., Hipola-Muñoz, R., Gomez-Sanchez, L., Tamayo-Morales, O., Llamas-Ramos, I., González-Viejo, N., Magdalena-Belio, J. F., Otegui-Ilarduya, L., Rubio-Galan, F. J., Sauras-Yera, C. I., Melguizo-Bejar, A., Gil-Train, M. J., Iribarne-Ferrer, M., Magdalena-González, O., Lafuente-Ripolles, M. A., Mar Martínez, M., Salcedo-Aguilar, F., Muelas-Herraiz, F., Molina-Morate, M. A., Pérez-Parra, A., Madero, F., Garcia-Imbroda, A., Izquierdo, J. M., Monterde, M. L., Rodriguez-Vizcaino, V., Soriano-Cano, A., Pozuelo-Carrascosa, D. P., Galvez-Adalia, E., del Saz-Lara, A., Díez-Fernandez, A., Alvarez-Bueno, C., Cavero-Redondo, I., Ramírez-Manent, J. I., Ferrer-Perelló, J. L., Romero-Palmer, J. E., Sarmiento-Cruz, M., Artigues, G., Mudrychova, J., Albaladejo-Blanco, M., Moyá-Seguí, M. I., Vidal-Ribas, C., Lorente-Montalvo, P., Torrens-Darder, I., Torrens-Darder, M. M., Pascual-Calleja, L., Álvarez-Miguel, M. J., de Arriba-Gómez, M. D., Rodríguez-Fernández, M., Arranz-Hernando, I., Ramos-De la Torre, S., Arqueaga-Luengo, A., Moreno-Moreno, M. E., Marcos-García, A., Manrique-Vinagre, N., Palomo-Blazquez, N., Montalvillo-Montalvillo, J. L., Fernández-Rodríguez, M. E., González-Moro, A., Santiago-Pastor, M., Pérez-Concejo, M. I., Rubio-Fernández, A., Gomez-Arranz, A., Fernandez-Alonso, C., Rodriguez-Dominguez, D., Repiso-Gento, I., de la Cal-De la Fuente, A., Aragon-Garcia, R., Diez-Garcia, M. A., Ibañes-Jalon, E., Castrillo-Sanz, I., Corcho-Castaño, A. M., Jimenez-Lopez, E., Correa-Gonzalez, D., Barruso-Villafaina, L., Peña-Garcia, I., Escudero-Terron, D., Mena-Martin, P., Fraile-Gomez, R., Alonso-Gomez, A., Urueña, P., Martinez-Bermejo, F., Hernandez-San Jose, C., Nuñez-Gomez, M., Sanz-Capdepont, P., Pazos-Revuelta, A. I., Perez-Niño, S., and Junquera-Del Pozo, M. E. Effectiveness of an

mHealth Intervention Combining a Smartphone App and Smart Band on Body Composition in an Overweight and Obese Population: Randomized Controlled Trial (EVIDENT 3 Study). *JMIR mHealth and uHealth 8*, 11 (nov 2020).

[227] Lunde, P., Bye, A., Bergland, A., and Nilsson, B. B. Effects of individualized follow-up with a smartphone-application after cardiac rehabilitation: Protocol of a randomized controlled trial. *BMC Sports Science, Medicine and Rehabilitation 11*, 1 (nov 2019), 34.

[228] Lupton, D. Critical Perspectives on Digital Health Technologies. *Sociology Compass 8*, 12 (dec 2014), 1344–1359.

[229] Lynch, B. M., Courneya, K. S., and Friedenreich, C. M. A case-control study of lifetime occupational sitting and likelihood of breast cancer. *Cancer Causes and Control 24*, 6 (jun 2013), 1257–1262.

[230] Lyons, E. J., Lewis, Z. H., Mayrsohn, B. G., and Rowland, J. L. Behavior Change Techniques Implemented in Electronic Lifestyle Activity Monitors: A Systematic Content Analysis. *Journal of Medical Internet Research 16*, 8 (aug 2014), e192.

[231] Mac Aonghusa, P., and Michie, S. Artificial Intelligence and Behavioral Science Through the Looking Glass: Challenges for Real-World Application. *Annals of Behavioral Medicine: A Publication of the Society of Behavioral Medicine 54*, 12 (dec 2020), 942.

[232] Maddison, R., Stewart, R., Doughty, R., Scott, T., Kerr, A., Benatar, J., Whittaker, R., Rawstorn, J. C., Rolleston, A., Jiang, Y., Estabrooks, P., Sullivan, R. K., Bartley, H., and Pfaeffli Dale, L. Text4Heart II - improving medication adherence in people with heart disease: A study protocol for a randomized controlled trial. *Trials 19*, 1 (jan 2018).

[233] Mainous, A. G., Tanner, R. J., Rahmanian, K. P., Jo, A., and Carek, P. J. Effect of Sedentary Lifestyle on Cardiovascular Disease Risk Among Healthy Adults With Body Mass Indexes 18.5 to 29.9 kg/m 2. *American Journal of Cardiology 123*, 5 (mar 2019), 764–768.

[234] Makalesi, A., Karapinar Senturk, Z., and Uzun, S. An Improved Deep Learning Based Cervical Cancer Detection Using a Median Filter Based Preprocessing. *European Journal of Science and Technology Special Issue 32*, 32 (2021), 50–58.

[235] Mamykina, L., A. Epstein, D., Klasnja, P., Sprujt-Metz, D., Meyer, J., Czerwinski, M., Althoff, T., Choe, E. K., De Choudhury, M., and Lim, B. Grand challenges for personal informatics and ai. In *Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems* (New York, NY, USA, 2022), CHI EA '22, Association for Computing Machinery.

[236] Manning, V., Piercy, H., Garfield, J. B. B., and Lubman, D. I. Personalized approach bias modification smartphone app ("SWIPE") to reduce alcohol use among people drinking at hazardous or harmful levels: Protocol for an open-label feasibility study. *JMIR Research Protocols 9*, 8 (aug 2020).

[237] Manuvinakurike, R., Velicer, W. F., and Bickmore, T. W. Automated indexing of Internet stories for health behavior change: Weight loss attitude pilot study. *Journal of Medical Internet Research 16*, 12 (dec 2014).

[238] Marsaux, C. F., Celis-Morales, C., Fallaize, R., Macready, A. L., Kolossa, S., Woolhead, C., O'Donovan, C. B., Forster, H., Navas-Carretero, S., San-Cristobal, R., Lambrinou, C. P., Moschonis, G., Surwillo, A., Godlewska, M., Goris, A., Hoonhout, J., Drevon, C. A., Manios, Y., Traczyk, I., Walsh, M. C., Gibney, E. R., Brennan, L., Martinez, J. A., Lovegrove, J. A., Gibney, M. J., Daniel, H., Mathers, J. C., and Saris, W. H. Effects of a web-based personalized intervention on physical activity in European adults:a randomized controlled trial. *Journal of Medical Internet Research 17*, 10 (oct 2015), e231.

[239] Martin, C. K., Gilmore, L. A., Apolzan, J. W., Myers, C. A., Thomas, D. M., and Redman, L. M. Smartloss: A Personalized Mobile Health Intervention for Weight Management and Health Promotion. *JMIR mHealth and uHealth 4*, 1 (2016), e18.

[240] Martin, S. S., Feldman, D. I., Blumenthal, R. S., Jones, S. R., Post, W. S., McKibben, R. A., Michos, E. D., Ndumele, C. E., Ratchford, E. V., Coresh, J., and Blaha, M. J. mActive: A randomized clinical trial of an automated mHealth intervention for physical activity promotion. *Journal of the American Heart Association 4*, 11 (nov 2015).

[241] Martinho, A., Kroesen, M., and Chorus, C. A healthy debate: Exploring the views of medical doctors on the ethics of artificial intelligence. *Artificial Intelligence in Medicine 121* (nov 2021), 102190.

[242] Mason, D., Gilbert, H., and Sutton, S. Effectiveness of web-based tailored smoking cessation advice reports (iQuit): A randomized trial. *Addiction 107*, 12 (dec 2012), 2183–2190.

[243] Mathur, S., and Sutton, J. Personalized medicine could transform healthcare. *Biomedical reports 7*, 1 (jul 2017), 3–5.

[244] McClure, J. B., Anderson, M. L., Bradley, K., An, L. C., and Catz, S. L. Evaluating an adaptive and interactive mhealth smoking cessation and medication adherence program: A randomized pilot feasibility study. *JMIR mHealth and uHealth 4*, 3 (jul 2016).

[245] McCradden, M. D., Sarker, T., and Paprica, P. A. Original research: Conditionally positive: a qualitative study of public perceptions about using health data for artificial intelligence research. *BMJ Open 10*, 10 (oct 2020), 39798.

[246] McLennan, S., Fiske, A., Tigard, D., Müller, R., Haddadin, S., and Buyx, A. Embedded ethics: a proposal for integrating ethics into the development of medical AI. *BMC Medical Ethics 23*, 1 (dec 2022).

[247] Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., and Galstyan, A. A Survey on Bias and Fairness in Machine Learning.

[248] Mehta, N., Harish, V., Bilimoria, K., Morgado, F., Ginsburg, S., Law, M., and Das, S. Knowledge of and Attitudes on Artificial Intelligence in Healthcare: A Provincial Survey Study of Medical Students. *medRxiv* (jan 2021), 2021.01.14.21249830.

[249] Melchart, D., Löw, P., Wühr, E., Kehl, V., and Weidenhammer, W. Effects of a tailored lifestyle self-management intervention (TALENT) study on weight reduction: A randomized controlled trial. *Diabetes, Metabolic Syndrome and Obesity: Targets and Therapy 10* (jun 2017), 235–245.

[250] Mendes-Santos, C., Weiderpass, E., Santana, R., and Andersson, G. A guided internet-delivered individually-tailored ACT-influenced cognitive behavioural intervention to improve psychosocial outcomes in breast cancer survivors (iNNOVBC): Study protocol. *Internet Interventions 17* (sep 2019).

[251] Michalsen, H., Wangberg, S. C., Hartvigsen, G., Jaccheri, L., Muzny, M., Henriksen, A., Olsen, M. I., Thrane, G., Jahnsen, R. B., Pettersen, G., Arntzen, C., and Anke, A. Physical activity with tailored mHealth support for individuals with intellectual disabilities: study protocol for a randomized controlled trial (Preprint). *JMIR Research Protocols 9*, 6 (apr 2020), e19213.

[252] Michie, S., Ashford, S., Sniehotta, F. F., Dombrowski, S. U., Bishop, A., and French, D. P. A refined taxonomy of behaviour change techniques to help people change their physical activity and healthy eating behaviours: The CALO-RE taxonomy. *Psychology & Health 26*, 11 (nov 2011), 1479–1498.

[253] Michie, S., and Johnston, M. *Behavior Change Techniques.* Springer New York, New York, NY, 2013, pp. 182–187.

[254] Michie, S., Richardson, M., Johnston, M., Abraham, C., Francis, J., Hardeman, W., Eccles, M. P., Cane, J., and Wood, C. E. The Behavior Change Technique Taxonomy (v1) of 93 Hierarchically Clustered Techniques: Building an International Consensus for the Reporting of Behavior Change Interventions. *Annals of Behavioral Medicine 46*, 1 (aug 2013), 81–95.

[255] Michie, S., Thomas, J., Johnston, M., Aonghusa, P. M., Shawe-Taylor, J., Kelly, M. P., Deleris, L. A., Finnerty, A. N., Marques, M. M., Norris, E., O'Mara-Eves, A., and West, R. The

Human Behaviour-Change Project: Harnessing the power of artificial intelligence and machine learning for evidence synthesis and interpretation. *Implementation Science 12*, 1 (oct 2017), 121.

[256] Mittelstadt, B. Principles alone cannot guarantee ethical AI. *Nature Machine Intelligence 1*, 11 (nov 2019), 501–507.

[257] Mönninghoff, A., Kramer, J. N., Hess, A. J., Ismailova, K., Teepe, G. W., Car, L. T., Müller-Riemenschneider, F., and Kowatsch, T. Long-term Effectiveness of mHealth Physical Activity Interventions: Systematic Review and Meta-analysis of Randomized Controlled Trials. *Journal of Medical Internet Research 23*, 4 (apr 2021).

[258] Moore, D. J., Pasipanodya, E. C., Umlauf, A., Rooney, A. S., Gouaux, B., Depp, C. A., Atkinson, J. H., and Montoya, J. L. Individualized texting for adherence building (iTAB) for methamphetamine users living with HIV: A pilot randomized clinical trial. *Drug and Alcohol Dependence 189* (aug 2018), 154–160.

[259] Moreau, M., Gagnon, M.-P., and Boudreau, F. Development of a Fully Automated, Web-Based, Tailored Intervention Promoting Regular Physical Activity Among Insufficiently Active Adults With Type 2 Diabetes: Integrating the I-Change Model, Self-Determination Theory, and Motivational Interviewing Components. *JMIR Research Protocols 4*, 1 (feb 2015), e25.

[260] Morris, J. N., and Hardman, A. E. Walking to health. *Sports medicine (Auckland, N.Z.) 23*, 5 (may 1997), 306–332.

[261] Morrison, K. Artificial intelligence and the NHS: a qualitative exploration of the factors influencing adoption. *Future Healthc J 8*, 3 (nov 2021), e648–e654.

[262] Morrison, L. G. Theory-based strategies for enhancing the impact and usage of digital health behaviour change interventions: A review. *DIGITAL HEALTH 1* (jan 2015), 205520761559533.

[263] Morrison, L. G., Hargood, C., Pejovic, V., Geraghty, A. W. A., Lloyd, S., Goodman, N., Michaelides, D. T., Weston, A., Musolesi, M., Weal, M. J., and Yardley, L. The Effect of Timing and Frequency of Push Notifications on Usage of a Smartphone-Based Stress Management Intervention: An Exploratory Trial. *PLOS ONE 12*, 1 (jan 2017), e0169162.

[264] Mougiakakou, S. G., Valavanis, I. K., Karkalis, G., Marinos, S., Grimaldi, K. A., and Nikita, K. S. An integrated web-based platform for the provision of personalized advice in people at high risk for CVD. In *Final Program and Abstract Book - 9th International Conference on Information Technology and Applications in Biomedicine, ITAB 2009* (2009).

[265] Murphy, K., Di Ruggiero, E., Upshur, R., Willison, D. J., Malhotra, N., Cai, J. C., Malhotra, N., Lui, V., and Gibson, J. Artificial intelligence for good health: a scoping review of the ethics literature. *BMC Medical Ethics 22*, 1 (2021), 14.

[266] Nahum-Shani, I., Smith, S. N., Spring, B. J., Collins, L. M., Witkiewitz, K., Tewari, A., and Murphy, S. A. Just-in-Time Adaptive Interventions (JITAIs) in Mobile Health: Key Components and Design Principles for Ongoing Health Behavior Support. *Annals of Behavioral Medicine 52*, 6 (may 2018), 446–462.

[267] Naughton, F., Cooper, S., Foster, K., Emery, J., Leonardi-Bee, J., Sutton, S., Jones, M., Ussher, M., Whitemore, R., Leighton, M., Montgomery, A., Parrott, S., and Coleman, T. Large multicentre pilot randomized controlled trial testing a low-cost, tailored, self-help smoking cessation text message intervention for pregnant smokers (MiQuit). *Addiction 112*, 7 (jul 2017), 1238–1249.

[268] Nedungadi, P., Jayakumar, A., and Raman, R. Personalized Health Monitoring System for Managing Well-Being in Rural Areas. *Journal of Medical Systems 42*, 1 (jan 2018).

[269] Neuhauser, L., and Kreps, G. L. Participatory Design and Artificial Intelligence: Strategies to Improve Health Communication for Diverse Audiences. *undefined* (2011).

[270] Neumeier, W. H., Guerra, N., Thirumalai, M., Geer, B., Ervin, D., and Rimmer, J. H. POWERSforID: Personalized Online Weight and Exercise Response System for Individuals with Intellectual Disability: Study protocol for a randomized controlled trial. *Trials 18*, 1 (oct 2017).

[271] NHS. Exercise, 2019.

[272] NIHR. What is digital health technology and what can it do for me?

[273] Noar, S. M., Willoughby, J. F., Crosby, R., Webb, E. M., Van Stee, S. K., Feist-Price, S., and Davis, E. Acceptability of a Computer-Tailored Safer Sex Intervention for Heterosexually Active African Americans Attending an STI Clinic. *Journal of Primary Prevention 41*, 3 (jun 2020), 211–227.

[274] op den Akker, H., Jones, V. M., and Hermens, H. J. Tailoring real-time physical activity coaching systems: a literature survey and model. *User Modeling and User-Adapted Interaction 24*, 5 (oct 2014), 351–392.

[275] Pagoto, S., and Bennett, G. G. How behavioral science can advance digital health. *Translational Behavioral Medicine 3*, 3 (sep 2013), 271–276.

[276] Päivärinne, V., Kautiainen, H., Heinonen, A., and Kiviranta, I. Relations between subdomains of physical activity, sedentary lifestyle, and quality of life in young adult men. *Scandinavian Journal of Medicine & Science in Sports 28*, 4 (apr 2018), 1389–1396.

[277] Paladino, A. J., Anderson, J. N., Krukowski, R. A., Waters, T., Kocak, M., Graff, C., Blue, R., Jones, T. N., Buzaglo, J., Vidal, G., Schwartzberg, L., and Graetz, I. THRIVE study protocol: A randomized controlled trial evaluating a web-based app and tailored messages to improve adherence to adjuvant endocrine therapy among women with breast cancer. *BMC Health Services Research 19*, 1 (dec 2019).

[278] Paluch, A. E., Bajpai, S., Bassett, D. R., Carnethon, M. R., Ekelund, U., Evenson, K. R., Galuska, D. A., Jefferis, B. J., Kraus, W. E., Lee, I.-M., Matthews, C. E., Omura, J. D., Patel, A. V., Pieper, C. F., Rees-Punia, E., Dallmeier, D., Klenk, J., Whincup, P. H., Dooley, E. E., Gabriel, K. P., Palta, P., Pompeii, L. A., Chernofsky, A., Larson, M. G., Vasan, R. S., Spartano, N., Ballin, M., Nordström, P., Nordström, A., Anderssen, S. A., Hansen, B. H., Cochrane, J. A., Dwyer, T., Wang, J., Ferrucci, L., Liu, F., Schrack, J., Urbanek, J., Saint-Maurice, P. F., Yamamoto, N., Yoshitake, Y., Newton, R. L., Yang, S., Shiroma, E. J., and Fulton, J. E. Daily steps and all-cause mortality: a meta-analysis of 15 international cohorts. *The Lancet Public Health 7*, 3 (mar 2022), e219–e228.

[279] Paluch, A. E., Gabriel, K. P., Fulton, J. E., Lewis, C. E., Schreiner, P. J., Sternfeld, B., Sidney, S., Siddique, J., Whitaker, K. M., and Carnethon, M. R. Steps per Day and All-Cause Mortality in Middle-aged Adults in the Coronary Artery Risk Development in Young Adults Study. *JAMA Network Open 4*, 9 (sep 2021), e2124516–e2124516.

[280] Partridge, S. R., McGeechan, K., Hebden, L., Balestracci, K., Wong, A. T., Denney-Wilson, E., Harris, M. F., Phongsavan, P., Bauman, A., and Allman-Farinelli, M. Effectiveness of a mHealth Lifestyle Program with Telephone Support (TXT2BFiT) to Prevent Unhealthy Weight Gain in Young Adults: Randomized Controlled Trial. *JMIR mHealth and uHealth 3*, 2 (jun 2015).

[281] Peels, D. A., Hoogenveen, R. R., Feenstra, T. L., Golsteijn, R. H., Bolman, C., Mudde, A. N., Wendel-Vos, G. C., De Vries, H., and Lechner, L. Long-term health outcomes and cost-effectiveness of a computer-tailored physical activity intervention among people aged over fifty: Modelling the results of a randomized controlled trial. *BMC Public Health 14*, 1 (2014).

[282] Pega. What Consumers Really Think About AI: A Global Study, 2017.

[283] Peiris, D., Wright, L., News, M., Rogers, K., Redfern, J., Chow, C., and Thomas, D. A smartphone app to assist smoking cessation among aboriginal australians: Findings from a pilot randomized controlled trial. *Journal of Medical Internet Research 21*, 4 (apr 2019).

[284] Pelle, T., Bevers, K., Van Der Palen, J., Van Den Hoogen, F. H., and Van Den Ende, C. H. Development and evaluation of a tailored e-self-management intervention (dr. Bart app) for knee and/or hip osteoarthritis: Study protocol. *BMC Musculoskeletal Disorders 20*, 1 (aug 2019).

[285] Peters, G. J. Y., Ruiter, R. A., and Kok, G. Threatening communication: A critical re-analysis and a revised meta-analytic test of fear appeal theory. *Health Psychology Review 7*, SUPPL1 (2013).

[286] Pfirrmann, D., Haller, N., Huber, Y., Jung, P., Lieb, K., Gockel, I., Poplawska, K., Schattenberg, J. M., and Simon, P. Applicability of a web-based, individualized exercise intervention in patients with liver disease, cystic fibrosis, esophageal cancer, and psychiatric disorders: Process evaluation of 4 ongoing clinical trials. *Journal of Medical Internet Research 20*, 5 (may 2018).

[287] Phatak, S. S., Freigoun, M. T., Martín, C. A., Rivera, D. E., Korinek, E. V., Adams, M. A., Buman, M. P., Klasnja, P., and Hekler, E. B. Modeling individual differences: A case study of the application of system identification for personalizing a physical activity intervention. *Journal of biomedical informatics 79* (mar 2018), 82–97.

[288] Piette, J. D., Farris, K. B., Newman, S., An, L., Sussman, J., and Singh, S. The potential impact of intelligent systems for mobile health self-management support: Monte Carlo simulations of text message support for medication adherence. *Annals of behavioral medicine : a publication of the Society of Behavioral Medicine 49*, 1 (feb 2015), 84–94.

[289] Pinder, C., Vermeulen, J., Cowan, B. R., and Beale, R. Digital Behaviour Change Interventions to Break and Form Habits. *ACM Transactions on Computer-Human Interaction 25*, 3 (jun 2018), 1–66.

[290] Poirier, J., Bennett, W. L., Jerome, G. J., Shah, N. G., Lazo, M., Yeh, H. C., Clark, J. M., and Cobb, N. K. Effectiveness of an activity tracker- and internet-based adaptive walking program for adults: A randomized controlled trial. *Journal of Medical Internet Research 18*, 2 (feb 2016).

[291] Polaris Market Research. Fitness App Market Size, Growth & Value - Industry Report, 2020-2026, feb 2020.

[292] Postma, O. J., and Brokke, M. Personalisation in practice: The proven effects of personalisation. *Journal of Database Marketing & Customer Strategy Management 9*, 2 (2002), 137–142.

[293] Precker, M. Is 10,000 Steps Really a Magic Number for Health?, 2021.

[294] Presseau, J., Byrne-Davis, L. M., Hotham, S., Lorencatto, F., Potthoff, S., Atkinson, L., Bull, E. R., Dima, A. L., van Dongen, A., French, D., Hankonen, N., Hart, J., ten Hoor, G. A., Hudson, K., Kwasnicka, D., van Lieshout, S., McSharry, J., Olander, E. K., Powell, R., Toomey, E., and Byrne, M. Enhancing

the translation of health behaviour change research into practice: a selective conceptual review of the synergy between implementation science and health psychology. *https://doi.org/10.1080/17437199.2020.1866638* (2021).

[295] Presseau, J., Ivers, N. M., Newham, J. J., Knittle, K., Danko, K. J., and Grimshaw, J. M. Using a behaviour change techniques taxonomy to identify active ingredients within trials of implementation interventions for diabetes care. *Implementation Science 10*, 1 (apr 2015), 1–10.

[296] Prestwich, A., Sniehotta, F. F., Whittington, C., Dombrowski, S. U., Rogers, L., and Michie, S. Does theory influence the effectiveness of health behavior interventions? Meta-analysis. *Health Psychology 33*, 5 (may 2014), 465–474.

[297] Puddephatt, J. A., Leightley, D., Palmer, L., Jones, N., Mahmoodi, T., Drummond, C., Rona, R. J., Fear, N. T., Field, M., and Goodwin, L. A qualitative evaluation of the acceptability of a tailored smartphone alcohol intervention for a military population: Information about drinking for ex-serving personnel (inDEx) app. *JMIR mHealth and uHealth 7*, 5 (may 2019).

[298] Pyky, R., Koivumaa-Honkanen, H., Leinonen, A. M., Ahola, R., Hirvonen, N., Enwald, H., Luoto, T., Ferreira, E., Ikäheimo, T. M., Keinänen-Kiukaanniemi, S., Mäntysaari, M., Jämsä, T., and Korpelainen, R. Effect of tailored, gamified, mobile physical activity intervention on life satisfaction and self-rated health in young adolescent men: A population-based, randomized controlled trial (MOPO study). *Computers in Human Behavior 72* (jul 2017), 13–22.

[299] Quiñonez, S. G., Walthouwer, M. J. L., Schulz, D. N., and De Vries, H. MHealth or eHealth? Efficacy, use, and appreciation of a web-based computer-tailored physical activity intervention for Dutch adults: A randomized controlled trial. *Journal of Medical Internet Research 18*, 11 (nov 2016).

[300] Rabbi, M., Aung, M. H., Zhang, M., and Choudhury, T. MyBehavior: Automatic personalized health feedback from user behaviors and preferences using smartphones. In *UbiComp 2015 - Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (sep 2015), Association for Computing Machinery, Inc, pp. 707–718.

[301] Rahman, M. M., Liang, C. Y., Gu, D., Ding, Y., and Akter, M. Understanding Levels and Motivation of Physical Activity for Health Promotion among Chinese Middle-Aged and Older Adults: A Cross-Sectional Investigation. *Journal of Healthcare Engineering 2019* (2019).

[302] Rajanna, V., Lara-Garduno, R., Behera, D. J., Madanagopal, K., Goldberg, D., and Hammond, T. Step up life: A context aware health assistant. In *Proceedings of the 3rd ACM SIGSPATIAL International Workshop on the Use of GIS in Public Health, HealthGIS 2014 - In Conjuncture with the 22nd ACM SIGSPATIAL International Conference on*

Advances in Geographic Information Systems, ACM GIS 2014 (New York, New York, USA, nov 2014), Association for Computing Machinery, Inc, pp. 21–30.

[303] Rapp, A., and Cena, F. Personal informatics for everyday life: How users without prior self-tracking experience engage with personal data. *International Journal of Human-Computer Studies 94* (2016), 1–17.

[304] Rawstorn, J. C., Gant, N., Meads, A., Warren, I., and Maddison, R. Remotely delivered exercise-based cardiac rehabilitation: Design and content development of a novel mHealth platform. *JMIR mHealth and uHealth 4*, 2 (jun 2016).

[305] Recio-Rodriguez, J. I., Gómez-Marcos, M. A., Agudo-Conde, C., Ramirez, I., Gonzalez-Viejo, N., Gomez-Arranz, A., Salcedo-Aguilar, F., Rodriguez-Sanchez, E., Alonso-Domínguez, R., Sánchez-Aguadero, N., Gonzalez-Sanchez, J., and Garcia-Ortiz, L. EVIDENT 3 Study: A randomized, controlled clinical trial to reduce inactivity and caloric intake in sedentary and overweight or obese people using a smartphone application: Study protocol. *Medicine (United States) 97*, 2 (jan 2018).

[306] Reinwand, D., Kuhlmann, T., Wienert, J., De Vries, H., and Lippke, S. Designing a theory-and evidence-based tailored eHealth rehabilitation aftercare program in Germany and the Netherlands: Study protocol. *BMC Public Health 13*, 1 (dec 2013), 1081.

[307] Renfree, I., Harrison, D., Marshall, P., Stawarz, K., and Cox, A. Don't kick the habit: The role of dependency in habit formation apps. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems* (New York, NY, USA, 2016), CHI EA '16, Association for Computing Machinery, p. 2932–2939.

[308] Rigby, M. J. Ethical dimensions of using artificial intelligence in health care, feb 2019.

[309] Ringeval, M., Wagner, G., Denford, J., Paré, G., and Kitsiou, S. Fitbit-Based Interventions for Healthy Lifestyle Outcomes: Systematic Review and Meta-Analysis. *J Med Internet Res 2020;22(10):e23954 https://www.jmir.org/2020/10/e23954 22*, 10 (oct 2020), e23954.

[310] Rodriguez-Ruiz, A., Lång, K., Gubern-Merida, A., Broeders, M., Gennaro, G., Clauser, P., Helbich, T. H., Chevalier, M., Tan, T., Mertelmeier, T., Wallis, M. G., Andersson, I., Zackrisson, S., Mann, R. M., and Sechopoulos, I. Stand-Alone Artificial Intelligence for Breast Cancer Detection in Mammography: Comparison With 101 Radiologists. *JNCI Journal of the National Cancer Institute 111*, 9 (sep 2019), 916.

[311] Rooksby, J., Rost, M., Morrison, A., and Chalmers, M. Personal tracking as lived informatics. In *Proceedings of the SIGCHI Conference on*

Human Factors in Computing Systems (New York, NY, USA, 2014), CHI '14, Association for Computing Machinery, p. 1163–1172.

[312] Rosmalen, J. G., van Gils, A., Acevedo Mesa, M. A., Schoevers, R. A., Monden, R., and Hanssen, D. J. Development of Grip self-help: An online patient-tailored self-help intervention for functional somatic symptoms in primary care. *Internet Interventions 19* (mar 2020), 100297.

[313] Rothert, K., Strecher, V. J., Doyle, L. A., Caplan, W. M., Joyce, J. S., Jimison, H. B., Karm, L. M., Mims, A. D., and Roth, M. A. Web-based weight management programs in an integrated health care setting: A randomized, controlled trial. *Obesity 14*, 2 (feb 2006), 266–272.

[314] Rothman, A. J. "Is there nothing more practical than a good theory?": Why innovations and advances in health behavior change will arise if interventions are used to test and refine theory. *The international journal of behavioral nutrition and physical activity 1*, 1 (jul 2004).

[315] Sadasivam, R. S., Borglund, E. M., Adams, R., Marlin, B. M., and Houston, T. K. Impact of a collective intelligence tailored messaging system on smoking cessation: The perspect randomized experiment. *Journal of Medical Internet Research 18*, 11 (nov 2016).

[316] Saidj, M., Menai, M., Charreire, H., Weber, C., Enaux, C., Aadahl, M., Kesse-Guyot, E., Hercberg, S., Simon, C., and Oppert, J. M. Descriptive study of sedentary behaviours in 35,444 French working adults: Cross-sectional findings from the ACTI-Cités study. *BMC Public Health 15*, 1 (apr 2015).

[317] Saint-Maurice, P. F., Troiano, R. P., Bassett David R., J., Graubard, B. I., Carlson, S. A., Shiroma, E. J., Fulton, J. E., and Matthews, C. E. Association of Daily Step Count and Step Intensity With Mortality Among US Adults. *JAMA 323*, 12 (2020), 1151–1160.

[318] Saisubramanian, S., Zilberstein, S., and Kamar, E. Avoiding negative side effects due to incomplete knowledge of ai systems, 2020.

[319] Samaan, Z., Schulze, K. M., Middleton, C., Irvine, J., Joseph, P., Mente, A., Shah, B. R., Pare, G., Desai, D., and Anand, S. S. South asian heart risk assessment (SAHARA): Randomized controlled trial design and pilot study. *Journal of Medical Internet Research 15*, 8 (aug 2013).

[320] Sandal, L. F., Stochkendahl, M. J., Svendsen, M. J., Wood, K., Overas, C. K., Nordstoga, A. L., Villumsen, M., Rasmussen, C. D. N., Nicholl, B., Cooper, K., Kjaer, P., Mair, F. S., Sjogaard, G., Nilsen, T. I. L., Hartvigsen, J., Bach, K., Mork, P. J., and Sogaard, K. An app-delivered self-management program for people with low back pain: Protocol for the selfback randomized controlled trial. *Journal of Medical Internet Research 21*, 12 (dec 2019).

[321] Schaalma, H., and Kok, G. Decoding health education interventions: The times are a-changin'. *Psychology & Health 24*, 1 (jan 2009), 5–9.

[322] Schuit, A. S., Holtmaat, K., Hooghiemstra, N., Jansen, F., Lissenberg-Witte, B. I., Coupé, V. M., Van Linde, M. E., Becker-Commissaris, A., Reijneveld, J. C., Zijlstra, J. M., Sommeijer, D. W., Eerenstein, S. E., and Verdonck-De Leeuw, I. M. Efficacy and cost-utility of the eHealth application 'Oncokompas', supporting patients with incurable cancer in finding optimal palliative care, tailored to their quality of life and personal preferences: A study protocol of a randomized controlled trial. *BMC Palliative Care 18*, 1 (oct 2019).

[323] Schulz, D. N., Kremers, S. P., Vandelanotte, C., Van Adrichem, M. J., Schneider, F., Candel, M. J., and De Vries, H. Effects of a web-based tailored multiple-lifestyle intervention for adults: A two-year randomized controlled trial comparing sequential and simultaneous delivery modes. *Journal of Medical Internet Research 16*, 1 (jan 2014).

[324] Scott, C., De Barra, M., Johnston, M., De Bruin, M., Scott, N., Matheson, C., Bond, C., and Watson, M. C. Using the behaviour change technique taxonomy v1 (BCTTv1) to identify the active ingredients of pharmacist interventions to improve non-hospitalised patient health outcomes. *BMJ Open 10*, 9 (sep 2020), e036500.

[325] Shaffer, J. A. *Stages-of-Change Model.* Springer New York, New York, NY, 2013, pp. 1871–1874.

[326] Shin, G., Jarrahi, M. H., Fei, Y., Karami, A., Gafinowitz, N., Byun, A., and Lu, X. Wearable activity trackers, accuracy, adoption, acceptance and health impact: A systematic literature review. *Journal of Biomedical Informatics 93* (may 2019), 103153.

[327] Silva, L. R. B., Seguro, C. S., de Oliveira, C. G. A., Santos, P. O. S., de Oliveira, J. C. M., de Souza Filho, L. F. M., de Paula Júnior, C. A., Gentil, P., and Rebelo, A. C. S. Physical Inactivity Is Associated With Increased Levels of Anxiety, Depression, and Stress in Brazilians During the COVID-19 Pandemic: A Cross-Sectional Study. *Frontiers in Psychiatry 11* (nov 2020), 1257.

[328] Simons, D., De Bourdeaudhuij, I., Clarys, P., De Cocker, K., Vandelanotte, C., and Deforche, B. Effect and process evaluation of a smartphone app to promote an active lifestyle in lower educated working young adults: Cluster randomized controlled trial. *JMIR mHealth and uHealth 6*, 8 (aug 2018).

[329] Singleton, A., Partridge, S. R., Raeside, R., Regimbal, M., Hyun, K. K., Chow, C. K., Sherman, K., Elder, E., and Redfern, J. A text message intervention to support women's physical and mental health after breast cancer treatments (EMPOWER-SMS): A randomised controlled trial protocol. *BMC Cancer 19*, 1 (jul 2019), 660.

[330] Six, J. M. Identifying and Validating Assumptions and Mitigating Biases in User Research, oct 2015.

[331] Slota, S. C. Designing Across Distributed Agency: Values, participatory design and building socially responsible AI. *Computing Professionals for Social Responsibility: The Past, Present and Future Values of Participatory Design* (2020).

[332] Spark, L. C., Fjeldsoe, B. S., Eakin, E. G., and Reeves, M. M. Efficacy of a text message-delivered extended contact intervention on maintenance of weight loss, physical activity, and dietary behavior change. *JMIR mHealth and uHealth 3*, 3 (sep 2015).

[333] Spiel, K., Brulé, E., Frauenberger, C., Bailly, G., and Fitzpatrick, G. Micro-ethics for participatory design with marginalised children. In *Proceedings of the 15th Participatory Design Conference on Full Papers - PDC '18* (New York, New York, USA, 2018), vol. 1, Association for Computing Machinery (ACM), pp. 1–12.

[334] Spittaels, H., De Bourdeaudhuij, I., and Vandelanotte, C. Evaluation of a website-delivered computer-tailored intervention for increasing physical activity in the general population. *Preventive Medicine 44*, 3 (mar 2007), 209–217.

[335] Stamatakis, E., Ding, D., Hamer, M., Bauman, A. E., Lee, I. M., and Ekelund, U. Any public health guidelines should always be developed from a consistent, clear evidence base, dec 2019.

[336] Stawarz, K., Cox, A. L., and Blandford, A. Beyond self-tracking and reminders: Designing smartphone apps that support habit formation. *Conference on Human Factors in Computing Systems - Proceedings 2015-April* (apr 2015), 2653–2662.

[337] Storm, V., Dörenkämper, J., Reinwand, D. A., Wienert, J., De Vries, H., and Lippke, S. Effectiveness of a web-based computer-tailored multiple-lifestyle intervention for people interested in reducing their cardiovascular risk: A randomized controlled trial. *Journal of Medical Internet Research 18*, 4 (apr 2016).

[338] Suffoletto, B., Chung, T., Muench, F., Monti, P., and Clark, D. B. A text message intervention with adaptive goal support to reduce alcohol consumption among non-treatment-seeking young adults: Non-randomized clinical trial with voluntary length of enrollment. *JMIR mHealth and uHealth 6*, 2 (feb 2018).

[339] SurveyMonkey Intelligence. These fitness app statistics show what's going right (and wrong) for Fitbit.

[340] Sutton, R. S., and Barto, A. G. *Reinforcement Learning: An Introduction*, 2nd ed. Adaptive Computation and Machine Learning series. MIT Press, 2018.

[341] Swann, C., Jackman, P. C., Lawrence, A., Hawkins, R. M., Goddard, S. G., Williamson, O., Schweickle, M. J., Vella, S. A., Rosenbaum, S., and Ekkekakis, P. The (over)use of SMART goals for physical activity promotion: A narrative review and critique. *Health Psychology Review* (2022).

[342] Taj, F., Klein, M. C., and Van Halteren, A. Digital health behavior change technology: Bibliometric and scoping review of two decades of research, 2019.

[343] Taj, F., Klein, M. C. A., and Van Halteren, A. Motivating Machines: The Potential of Modeling Motivation as MoA for Behavior Change Systems. *Information 13*, 5 (2022).

[344] Tang, L. M., Meyer, J., Epstein, D. A., Bragg, K., Engelen, L., Bauman, A., and Kay, J. Defining Adherence: Making Sense of Physical Activity Tracker Data. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies 2*, 1 (mar 2018), 1–22.

[345] Tang, M. S. S., Moore, K., McGavigan, A., Clark, R. A., and Ganesan, A. N. Effectiveness of Wearable Trackers on Physical Activity in Healthy Adults: Systematic Review and Meta-Analysis of Randomized Controlled Trials. *JMIR mHealth and uHealth 8*, 7 (jul 2020).

[346] Tang, R., and Braver, T. S. Towards an Individual Differences Perspective in Mindfulness Training Research: Theoretical and Empirical Considerations. *Frontiers in Psychology 0* (may 2020), 818.

[347] Tate, D. F., Jackvony, E. H., and Wing, R. R. A randomized trial comparing human e-mail counseling, computer-automated tailored counseling, and no counseling in an internet weight loss program. *Archives of Internal Medicine 166*, 15 (aug 2006), 1620–1625.

[348] Teixeira, P. J., Carraça, E. V., Markland, D., Silva, M. N., and Ryan, R. M. Exercise, physical activity, and self-determination theory: A systematic review. *The International Journal of Behavioral Nutrition and Physical Activity 9* (jun 2012), 78.

[349] Teng, M., Singla, R., Yau, O., Lamoureux, D., Gupta, A., Hu, Z., Hu, R., Aissiou, A., Eaton, S., Hamm, C., Hu, S., Kelly, D., MacMillan, K. M., Malik, S., Mazzoli, V., Teng, Y. W., Laricheva, M., Jarus, T., and Field, T. S. Health Care Students' Perspectives on Artificial Intelligence: Countrywide Survey in Canada. *JMIR Med Educ 2022;8(1):e33390 https://mededu.jmir.org/2022/1/e33390 8*, 1 (jan 2022), e33390.

[350] Teychenne, M., Costigan, S. A., and Parker, K. The association between sedentary behaviour and risk of anxiety: a systematic review. *BMC Public Health 15*, 1 (jun 2015).

[351] The Royal Society. Portrayals and perceptions of AI and why they matter. Tech. rep., nov 2018.

[352] Thivel, D., Tremblay, A., Genin, P. M., Panahi, S., Rivière, D., and Duclos, M. Physical Activity, Inactivity, and Sedentary Behaviors: Definitions and Implications in Occupational Health. *Frontiers in Public Health 6* (oct 2018), 288.

[353] Thomas Craig, K. J., Morgan, L. C., Chen, C. H., Michie, S., Fusco, N., Snowdon, J. L., Scheufele, E., Gagliardi, T., and Sill, S. Systematic review of context-aware digital behavior change interventions to improve health. *Translational Behavioral Medicine 11*, 5 (may 2021), 1037.

[354] Tong, H. L., Quiroz, J. C., Kocaballi, A. B., Fat, S. C. M., Dao, K. P., Gehringer, H., Chow, C. K., and Laranjo, L. Personalized mobile technologies for lifestyle behavior change: A systematic review, meta-analysis, and meta-regression. *Preventive Medicine 148* (2021), 106532.

[355] Tremblay, M. S., Aubert, S., Barnes, J. D., Saunders, T. J., Carson, V., Latimer-Cheung, A. E., Chastin, S. F., Altenburg, T. M., and Chinapaw, M. J. Sedentary Behavior Research Network (SBRN) – Terminology Consensus Project process and outcome. *International Journal of Behavioral Nutrition and Physical Activity 14*, 1 (dec 2017), 75.

[356] Tremblay, M. S., Colley, R. C., Saunders, T. J., Healy, G. N., and Owen, N. Physiological and health implications of a sedentary lifestyle. *Applied Physiology, Nutrition, and Metabolism 35*, 6 (dec 2010), 725–740.

[357] Tseng, J. C., Lin, B. H., Lin, Y. F., Tseng, V. S., Day, M. L., Wang, S. C., Lo, K. R., and Yang, Y. C. An interactive healthcare system with personalized diet and exercise guideline recommendation. In *TAAI 2015 - 2015 Conference on Technologies and Applications of Artificial Intelligence* (feb 2016), Institute of Electrical and Electronics Engineers Inc., pp. 525–532.

[358] Twardowski, B., and Ryzko, D. IoT and context-aware mobile recommendations using Multi-Agent Systems. In *Proceedings - 2015 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology, WI-IAT 2015* (feb 2016), vol. 1, Institute of Electrical and Electronics Engineers Inc., pp. 33–39.

[359] Uribe, J. A., Duitama, J. F., and Gaviria Gómez, N. Personalized message emission in a mobile application for supporting therapeutic adherence. In *2011 IEEE 13th International Conference on e-Health Networking, Applications and Services, HEALTHCOM 2011* (2011), pp. 15–20.

[360] Valcarce-Torrente, M., Javaloyes, V., Gallardo, L., García-Fernández, J., and Planas-Anzano, A. Influence of Fitness Apps on Sports Habits, Satisfaction, and Intentions to Stay in Fitness Center Users: An Experimental Study. *International Journal of Environmental Research and Public Health 18*, 19 (oct 2021).

[361] van de Poel, I. Value-sensitive design: four challenges, 1 2010.

[362] Van Den Brekel-Dijkstra, K., Rengers, A. H., Niessen, M. A., De Wit, N. J., and Kraaijenhagen, R. A. Personalized prevention approach with use of a web-based cardiovascular risk assessment with tailored lifestyle follow-up in primary care practice - A pilot study. *European Journal of Preventive Cardiology 23*, 5 (mar 2016), 544–551.

[363] van der Meij, E., Anema, J. R., Leclercq, W. K., Bongers, M. Y., Consten, E. C., Schraffordt Koops, S. E., van de Ven, P. M., Terwee, C. B., van Dongen, J. M., Schaafsma, F. G., Meijerink, W. J., Bonjer, H. J., and Huirne, J. A. Personalised perioperative care by e-health after intermediate-grade abdominal surgery: a multicentre, single-blind, randomised, placebo-controlled trial. *The Lancet 392*, 10141 (jul 2018), 51–59.

[364] van Gils, A., Hanssen, D., van Asselt, A., Burger, H., and Rosmalen, J. Personalized, Web-Based, Guided Self-Help for Patients With Medically Unexplained Symptoms in Primary Care: Protocol for a Randomized Controlled Trial. *JMIR Research Protocols 8*, 10 (oct 2019), e13738.

[365] Van Grieken, A., Vlasblom, E., Wang, L., Beltman, M., Boere-Boonekamp, M. M., L'Hoir, M. P., and Raat, H. Personalized web-based advice in combination with well-child visits to prevent overweight in young children: Cluster randomized controlled trial. *Journal of Medical Internet Research 19*, 7 (2017).

[366] Van Uffelen, J. G., Khan, A., and Burton, N. W. Gender differences in physical activity motivators and context preferences: A population-based study in people in their sixties. *BMC Public Health 17*, 1 (jul 2017), 1–11.

[367] Vandelanotte, C., and De Bourdeaudhuij, I. Acceptability and feasibility of a computer-tailored physical activity intervention using stages of change: Project FAITH. *Health Education Research 18*, 3 (jun 2003), 304–317.

[368] Vandelanotte, C., Short, C., Plotnikoff, R. C., Hooker, C., Canoy, D., Rebar, A., Alley, S., Schoeppe, S., Mummery, W. K., and Duncan, M. J. TaylorActive - Examining the effectiveness of web-based personally-tailored videos to increase physical activity: a randomised controlled trial protocol. *BMC Public Health 15*, 1 (oct 2015).

[369] Varadharajan, V., Kannav, V., and Pasala, A. Sensor based coaching for a fit and healthy society. In *International Symposium on Technology and Society, Proceedings* (dec 2016), vol. 2016-December, Institute of Electrical and Electronics Engineers Inc., pp. 81–85.

[370] Vasankari, V., Halonen, J., Husu, P., Vähä-Ypyä, H., Tokola, K., Suni, J., Sievänen, H., Anttila, V., Airaksinen, J., Vasankari, T., and Hartikainen, J. Personalised eHealth intervention to increase

physical activity and reduce sedentary behaviour in rehabilitation after cardiac operations: Study protocol for the PACO randomised controlled trial (NCT03470246). *BMJ Open Sport and Exercise Medicine 5*, 1 (jul 2019).

[371] Verbiest, M., Borrell, S., Dalhousie, S., Tupa'I-Firestone, R., Funaki, T., Goodwin, D., Grey, J., Henry, A., Hughes, E., Humphrey, G., Jiang, Y., Jull, A., Pekepo, C., Schumacher, J., Te Morenga, L., Tunks, M., Vano, M., Whittaker, R., and Mhurchu, C. N. A co-designed, culturally-tailored mhealth tool to support healthy lifestyles in māori and pasifika communities in New Zealand: Protocol for a cluster randomized controlled trial. *Journal of Medical Internet Research 20*, 8 (aug 2018).

[372] Villarreal, V., Hervas, R., Fontecha, J., and Bravo, J. Mobile Monitoring Framework to Design Parameterized and Personalized m-Health Applications According to the Patient's Diseases. *Journal of Medical Systems 39*, 10 (oct 2015).

[373] Volders, E., Bolman, C. A., De Groot, R. H., Verboon, P., and Lechner, L. The effect of active plus, a computer-tailored physical activity intervention, on the physical activity of older adults with chronic illness(es)-A cluster randomized controlled trial. *International Journal of Environmental Research and Public Health 17*, 7 (apr 2020), 2590.

[374] Voncken-Brewster, V., Tange, H., Moser, A., Nagykaldi, Z., De Vries, H., and Van Der Weijden, T. Integrating a tailored e-health self-management application for chronic obstructive pulmonary disease patients into primary care: A pilot study. *BMC Family Practice 15*, 1 (jan 2014).

[375] Walthouwer, M. J. L., Oenema, A., Lechner, L., and De Vries, H. Comparing a video and text version of a web-based computer-tailored intervention for obesity prevention: A randomized controlled trial. *Journal of Medical Internet Research 17*, 10 (oct 2015).

[376] Wang, Q., Egelandsdal, B., Amdam, G. V., Almli, V. L., and Oostindjer, M. Diet and Physical Activity Apps: Perceived Effectiveness by App Users. *JMIR mHealth and uHealth 4*, 2 (jun 2016).

[377] Wangberg, S. C., Nilsen, O., Antypas, K., and Gram, I. T. Effect of Tailoring in an Internet-Based Intervention for Smoking Cessation: Randomized Controlled Trial. *J Med Internet Res 2011;13(4):e121 https://www.jmir.org/2011/4/e121 13*, 4 (dec 2011), e1605.

[378] Western, M. J., Armstrong, M. E. G., Islam, I., Morgan, K., Jones, U. F., and Kelson, M. J. Improving children's fundamental movement skills through a family-based physical activity program: results from the "Active 1+FUN" randomized controlled trial. *Int J Behav Nutr Phys Act 18* (2021), 148.

[379] Westmaas, J. L., Bontemps-Jones, J., Hendricks, P. S., Kim, J., and Abroms, L. C. Randomised controlled trial of stand-alone tailored emails for smoking cessation. *Tobacco Control 27*, 2 (mar 2018), 136–146.

[380] Wever, R., Van Kuijk, J., and Boks, C. User-centred design for sustainable behavior. *International Journal of Sustainable Engineering 1*, 1 (2008).

[381] Weymann, N., Dirmaier, J., Von Wolff, A., Kriston, L., and Härter, M. Effectiveness of a Web-based tailored interactive health communication application for patients with type 2 diabetes or chronic low back pain: Randomized controlled trial. *Journal of Medical Internet Research 17*, 3 (mar 2015).

[382] Whittlestone, J., Nyrup, R., Alexandrova, A., and Cave, S. The Role and Limits of Principles in AI Ethics: Towards a Focus on Tensions.

[383] Wilke, J., Mohr, L., Tenforde, A. S., Edouard, P., Fossati, C., González-Gross, M., Ramírez, C. S., Laiño, F., Tan, B., Pillay, J. D., Pigozzi, F., Jimenez-Pavon, D., Novak, B., Jaunig, J., Zhang, M., van Poppel, M., Heidt, C., Willwacher, S., Yuki, G., Lieberman, D. E., Vogt, L., Verhagen, E., Hespanhol, L., and Hollander, K. A Pandemic within the Pandemic? Physical Activity Levels Substantially Decreased in Countries Affected by COVID-19. *International Journal of Environmental Research and Public Health 2021, Vol. 18, Page 2235 18*, 5 (feb 2021), 2235.

[384] Willems, R. A., Bolman, C. A. W., Mesters, I., Kanera, I. M., Beaulen, A. A. J. M., and Lechner, L. Short-term effectiveness of a web-based tailored intervention for cancer survivors on quality of life, anxiety, depression, and fatigue: randomized controlled trial. *Psycho-Oncology 26*, 2 (feb 2017), 222–230.

[385] Williams, D., Tanimul Ahsan, G. M., Addo, I., Ahamed, S. I., Petereit, D., Burhansstipanov, L., Krebs, L., and Dignan, M. Building a Tailored Text Messaging System for Smoking Cessation in Native American Populations. In *Proceedings - International Computer Software and Applications Conference* (jun 2018), vol. 1, IEEE Computer Society, pp. 866–874.

[386] Wilson, H. J., Palk, G., Sheehan, M. C., Wishart, D., and Watson, B. Steering Clear of Driving After Drinking: a Tailored e-Health Intervention for Reducing Repeat Offending and Modifying Alcohol Use in a High-Risk Cohort. *International Journal of Behavioral Medicine 24*, 5 (oct 2017), 694–702.

[387] Wilson, P. M., Rodgers, W. M., Blanchard, C. M., and Gessell, J. The Relationship Between Psychological Needs, Self-Determined Motivation, Exercise Attitudes, and Physical Fitness1. *Journal of Applied Social Psychology 33* (2003), 2373–2392.

[388] Withall, J., Jago, R., and Fox, K. R. Why some do but most don't. Barriers and enablers to engaging low-income groups in physical activity programmes: a mixed methods study. *BMC Public Health 11* (2011), 507.

[389] Wittink, H., Engelbert, R., and Takken, T. The dangers of inactivity; exercise and inactivity physiology for the manual therapist. *Manual Therapy 16*, 3 (jun 2011), 209–216.

[390] Wong, S. H., Tan, Z. Y. A., Cheng, L. J., and Lau, S. T. Wearable technology-delivered lifestyle intervention amongst adults with overweight and obese: A systematic review and meta-regression. *International Journal of Nursing Studies 127* (mar 2022), 104163.

[391] Wood, C. E., Richardson, M., Johnston, M., Abraham, C., Francis, J., Hardeman, W., and Michie, S. Applying the behaviour change technique (BCT) taxonomy v1: a study of coder training. *Translational Behavioral Medicine 5*, 2 (jun 2015), 134–148.

[392] Woods, T., and Ream, M. *Live Longer with AI How Artificial Intelligence Is Helping Us Extend Our Healthspan and Live Better Too.* Packt Publishing, Birmingham, sep 2020.

[393] World Health Organization. Physical activity, 2020.

[394] Xie, Z., Jo, A., and Hong, Y. R. Electronic wearable device and physical activity among US adults: An analysis of 2019 HINTS data. *International Journal of Medical Informatics 144* (dec 2020), 104297.

[395] Xu, X., Tupy, S., Robertson, S., Miller, A. L., Correll, D., Tivis, R., and Nigg, C. R. Successful adherence and retention to daily monitoring of physical activity: Lessons learned. *PLOS ONE 13*, 9 (sep 2018), e0199838.

[396] Yang, C.-H., Maher, J. P., and Conroy, D. E. Implementation of Behavior Change Techniques in Mobile Applications for Physical Activity. *American Journal of Preventive Medicine 48*, 4 (apr 2015), 452–455.

[397] Yardley, L., Morrison, L., Bradbury, K., and Muller, I. The person-based approach to intervention development: application to digital health-related behavior change interventions. *Journal of medical Internet research 17*, 1 (jan 2015), e30.

[398] Yom-Tov, E., Feraru, G., Kozdoba, M., Mannor, S., Tennenholtz, M., and Hochberg, I. Encouraging Physical Activity in Patients With Diabetes: Intervention Using a Reinforcement Learning System. *Journal of medical Internet research 19*, 10 (oct 2017), e338.

[399] Young, M. D., and Morgan, P. J. Effect of a gender-Tailored ehealth weight loss program on the depressive symptoms of overweight and obese men: Pre-post study. *Journal of Medical Internet Research 20*, 1 (jan 2018).

[400] Zech, J. R., Badgeley, M. A., Liu, M., Costa, A. B., Titano, J. J., and Oermann, E. K. Variable generalization performance of a deep learning model to detect pneumonia in chest radiographs: A cross-sectional study. *PLoS Medicine 15*, 11 (nov 2018).

[401] Zervou, F., Stavrou, N. A., Koehn, S., Zounhia, K., and Psychountaki, M. Motives for exercise participation: The role of individual and psychological characteristics. *http://www.editorialmanager.com/cogentpsychology 4*, 1 (jan 2017).

[402] Zhou, M., Fukuoka, Y., Mintz, Y., Goldberg, K., Kaminsky, P., Flowers, E., and Aswani, A. Evaluating machine learning–based automated personalized daily step goals delivered through a mobile phone app: Randomized controlled trial. *JMIR mHealth and uHealth 6*, 1 (jan 2018), e28.

[403] Zhou, M., Yang, D., Chen, Y., Xu, Y., Xu, J.-F., Jie, Z., Yao, W., Jin, X., Pan, Z., Tan, J., Wang, L., Xia, Y., Zou, L., Xu, X., Wei, J., Guan, M., Yan, F., Feng, J., Zhang, H., Qu, J., Chen, Y., Xu, Y., Yao, W., Pan, Z., Tan, J., Wang, L., Xia, Y., Zou, L., Xu, X., Wei, J., and Guan, M. Deep learning for differentiating novel coronavirus pneumonia and influenza pneumonia. *Annals of Translational Medicine 9*, 2 (jan 2021), 111–111.

[404] Zhou, Y., Zhao, H., and Peng, C. Association of sedentary behavior with the risk of breast cancer in women: update meta-analysis of observational studies. *Annals of Epidemiology 25* (2015), 687–697.

[405] Zhu, J., Dallal, D. H., Gray, R. C., Villareale, J., Forman, E. M., Arigo, D., and Ontañón, S. Personalization Paradox in Behavior Change Apps: Lessons from a Social Comparison-Based Personalized App for Physical Activity; Personalization Paradox in Behavior Change Apps: Lessons from a Social Comparison-Based Personalized App for Physical Activity. *Proc. ACM Hum.-Comput. Interact 5*, CSCW1 (2021), 116.

APPENDIX A

APPLICATION CODE

A.1 Application Python Algorithm

```
from dqn import Agent
import numpy as np
import random
from tensorflow.keras.models import Sequential, load_model
from gym.spaces import Discrete, Box

agent = None
eps_history = None
action = 0
averageSteps = []
currentSteps = 0
observation = 0
done = 0

######################################################################
### - First value of example set is the user step count. Second value
### - is the action chosen by the algorithm
######################################################################

def calculateReward(userStepCount, newStepCount):
    if newStepCount == 0:
        change = 0 - userStepCount

    elif userStepCount == 0:
        change = newStepCount
    else:
        if userStepCount > newStepCount:
            change = (((userStepCount - newStepCount)
            /userStepCount) * 100)
        else:
            change = (((newStepCount - userStepCount)
            /newStepCount) * 100)
    if change >= 20:
        reward = 50
    elif 30 > change >= 15:
        reward = 30
    elif 20 > change >= 10:
        reward = 15
    elif 10 > change >= 5:
        reward = 10
    elif 5 > change >= 0:
        reward = 5
    else:
        reward = -50
    return reward


 #Return loaded agent from save file.
def load_agent():
    save_folder = '/data/user/0/DPScott.AIBC.smartPedometer/files/'
```

```
    fname='dqn_model.h5'
    save_path = save_folder+fname
    print("save path" + save_path)


    #Load File
    agent = load_model(save_path)
    return agent

def reset():
    state = np.array([0, 0])
    return state

def actionFunction():
    global action
    global agent
    observation = reset()
    action = agent.choose_action(observation)
    return action

def newAction():
    global action
    global observation
    action = agent.choose_action(observation)
    return action

def firstStep(action, userStepCount, newStepCount):
    global averageSteps
    global currentSteps
    state[1] = int(action) * 100 + random.randint(-50, 50)
    state[0] = newStepCount
    averageSteps.append(userStepCount)
    averageSteps.append(state[0])
    # Calculate reward
    reward = calculateReward(userStepCount, state[0])
    currentSteps = state[0]
    # Set placeholder for info
    info = {}
    print(averageSteps)
    # Return step information
    return np.array(state), reward, info

## returns the actual step count number,
### used for displaying fake peer to user.
def getSteps(action):
    return (int(action)+1) * 100 + random.randint(-50, 50)


def step(action, userStepCount, newStepCount):
    global averageSteps
    global currentSteps
    currentSteps = userStepCount
    state[1] = int(action) * 100 + random.randint(-50, 50)
    state[0] = newStepCount
    averageSteps.append(state[0])
    average = np.mean(averageSteps)
    #sum(averageSteps)/ len(averageSteps)
    print("average")
    print(average)
    # Calculate reward
    reward = calculateReward(average, state[0])
    currentSteps = state[0]
    # Set placeholder for info
    info = {}
    # Return step information
    print(averageSteps)
    return np.array(state), reward, info


def chunkRun(activitySteps, activityActions, feedback):
    print("Begin Chunk Run")
    global done
    global scores
    global observation
    global eps_history
    global agent
    activitySet=createListOfActivityHistory(activitySteps,
    activityActions)
    activitySet[0]
    score = 0
    i = 1
    j = 0
```

```
    observation = reset()
    for pair in activitySet:
        if pair == activitySet[-1]:
            done = 1
        if pair == activitySet[1]:
            observation_, reward, info = firstStep(pair[1],
            currentSteps, pair[0])
            score += (reward * feedback[j])
            j += 1
            agent.remember(observation, action, reward,
            observation_, done)
            observation = observation_
            agent.learn()
            eps_history.append(agent.epsilon)
            scores.append(score)
            avg_score = score
            print('episode: ', 0,'score: %.2f' % score,
                  ' average score %.2f' % avg_score)
            print(observation)
        else:
            observation_, reward, info = step(pair[1],
            currentSteps, pair[0])
            score += (reward * feedback[j])
            j += 1
            agent.remember(observation, action, reward,
            observation_, done)
            observation = observation_
            agent.learn()
            eps_history.append(agent.epsilon)
            print(eps_history)
            scores.append(score)
            avg_score = np.mean(scores[max(0, i-100):(i+1)])
            print('episode: ', i,'score: %.2f' % score,
                  ' average score %.2f' % avg_score)
            print(eps_history)
        i = i+1
    done = 0
    scores=[]
    agent.save_model()
    return observation, avg_score

def chunkLoad(activitySteps, activityActions, feedback):
    print("Begin Chunk Load")
    global agent

    agent.load_model()
    global done
    global scores
    global observation
    global eps_history
    activitySet=createListOfActivityHistory(activitySteps,
    activityActions)
    activitySet[0]
    score = 0
    i = 1
    observation = reset()
    for pair in activitySet:
        if pair == activitySet[-1]:
            done = 1
        if pair == activitySet[1]:
            observation_, reward, info = firstStep(pair[1],
            currentSteps, pair[0])
            score += (reward * feedback[j])
            j += 1
            agent.remember(observation, action, reward,
            observation_, done)
            observation = observation_
            agent.learn()
            eps_history.append(agent.epsilon)
            scores.append(score)
            avg_score = score
            print('episode: ', 0,'score: %.2f' % score,
                  ' average score %.2f' % avg_score)
            print(observation)
        else:
            observation_, reward, info = step(pair[1],
            currentSteps, pair[0])
            score += (reward * feedback[j])
            j += 1
            agent.remember(observation, action, reward,
            observation_, done)
            observation = observation_
```

```
                agent.learn()
                eps_history.append(agent.epsilon)
                print(eps_history)
                scores.append(score)
                avg_score = np.mean(scores[max(0, i-100):(i+1)])
                print('episode: ', i,'score: %.2f' % score,
                      ' average score %.2f' % avg_score)
                print("HERE")
                print(eps_history)
            i = i+1
        done = 0
        scores=[]
        agent.save_model()
        return observation, avg_score

def mainFirstDay():
    global scores
    global action
    global agent
    global state
    global eps_history
    activitySet = exampleSet
    stepGoal = 1000
    numberOfActions = int(stepGoal / 100) * 2
    action_space = Discrete(numberOfActions)
    observation_space = Box(low=np.array([0, 0]),
    high=np.array([10_000_000, 10_000_000]))
    state = np.array([0, 0])
    states = observation_space.shape[0]
    actions = action_space.n
    lr = 0.001
    n_games = 10
    agent = Agent(gamma=0.8, epsilon=1.0, alpha=lr,
    input_dims=states, n_actions=actions, mem_size=1_000_000,
    batch_size=128, epsilon_dec=0.996, epsilon_end=0.01)


    scores = []
    eps_history = []
    action = actionFunction()

def main(storedObservationValue):
    global scores
    global action
    global agent
    global state
    global eps_history
    global observation
    observation = np.array(storedObservationValue)
    activitySet = exampleSet
    stepGoal = 1000
    numberOfActions = int(stepGoal / 100) * 2
    action_space = Discrete(numberOfActions)
    observation_space = Box(low=np.array([0, 0]),
    high=np.array([10_000_000, 10_000_000]))
    state = np.array([0, 0])
    states = observation_space.shape[0]
    actions = action_space.n
    lr = 0.001
    n_games = 10
    agent = Agent(gamma=0.8, epsilon=1.0, alpha=lr,
    input_dims=states, n_actions=actions, mem_size=1_000_000,
    batch_size=128, epsilon_dec=0.996, epsilon_end=0.01)
    agent.load_model()


    scores = []
    eps_history = []
    action = newAction()


def createListOfActivityHistory(activitySteps, activityActions):
    #loop through the length of both
    #for the current element i, we will set activitySet(i)
    to (activitySteps(i), activityActions(i))
    activitySet = []
    for i in range(len(activitySteps)):
        pair = (activitySteps[i], activityActions[i])
        activitySet.append(pair)

    print(activitySet)
    return activitySet
```

A.2 Android-Python Communication Code

```java
public class ExploreExploitPythonInterface {

    private static String MyPreferences = "My_Prefs";
    private static String SavedAction = "Saved_Action";
    private static String firstRunOfDQN = "First_Run_Of_DQN";
    private static String ActionHistory = "Action_History";
    private static String FeedbackHistory = "Feedback_History";
    private static String StepHistory = "Step_History";
    private static String Observation_Path = "Observation_Path";
    private static String Average_Score = "Average_Score";
    public static final String FIRST_TIME_FEEDBACK = "FIRST_FEEDBACK";
    public static String feedbackResponse;
    public static double feedbackMod = 0;
    public static Boolean firstFeedbackCheck = true;
    public static ArrayList<Double> feedbackHistory = new ArrayList<>();

    public static void catchFeedbackAnswer(ParticipantResponseData
    prd, Context context) {
        feedbackResponse = prd.getResponse();

        ArrayList<Double> feedbackHistory = new ArrayList<>();
        SharedPreferences prefs = context.getSharedPreferences
        (MyPreferences, Context.MODE_PRIVATE);
        SharedPreferences.Editor edit = prefs.edit();
        Gson gson = new Gson();

        //load actions from array
        String feedbackHistoryJSON = prefs.getString(FeedbackHistory,
        null);
        Type feedbackHistorytype = new TypeToken<ArrayList<Double>>()
        {}.getType();
        feedbackHistory = gson.fromJson(feedbackHistoryJSON,
        feedbackHistorytype);

        //append actions to array
        if (feedbackHistory == null) {
            feedbackHistory = new ArrayList<Double>();
        }
        feedbackHistory.add(feedbackModifier(feedbackResponse));

        feedbackHistoryJSON = gson.toJson(feedbackHistory);
        edit.putString(FeedbackHistory, feedbackHistoryJSON);

        edit.apply();
    }

    public static void applyFeedbackAnswer(Context context) {
        SharedPreferences prefs = context.getSharedPreferences(MyPreferences, Context.MODE_PRIVATE);
        SharedPreferences.Editor edit = prefs.edit();

        Integer[] stepHistory = getStepsHistory(context);
        Integer[] actionHistory = getActionHistory(context);
        boolean firstFeedback = prefs.getBoolean(FIRST_TIME_FEEDBACK, true);

        for (int q = 0; q < (actionHistory.length)-1; q++) {
            if (firstFeedback == false) {
                if(q >= feedbackHistory.size()) {
                    feedbackHistory.add(feedbackModifier(feedbackResponse));
                } else if (feedbackHistory.get(q) == null) {
                    feedbackHistory.add(feedbackModifier("Didn't See It"));
                } else {
                    Log.d("Array Content Check", "Array At Point: " + feedbackHistory.get(q));
                    feedbackHistory.set(q, feedbackHistory.get(q));
                }
            } else {
                feedbackHistory.add(feedbackModifier(feedbackResponse));
            }
        }
        feedbackHistory.add(feedbackModifier(feedbackResponse));
        edit.putBoolean(FIRST_TIME_FEEDBACK, false);


```

```
    }

    public static double feedbackModifier(String feedbackResponse) {
        if (feedbackResponse == null) {
            feedbackMod = 1.0;
        } else {
            if (feedbackResponse.equals("Motivated Me.")) {
                feedbackMod = 2;
            }
            if (feedbackResponse.equals("Demotivated Me.")) {
                feedbackMod = 0.5;
            }
            if (feedbackResponse.equals("Didn't Affect Me.")) {
                feedbackMod = 0.75;
            }
            if (feedbackResponse.equals("Didn't See It.")) {
                feedbackMod = 0.0;
            }
        }
        return feedbackMod;
    }

    public static void setAverageScore(Context context, float averageScore) {
        SharedPreferences prefs = context.getSharedPreferences(MyPreferences, Context.MODE_PRIVATE);
        SharedPreferences.Editor edit = prefs.edit();
        edit.putFloat(Average_Score, averageScore);
        edit.apply();
    }

    public static float getAverageScore(Context context) {
        SharedPreferences prefs = context.getSharedPreferences(MyPreferences, Context.MODE_PRIVATE);
        return prefs.getFloat(Average_Score, 0.0f);
    }

    public static void chunkRun(Context context) {
        SharedPreferences prefs = context.getSharedPreferences(MyPreferences, Context.MODE_PRIVATE);
        SharedPreferences.Editor edit = prefs.edit();

        boolean firstRun = prefs.getBoolean(firstRunOfDQN, true);

    if (firstRun) {
        Python py = Python.getInstance();
        PyObject pyobj = py.getModule("main"); // pyobj for class.
        PyObject pymainobj = pyobj.callAttr("mainFirstDay");
        Integer[] stepHistory = getStepsHistory(context);
        Integer[] actionHistory = getActionHistory(context);
        Double[] feedbackHistory = getFeedbackHistory(context);
        Double[] feed = new Double[actionHistory.length];

        if (feedbackHistory.length < actionHistory.length) {
            for (int z = 0; z < (feedbackHistory.length); z++) {
                feed[z] = feedbackHistory[z];
            }
            for (int x = feedbackHistory.length; x < (actionHistory.length); x++) {
                feed[x] = 1.0;
            }
            feedbackHistory = feed;
        }

        PyObject pyObs = pyobj.callAttr("chunkRun", stepHistory, actionHistory, feedbackHistory);
        List<PyObject> pyObsList = pyObs.asList();
        int[] observation = {};
        int[] observationList = pyObsList.get(0).toJava(int[].class);
        observation = observationList;

        setObservation(context, observation);

        float avg_score= pyObsList.get(1).toJava(float.class);

        setAverageScore(context, avg_score);

        edit.putBoolean(firstRunOfDQN, false);
        edit.apply();
    } else {
        Log.i("WARNING", "Can't run ChunkRun because firstRunOfDQN is false");
    }
    resetUserActionSteps(context);

}
public static void chunkLoad(Context context) {
    SharedPreferences prefs = context.getSharedPreferences(MyPreferences, Context.MODE_PRIVATE);
    SharedPreferences.Editor edit = prefs.edit();
```

```java

    Python py = Python.getInstance();
    PyObject pyobj = py.getModule("main");
    PyObject pymainobj = pyobj.callAttr("main",getObservation(context));
    Integer[] stepHistory = getStepsHistory(context);
    Integer[] actionHistory = getActionHistory(context);
    Double[] feedbackHistory = getFeedbackHistory(context);
    Double[] feed = new Double[actionHistory.length];

    if (feedbackHistory.length < actionHistory.length) {
        for (int z = 0; z < (feedbackHistory.length); z++) {
            feed[z] = feedbackHistory[z];
        }
        for (int x = feedbackHistory.length; x < (actionHistory.length); x++) {
            feed[x] = 1.0;
        }
        feedbackHistory = feed;
    }

    PyObject pyObs = pyobj.callAttr("chunkLoad", stepHistory, actionHistory, feedbackHistory);
    List<PyObject> pyObsList = pyObs.asList();
    int[] observation = {};
    int[] observationList = pyObsList.get(0).toJava(int[].class);
    observation = observationList;

    setObservation(context, observation);//callAttr is for function two params, ActivitySteps and ActivityHistory expects an array of e

    float avg_score= pyObsList.get(1).toJava(float.class);


    setAverageScore(context, avg_score);

    //DO WE NEED TO RESET ACTION HISTORY AND STEPS HISTORY - Yes not 100% certain(?)
    resetUserActionSteps(context);
}

public static void setObservation(Context context, int[] observation) {

    SharedPreferences prefs = context.getSharedPreferences(MyPreferences, Context.MODE_PRIVATE);
    SharedPreferences.Editor edit = prefs.edit();
    Gson gson = new Gson();
    String observationJSON = gson.toJson(observation);
    edit.putString(Observation_Path, observationJSON);

    edit.apply();
}

public static int[] getObservation(Context context) {
    SharedPreferences prefs = context.getSharedPreferences(MyPreferences, Context.MODE_PRIVATE);
    Gson gson = new Gson();

    String observationJSON = prefs.getString(Observation_Path, null);
    Type observationType = new TypeToken<int[]>() {}.getType();
    int [] observation = gson.fromJson(observationJSON, observationType);

    return observation;
}

public static boolean getFirstRun(Context context) {
    SharedPreferences sp = context.getSharedPreferences(MyPreferences, Context.MODE_PRIVATE);
    return sp.getBoolean(firstRunOfDQN, true);
}

public static void saveUserActionSteps(Context context, int steps) {
    int currentAction = loadSavedAction(context);
    ArrayList<Integer> actionHistory = new ArrayList<>();
    ArrayList<Integer> stepHistory = new ArrayList<>();
    SharedPreferences prefs = context.getSharedPreferences(MyPreferences, Context.MODE_PRIVATE);
    SharedPreferences.Editor edit = prefs.edit();
    Gson gson = new Gson();

    String actionHistoryJSON = prefs.getString(ActionHistory, null);
    Type actionHistorytype = new TypeToken<ArrayList<Integer>>() {}.getType();
    actionHistory = gson.fromJson(actionHistoryJSON, actionHistorytype);
    String stepHistoryJSON = prefs.getString(StepHistory, null);
    Type stepHistorytype = new TypeToken<ArrayList<Integer>>() {}.getType();
    stepHistory = gson.fromJson(stepHistoryJSON, stepHistorytype);

    if (actionHistory == null) {
        actionHistory = new ArrayList<Integer>();
    }
    actionHistory.add(loadSavedAction(context));
```

```
    if (stepHistory == null) {
        stepHistory = new ArrayList<Integer>();
    }
    stepHistory.add(steps);

    actionHistoryJSON = gson.toJson(actionHistory);
    edit.putString(ActionHistory, actionHistoryJSON);

    stepHistoryJSON = gson.toJson(stepHistory);
    edit.putString(StepHistory, stepHistoryJSON);

    edit.apply();


}

public static Double[] getFeedbackHistory(Context context) {

    ArrayList<Double> feedbackHistory = new ArrayList<>();
    SharedPreferences prefs = context.getSharedPreferences(MyPreferences, Context.MODE_PRIVATE);
    SharedPreferences.Editor edit = prefs.edit();
    Gson gson = new Gson();

    String feedbackHistoryJSON = prefs.getString(FeedbackHistory, null);
    Type feedbackHistorytype = new TypeToken<ArrayList<Double>>() {}.getType();
    feedbackHistory = gson.fromJson(feedbackHistoryJSON, feedbackHistorytype);
    Double[] feedbackArray = {};
    if (feedbackHistory!=null){
        feedbackArray = feedbackHistory.toArray(new Double[0]);
    } else {
    }



    return feedbackArray;
    }

public static Integer[] getActionHistory(Context context) {

    ArrayList<Integer> actionHistory = new ArrayList<>();
    SharedPreferences prefs = context.getSharedPreferences(MyPreferences, Context.MODE_PRIVATE);
    SharedPreferences.Editor edit = prefs.edit();
    Gson gson = new Gson();

    String actionHistoryJSON = prefs.getString(ActionHistory, null);
    Type actionHistorytype = new TypeToken<ArrayList<Integer>>() {}.getType();
    actionHistory = gson.fromJson(actionHistoryJSON, actionHistorytype);
    Integer[] actionArray = {};
    if (actionHistory!=null){
        actionArray = actionHistory.toArray(new Integer[0]);
    } else {
    }

    //end
    return actionArray;
}

public static Integer[] getStepsHistory(Context context) {

    ArrayList<Integer> stepHistory = new ArrayList<>();
    SharedPreferences prefs = context.getSharedPreferences(MyPreferences, Context.MODE_PRIVATE);
    SharedPreferences.Editor edit = prefs.edit();
    Gson gson = new Gson();

    String stepHistoryJSON = prefs.getString(StepHistory, null);
    Type stepHistorytype = new TypeToken<ArrayList<Integer>>() {}.getType();
    stepHistory = gson.fromJson(stepHistoryJSON, stepHistorytype);
    Integer[] stepArray = {};
    if (stepHistory!=null){
        stepArray = stepHistory.toArray(new Integer[0]);
    } else {
    }
    return stepArray;
}

public static void resetUserActionSteps(Context context) {

    ArrayList<Integer> actionHistory = new ArrayList<>();
    ArrayList<Integer> stepHistory = new ArrayList<>();
    SharedPreferences prefs = context.getSharedPreferences(MyPreferences, Context.MODE_PRIVATE);
    SharedPreferences.Editor edit = prefs.edit();
    Gson gson = new Gson();
```

```

    String actionHistoryJSON = prefs.getString(ActionHistory, null);
    Type actionHistorytype = new TypeToken<ArrayList<Integer>>() {}.getType();
    actionHistory = gson.fromJson(actionHistoryJSON, actionHistorytype);
    String stepHistoryJSON = prefs.getString(StepHistory, null);
    Type stepHistorytype = new TypeToken<ArrayList<Integer>>() {}.getType();
    stepHistory = gson.fromJson(stepHistoryJSON, stepHistorytype);

    actionHistory.clear();
    stepHistory.clear();

    actionHistoryJSON = gson.toJson(actionHistory);
    edit.putString(ActionHistory, actionHistoryJSON);

    stepHistoryJSON = gson.toJson(stepHistory);
    edit.putString(StepHistory, stepHistoryJSON);

    edit.apply();
    //end
}

    public static int getAction(Context context) {
        int action = 0;
        Python py = Python.getInstance();
        PyObject pyobj = py.getModule("main");
        PyObject pymainobj = pyobj.callAttr("mainFirstDay");
        PyObject pyaction = pyobj.callAttr("actionFunction");
        action = pyaction.toInt();

        saveCurrentAction(context, action);
        return action;
    }

    public static int getNewAction(Context context, int[] observation) {
        int action = 0;
        Python py = Python.getInstance();
        PyObject pyobj = py.getModule("main");
        PyObject pymainobj = pyobj.callAttr("main", observation);
        PyObject pyaction = pyobj.callAttr("newAction"); //loaded keras model.
        action = pyaction.toInt();

        //save actions
        saveCurrentAction(context, action);
        return action;
    }

    public static int getFakePeerSteps(Context context) {
        int steps;

        Python py = Python.getInstance();
        PyObject pyobj = py.getModule("main");
        PyObject pysteps = pyobj.callAttr("getSteps", loadSavedAction(context));
        steps = pysteps.toInt();
        return steps;
    }

    public static void saveCurrentAction(Context context, int action) {
        //define sharedPref for currentAction
        //save current action as sharedPref
        SharedPreferences prefs = context.getSharedPreferences(MyPreferences, Context.MODE_PRIVATE);
        SharedPreferences.Editor edit = prefs.edit();

        edit.putInt(SavedAction, action);

        edit.apply();

        Log.i("Info:" , "Action saved!");

    }

    public static int loadSavedAction(Context context) {
        SharedPreferences prefs = context.getSharedPreferences(MyPreferences, Context.MODE_PRIVATE);
        return prefs.getInt(SavedAction,0);
    }
}
```

A.3 Full Storage Algorithm

```
String username = intent.getStringExtra("USERNAME");
String dateString = intent.getStringExtra("DATE_STRING");
StepCount stepCount = (StepCount) intent.getSerializableExtra("STEP_COUNT");
int totalSteps = Integer.parseInt(intent.getStringExtra("TOTAL_STEPS"));

//Application specific data.
//Check application type
SharedPreferences appTypeSharedPref = PreferenceManager
  .getDefaultSharedPreferences(this.getApplicationContext());
String appName = appTypeSharedPref.getString("APP_NAME","BASE");
//check for app type and record data for uploading respectively.
if (appName.equals("REWARDS")) {

    int badge = appTypeSharedPref.getInt("BADGE",0);
    int rankName = appTypeSharedPref.getInt("RANK_NAME", 0);
    int rankNumber = appTypeSharedPref.getInt("RANK_NUMBER", 0);
    int streakCounter = appTypeSharedPref.getInt("STREAK", 0);

    //load it into a stepcount username date that incorporates everything...

    ArrayList<StepCountUsernameDate> stepCountList = new ArrayList<>();

    StepCountUsernameDate stepCountUsernameDateRewards = new
    StepCountUsernameDate(username, dateString, totalSteps, stepCount,
      this.getApplicationContext());

    stepCountUsernameDateRewards.setStepCountUsernameDateRewards(username,
      dateString, totalSteps, stepCount, badge, rankName, rankNumber,
        streakCounter, this.getApplicationContext());

    stepCountList.add(stepCountUsernameDateRewards);

    saveToPref(stepCountList);

    //if there is a valid internet connection,
    //send each item in stepCountList to the database
    if (isInternetAvailable()) {

        for (StepCountUsernameDate e : stepCountList) {

            uploadDataRewards(e);

        }

        stepCountList.clear();

    } else {
        Toast.makeText(this, "Internet connection unavailable,
          storing data " +  "locally...", Toast.LENGTH_LONG).show();
    }
    saveToPref(stepCountList);

} else if (appName.equals("GRADED")) {
    SharedPreferences sharedPref = PreferenceManager
      .getDefaultSharedPreferences(this);
    int currentGoalIndex = sharedPref.getInt("currentGoalIndex", -1);

    ArrayList<StepCountUsernameDate> stepCountList = new ArrayList<>();

    StepCountUsernameDate stepCountUsernameDateGraded = new
      StepCountUsernameDate(username,
        dateString, totalSteps, stepCount,
          this.getApplicationContext());

    stepCountUsernameDateGraded.setStepCountUsernameDateGraded(username,
      dateString, totalSteps, stepCount, currentGoalIndex,
        this.getApplicationContext());

    stepCountList.add(stepCountUsernameDateGraded);

    saveToPref(stepCountList);

    //if there is a valid internet connection,
    //send each item in stepCountList to the database
    if (isInternetAvailable()) {

        for (StepCountUsernameDate e : stepCountList) {
```

```

            uploadDataGraded(e);

        }

        stepCountList.clear();

    } else {
        Toast.makeText(this, "Internet connection unavailable,
          storing data " + "locally...", Toast.LENGTH_LONG).show();
    }
    saveToPref(stepCountList);

} else {

    // If internet is not available, add the data to an array of strings
    // put in shared pref type string
    // reload them into arraylist when internet is available...

    ArrayList<StepCountUsernameDate> stepCountList = new ArrayList<>();

    stepCountList = loadStepCountFromPref();
    StepCountUsernameDate stepCountUsernameDate = new StepCountUsernameDate
      (username, dateString, totalSteps, stepCount, getApplicationContext());

    stepCountList.add(stepCountUsernameDate);

    saveToPref(stepCountList);

    //if there is a valid internet connection,
    //send each item in stepCountList to the database
    if (isInternetAvailable()) {

        for (StepCountUsernameDate e : stepCountList) {

            uploadDataBase(e);

        }

        stepCountList.clear();

    } else {
        //it didn't work... save the data
        Toast.makeText(this, "Internet connection unavailable,
        storing data " + "locally...", Toast.LENGTH_LONG).show();
    }
    saveToPref(stepCountList);
    //restart acceleration service if down?
}
```

APPENDIX B

EFFECT-LED DESIGN MATERIALS

B.1 Exploratory Study

B.1.1 Recruitment Materials

Participant-User Recruitment

Behaviour Change Interventions are extremely productive tools in improving certain behaviours of a set of users. Physical activity interventions, such as those delivered by Fitbits and similar devices and services, often employ very similar techniques. This may be due to the developers going with their own gut feelings as to what they feel would be most effective, or these same developers could just be going with the most common techniques from other interventions. These techniques could potentially not be achieving the highest level of change from users.

This study aims to employ the assistance of experts from Behaviour Change and Interaction Design to design similar interventions which use the full range of Behaviour Change Techniques available to create interventions aimed towards maximum impact. These interventions will be designed to be implemented on digital platforms and these digital implementations will be driven by AI, with the fullest extent of personalisation possible for all users.

For this study, we are looking to recruit a set of 'users' who would be able to pass some level of judgement on these implementations, in particular looking at how they would feel about using them, especially with regard to the intelligent AI and personalisation aspects.

To participate, you would need to be available from 10am to 3:30pm on Friday 26th July. Reimbursement will be available for this study, and no personal data will be required. There are no prior requirements to taking part in this study, although an existing interest in fitness technology and the idea of fitness or physical activity may help you to both get more from this study and connect further with the implementations presented to you.

Participant-Expert Recruitment Example

I will be running a design study later this month (23rd and 26th) looking at designing behaviour change interventions on digital platforms, from a technique-first standpoint and making use of certain technology features to design them. As this is similar to certain projects you have been working on, I was wondering if you would like to take part?

You would be included in the 'Behaviour Change Experts' group, working with participants from here in Computer Science to design these implementations, which will then be judged further and discussed.

Attached is some more information, let me know if you have any further questions and if you would be interested in taking part.

B.1.2 Workshop Materials

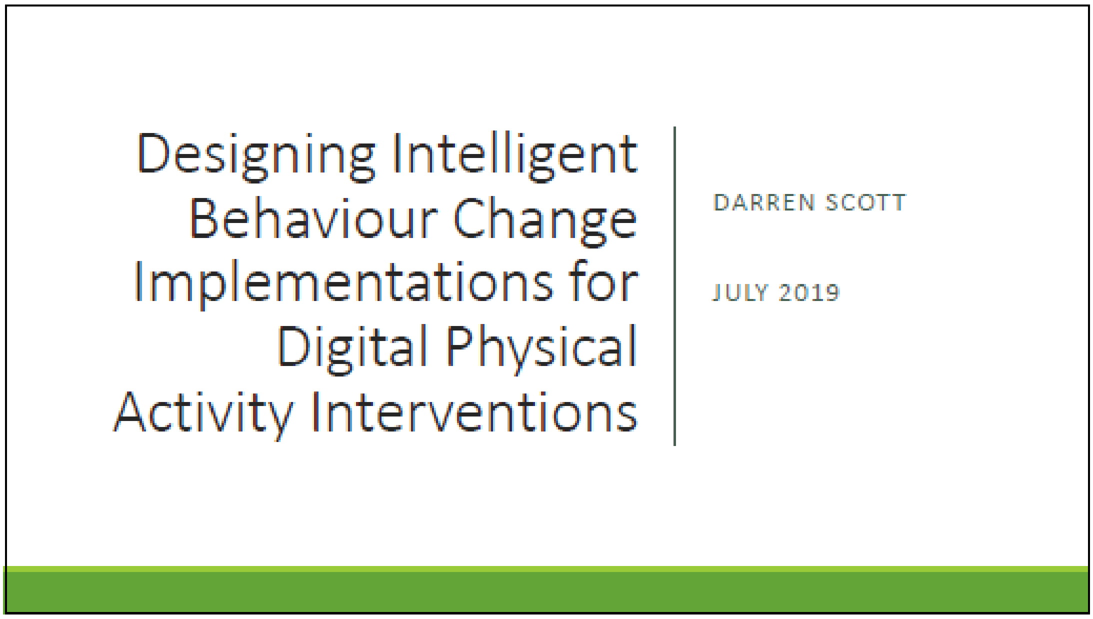
Design Guidelines

Here are some rules and guidelines to keep in mind when designing your Behaviour Change Implementations. The ideal outcome is that your BCI fulfils as many of these as possible while still providing the maximum possible level of impact to the intended changing behaviour.

- The designed application must regard the outcome of improved activity as its paramount focus, regarding the user as a secondary concern.
- The designed application must be feasibly run and used on a mobile device or similar portable system
- The implementation of the design in question must be possible, using only data that could feasibly be obtained, be it passively or through user input data
- The implementation should be as unobtrusive as possible through design, ensuring that real-world responsibilities are not interrupted or overshadowed by the implementation.
- The implementation should use as many forms of data as possible to achieve the highest potential impact, and any data that can improve the performance of a given technique should be harnessed to the greatest possible ability.

Expert and User Presentations

Slides below shown to Experts and Users respectively at the beginning of workshop days.


Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
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JULY 2019

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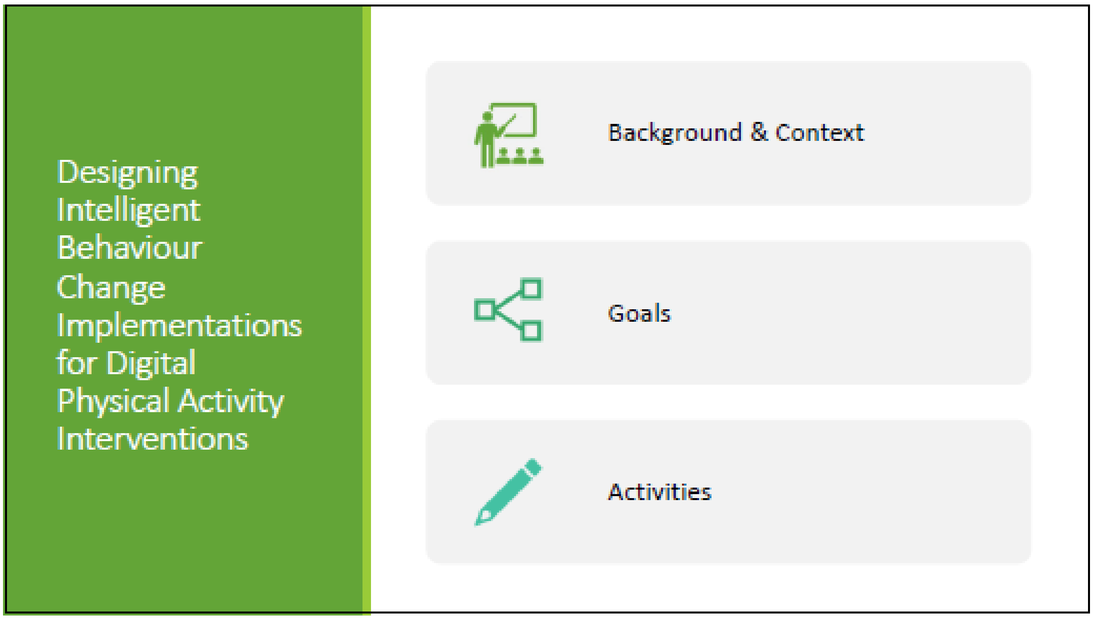
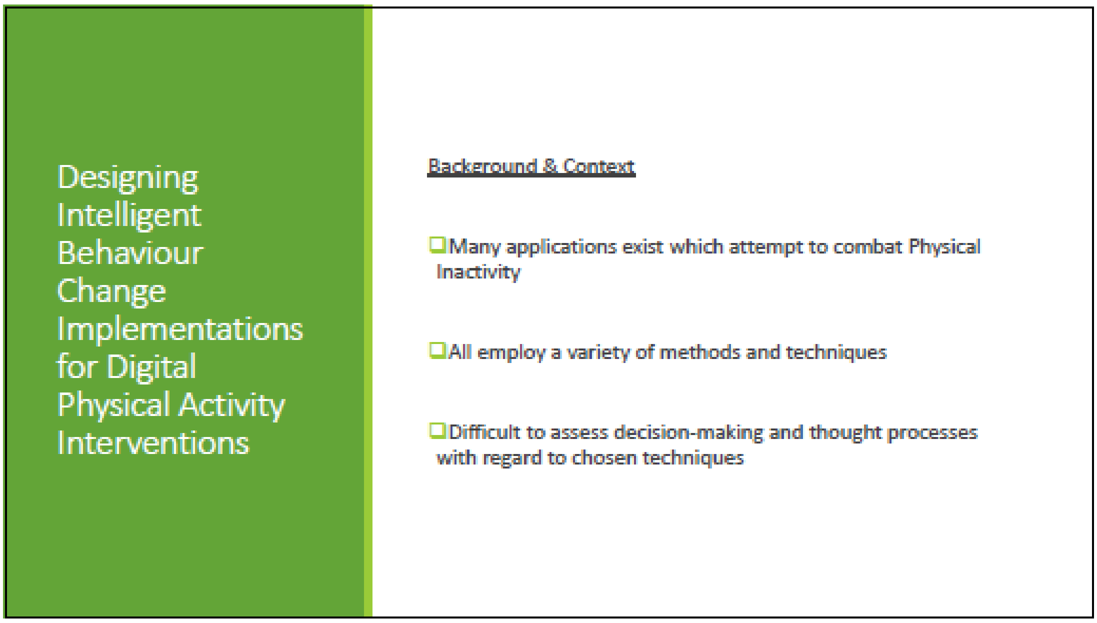
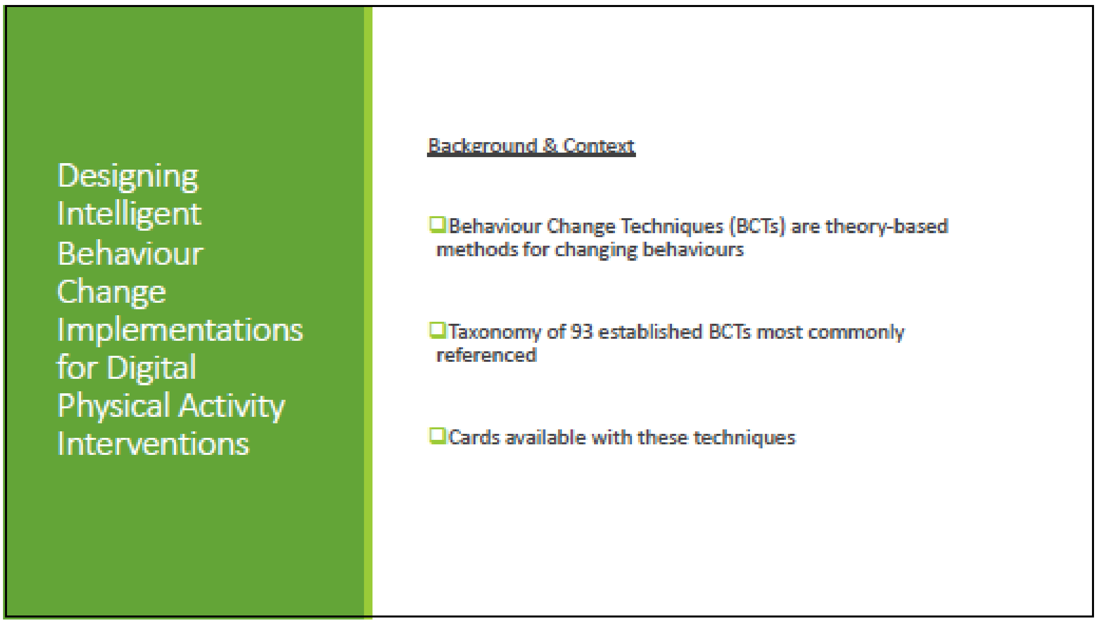

Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
Background & Context
Goals
Activities

2


Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
Background & Context
Many applications exist which attempt to combat Physical Inactivity
All employ a variety of methods and techniques
Difficult to assess decision-making and thought processes with regard to chosen techniques

3


Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
Background & Context
Behaviour Change Techniques (BCTs) are theory-based methods for changing behaviours
Taxonomy of 93 established BCTs most commonly referenced
Cards available with these techniques

4

Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions

Background & Context

- While digital interventions exist, they are often not directly designed with regard to the BCT taxonomy.
- BCTs in digital implementations often found after-the-fact, with no true consensus on mapping
- "Applying the taxonomy to apps forced the researchers to translate the strategies into app functionalities. Following this logic, the researchers had to score each app based on what they observed." – Middelweerd et at., 2014

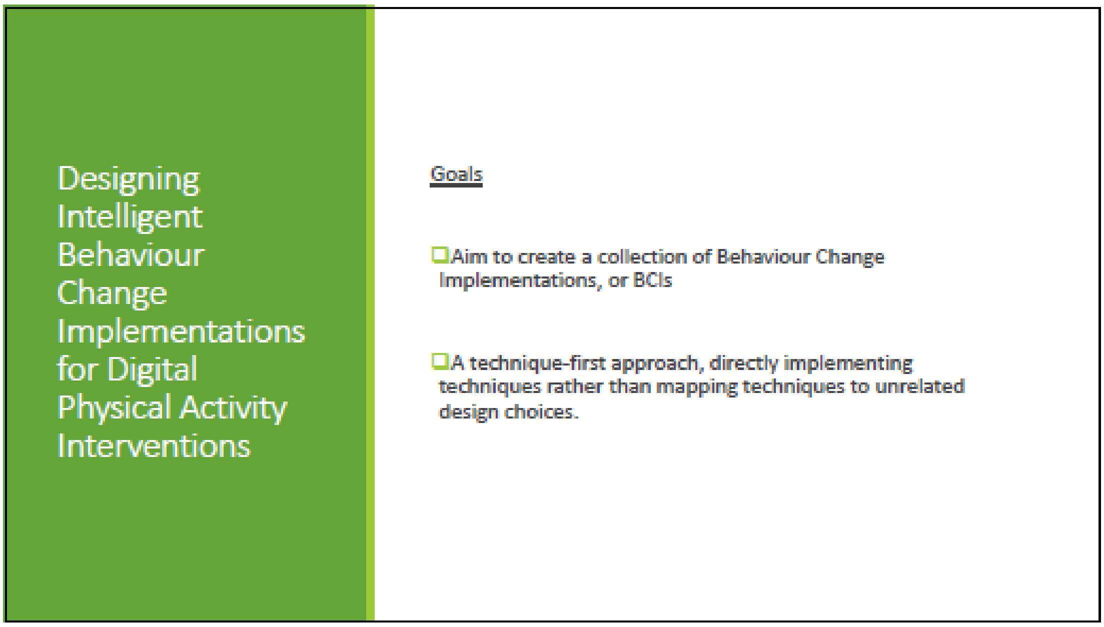
5

Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions

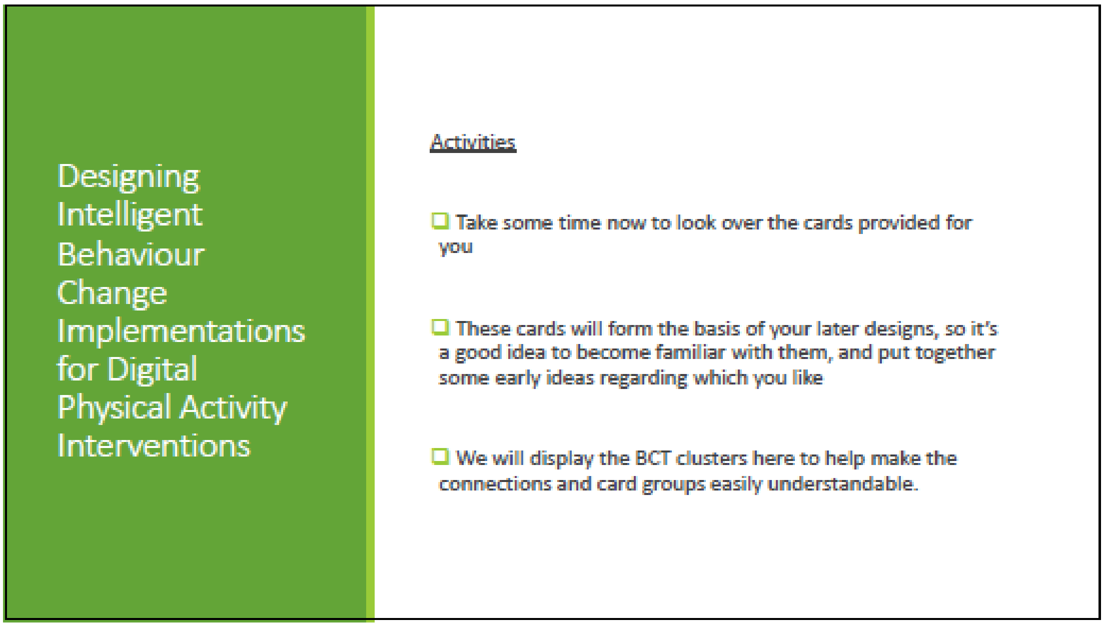
Goals

- Designing these interventions with direct regard to the BCT Taxonomy.
- Provided with technique cards and implementation component cards.
- Opinions and approaches of domain experts concerning techniques and implementations.

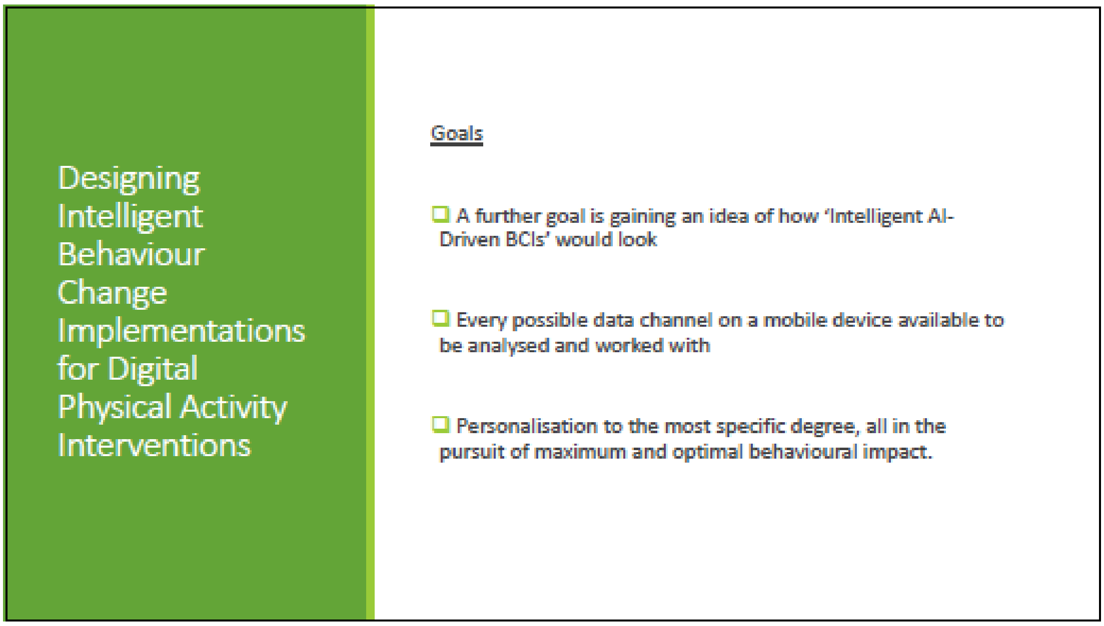
6


Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
Goals
Aim to create a collection of Behaviour Change Implementations, or BCIs
A technique-first approach, directly implementing techniques rather than mapping techniques to unrelated design choices.

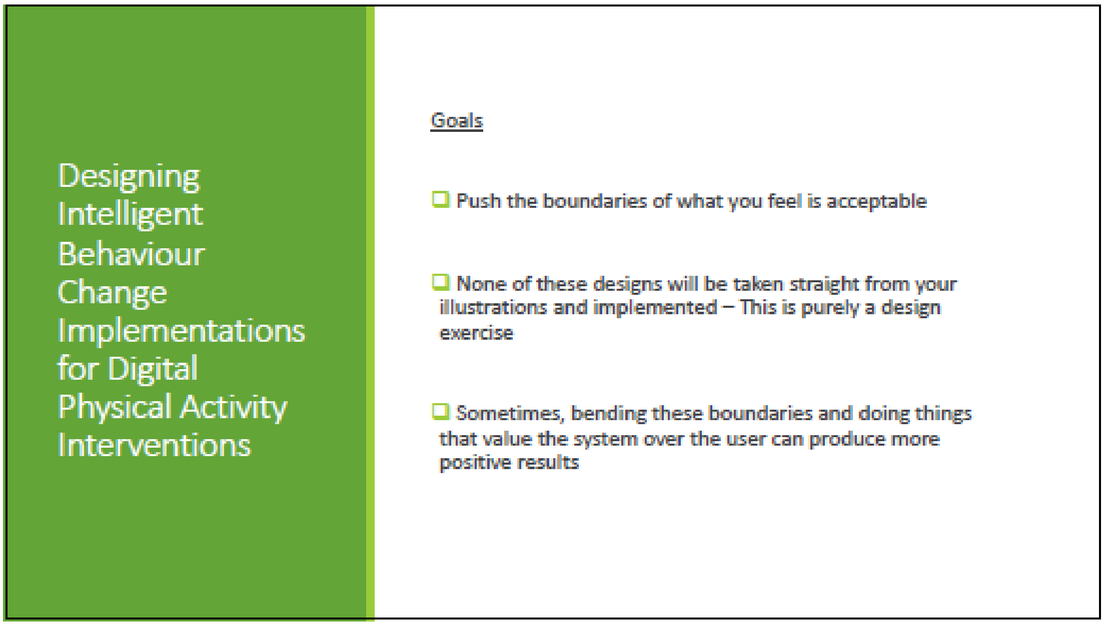
7


Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
Activities
Take some time now to look over the cards provided for you
These cards will form the basis of your later designs, so it's a good idea to become familiar with them, and put together some early ideas regarding which you like
We will display the BCT clusters here to help make the connections and card groups easily understandable.

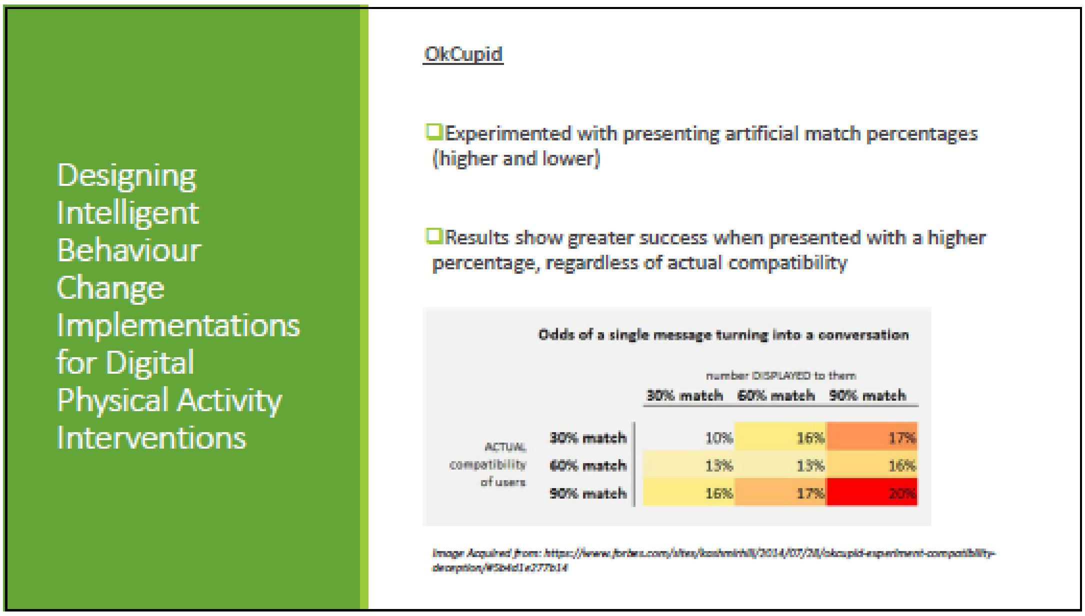
8


Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
Goals
A further goal is gaining an idea of how 'Intelligent AI-Driven BCIs' would look
Every possible data channel on a mobile device available to be analysed and worked with
Personalisation to the most specific degree, all in the pursuit of maximum and optimal behavioural impact.

9


Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
Goals
Push the boundaries of what you feel is acceptable
None of these designs will be taken straight from your illustrations and implemented – This is purely a design exercise
Sometimes, bending these boundaries and doing things that value the system over the user can produce more positive results

10


Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
OkCupid
Experimented with presenting artificial match percentages (higher and lower)
Results show greater success when presented with a higher percentage, regardless of actual compatibility
Odds of a single message turning into a conversation
number DISPLAYED to them
ACTUAL compatibility of users

	30% match	60% match	90% match
30% match	10%	16%	17%
60% match	13%	13%	16%
90% match	16%	17%	20%

Image Acquired from: https://www.forbes.com/sites/kashmirhill/2014/07/28/okcupid-experiment-compatibility-deception/#5b4d1e277b14

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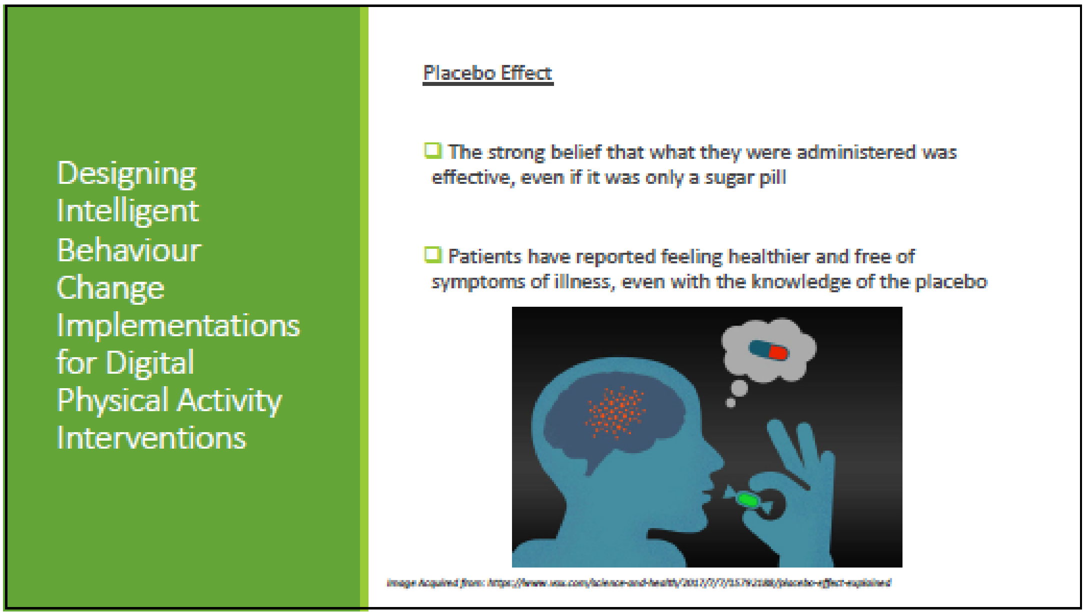
Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
Placebo Effect
The strong belief that what they were administered was effective, even if it was only a sugar pill
Patients have reported feeling healthier and free of symptoms of illness, even with the knowledge of the placebo
Image Acquired from: https://www.vox.com/science-and-health/2017/7/7/15792188/placebo-effect-explained

12

Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions

Virtual Peers

- Algorithms designed to imitate the actions and data input of a real user
- Can have a positive effect through competition if the user is consistently ahead of or behind the algorithm output

Jeffrey Laut, Francesco Cappa, Oded Nov, and Mauri Porfiri. 2017. Increasing citizen science contribution using a virtual peer. Journal of the Association for Information Science and Technology 68, 3 (mar 2017), 583–593. DOI:http://dx.doi.org/10.1002/asi.23685

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Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions

Activities

- Focus mostly on the overall impact of your implementations
- Take an 'Outcome-Driven' approach – The intervention outcome of improved health always comes first.
- Design your implementations to utilise the AI-Driven approach discussed before – All data is available if it increases the potential impact.
- Do not be concerned about overstepping any clear 'boundaries' – We cannot discover anything about these boundaries if you do not break them!

14

START DESIGNING – SEE WHAT YOU CAN COME UP WITH

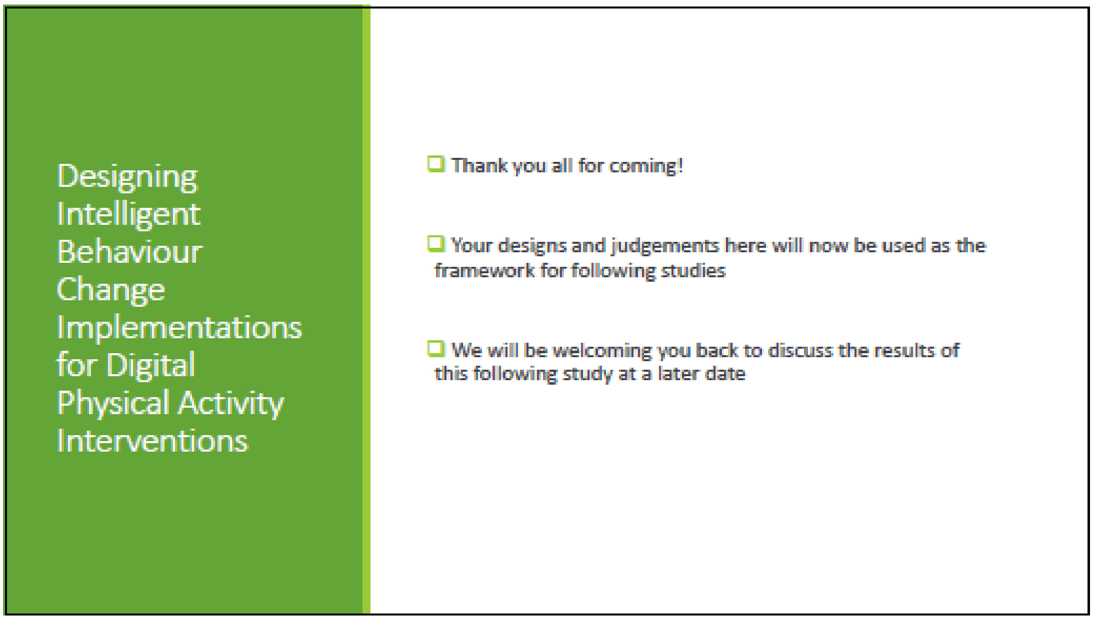
Designing Intelligent Behavior Change Implementations for Digital Physical Activity Interventions

15

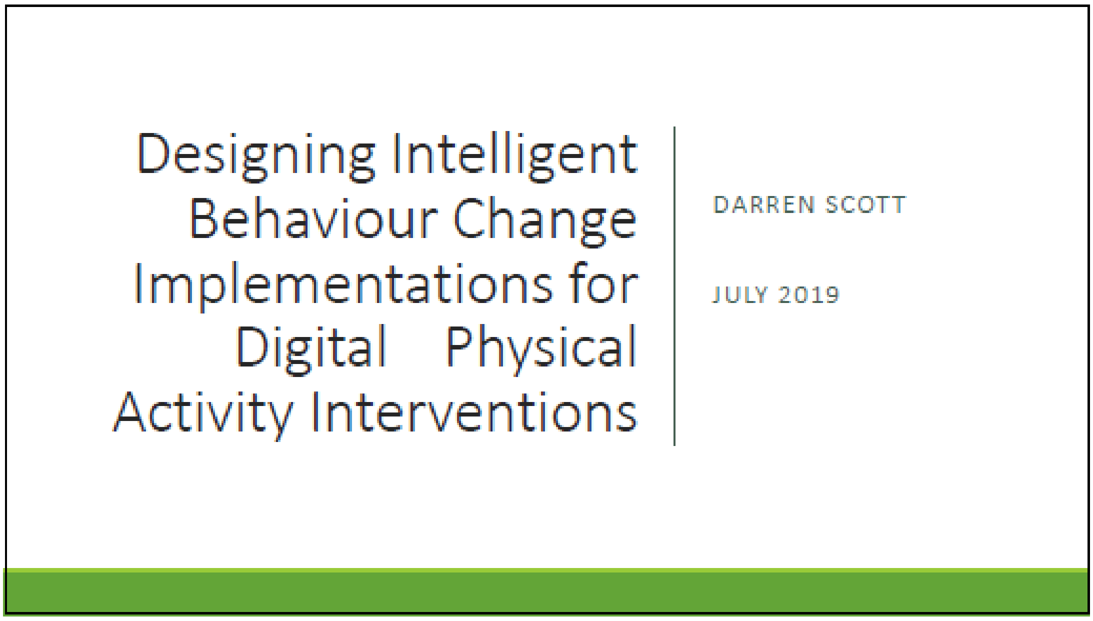
Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions

- Now it's time to share your ideas
- Share your techniques and rankings set out during the design sessions, and explain your thoughts on what you've made
- You are all welcome to disagree with placements and discuss judgement, whatever you feel is important to note in scoring these interventions

16


Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
Thank you all for coming!
Your designs and judgements here will now be used as the framework for following studies
We will be welcoming you back to discuss the results of this following study at a later date

17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JULY 2019

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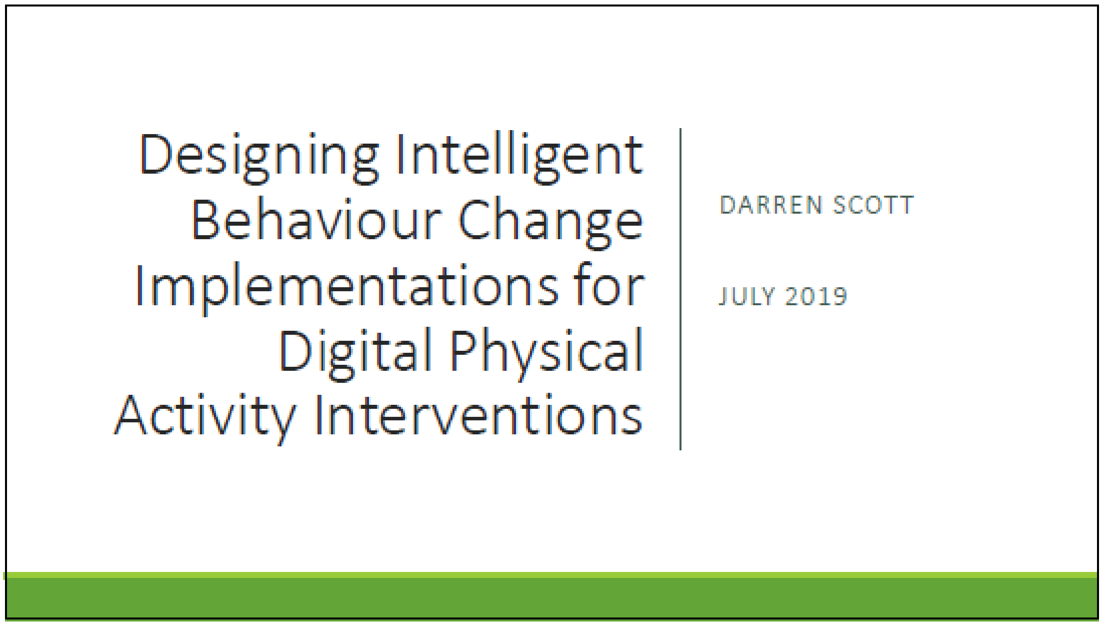
Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
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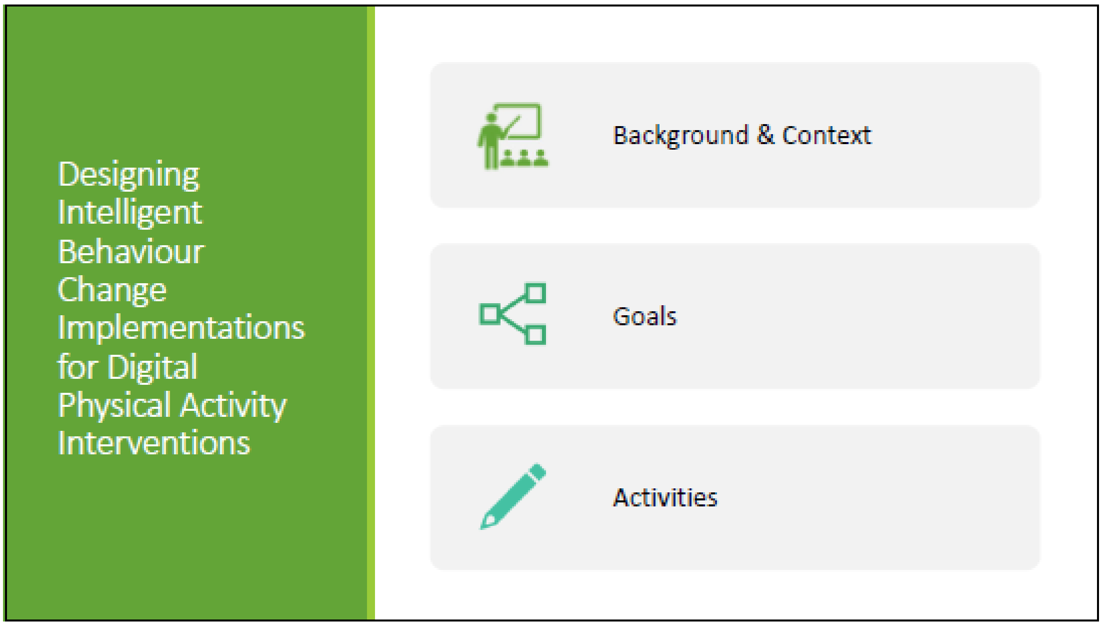
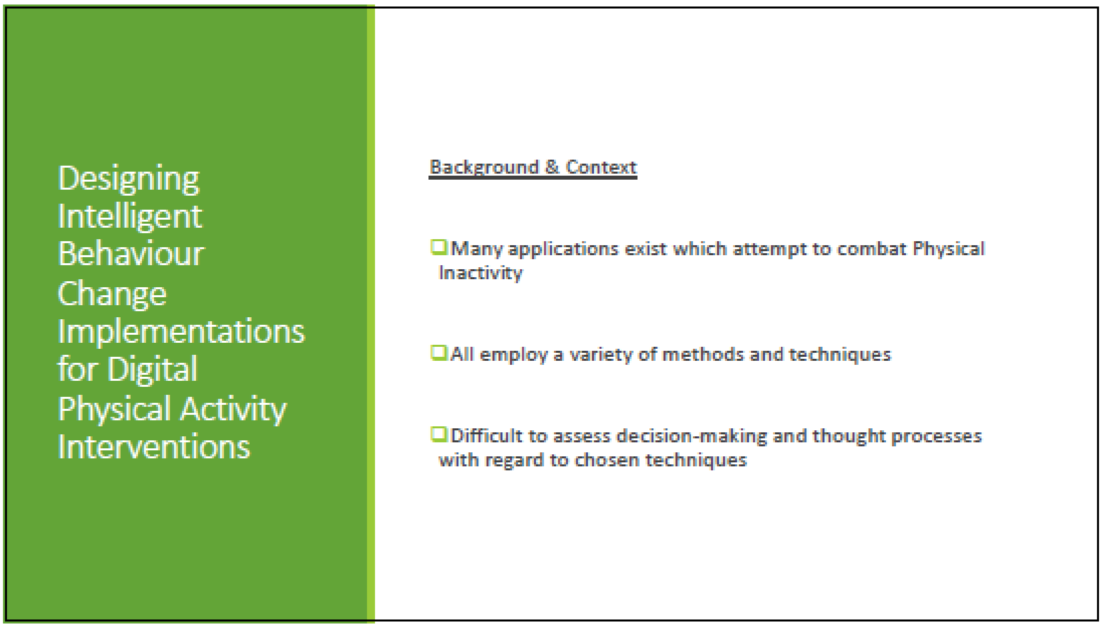

Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
Background & Context
Goals
Activities

2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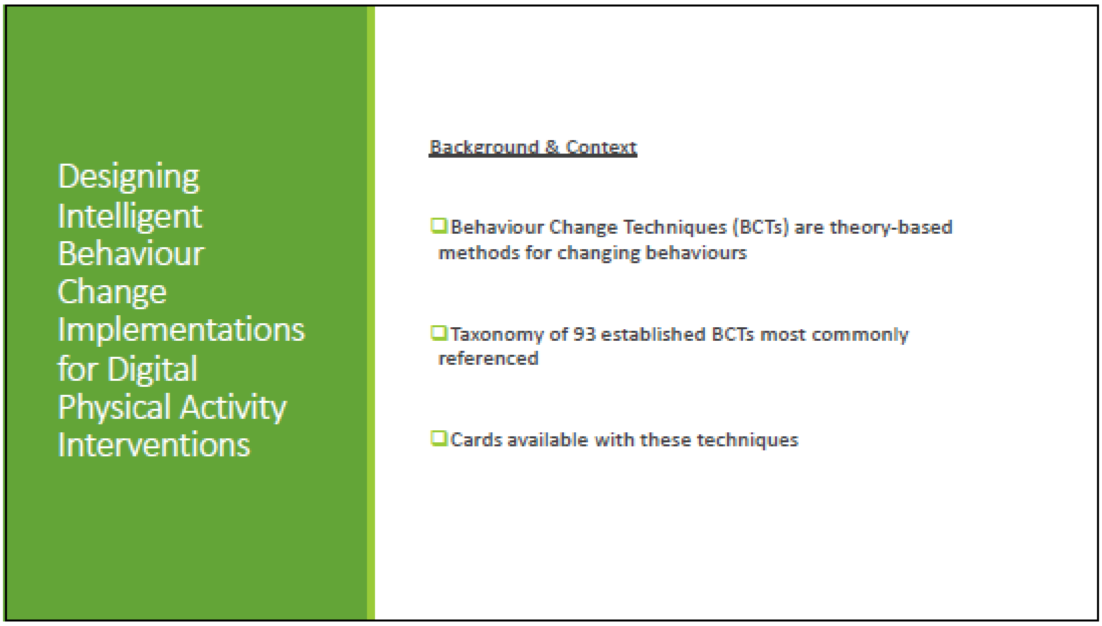
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- "Applying the taxonomy to apps forced the researchers to translate the strategies into app functionalities. Following this logic, the researchers had to score each app based on what they observed." – Middelweerd et at., 2014

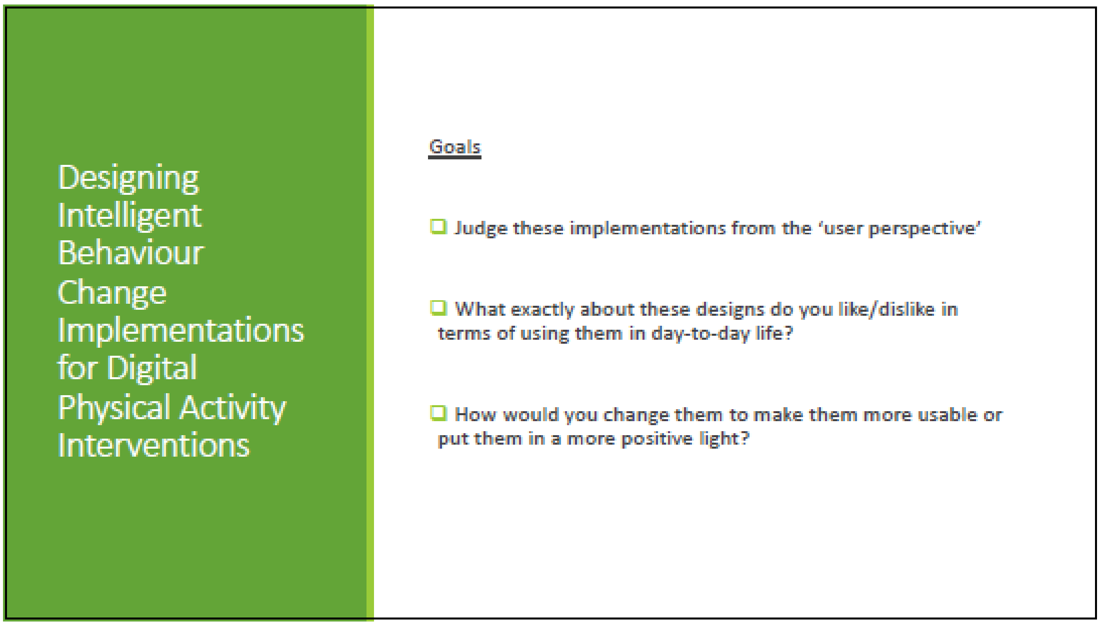
5

Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions

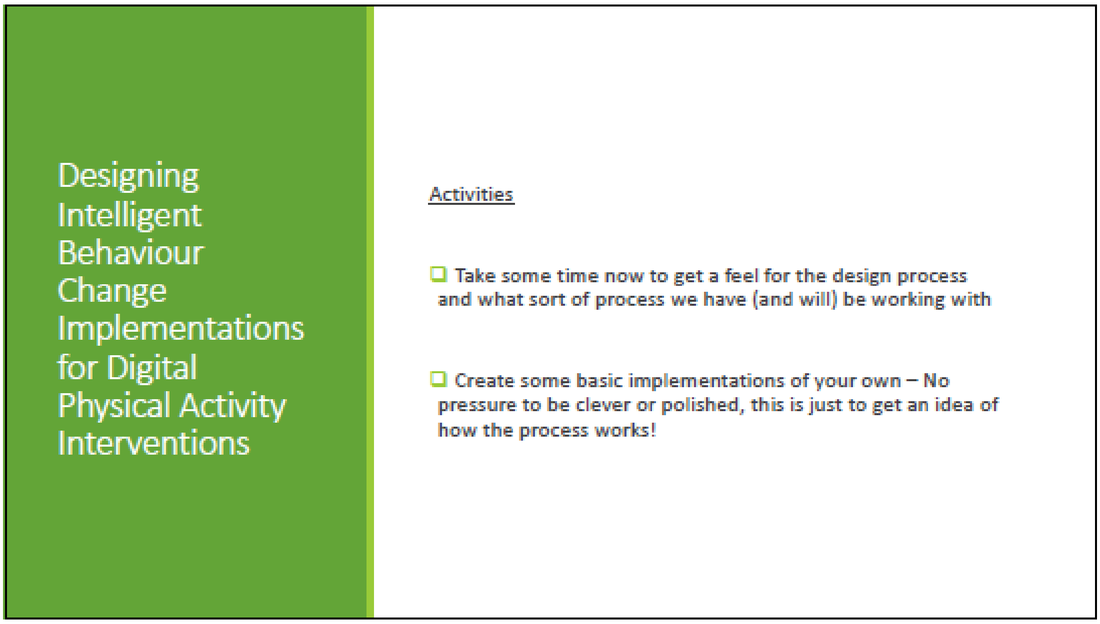
Background & Context

- Earlier this week, we asked domain experts to create their own Behaviour Change Implementations
- These were designed with the aim of being intelligent, using all possible data, aiming for the highest level of impact and with the potential to be personalised to every degree
- Every design choice was made to maximise impact, across a number of implementation designs.

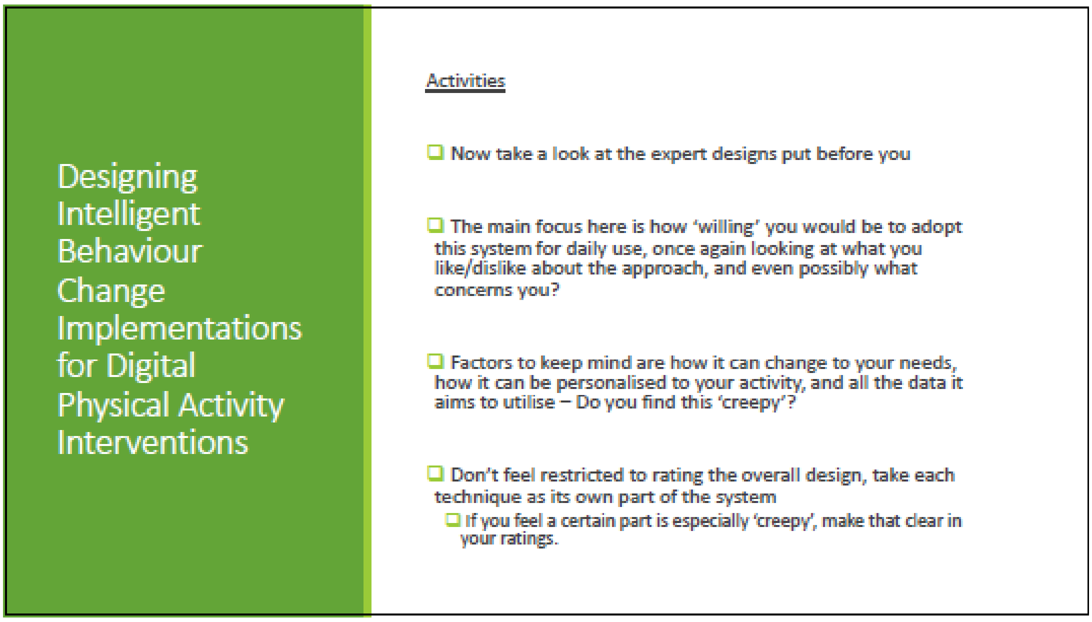
6


Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
Goals
Judge these implementations from the 'user perspective'
What exactly about these designs do you like/dislike in terms of using them in day-to-day life?
How would you change them to make them more usable or put them in a more positive light?

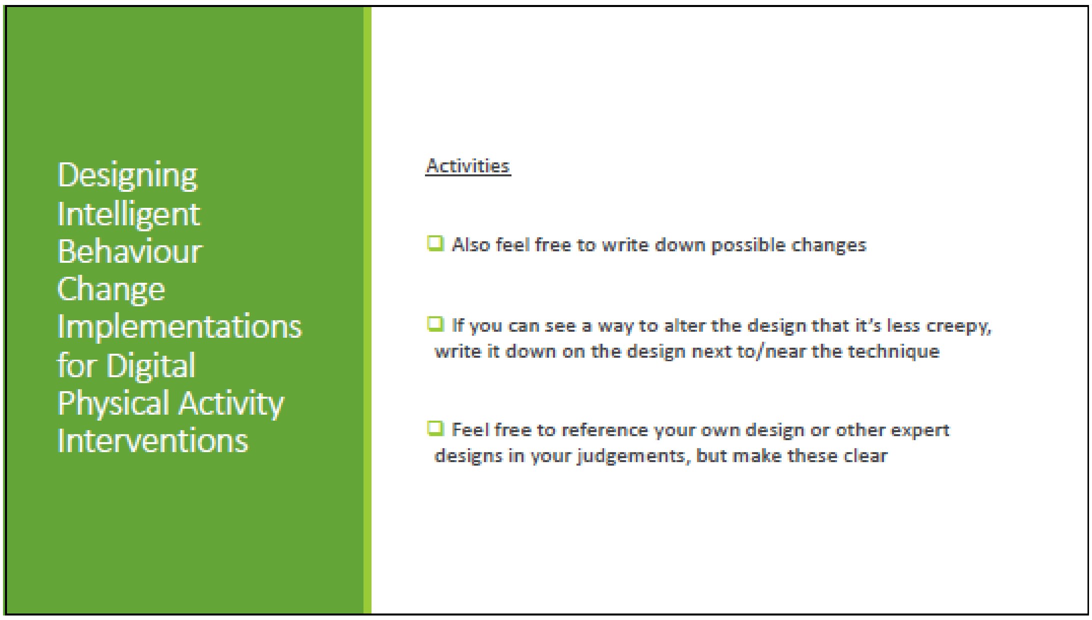
7


Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
Activities
Take some time now to get a feel for the design process and what sort of process we have (and will) be working with
Create some basic implementations of your own – No pressure to be clever or polished, this is just to get an idea of how the process works!

8


Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
Activities
Now take a look at the expert designs put before you
The main focus here is how 'willing' you would be to adopt this system for daily use, once again looking at what you like/dislike about the approach, and even possibly what concerns you?
Factors to keep mind are how it can change to your needs, how it can be personalised to your activity, and all the data it aims to utilise – Do you find this 'creepy'?
Don't feel restricted to rating the overall design, take each technique as its own part of the system
If you feel a certain part is especially 'creepy', make that clear in your ratings.

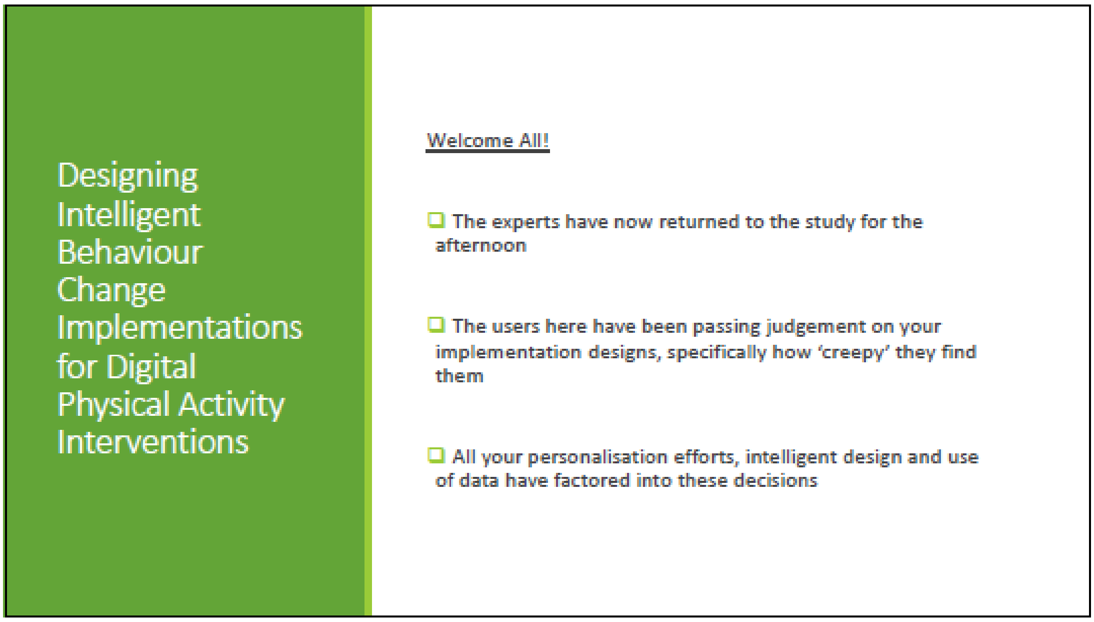
9


Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
Activities
Also feel free to write down possible changes
If you can see a way to alter the design that it's less creepy, write it down on the design next to/near the technique
Feel free to reference your own design or other expert designs in your judgements, but make these clear

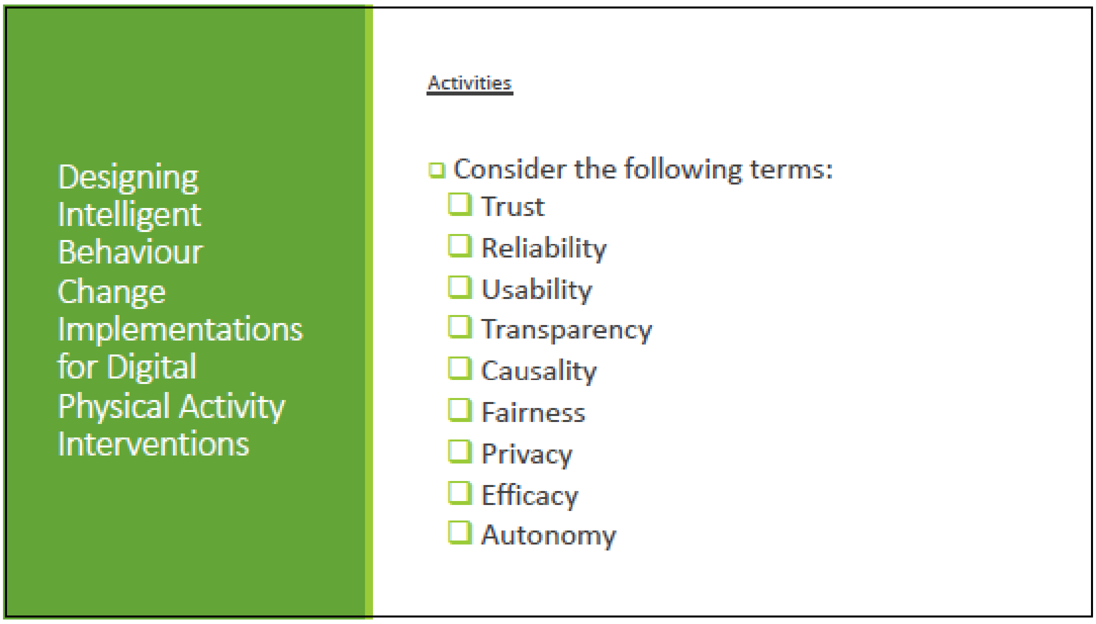
10


START YOUR JUDGEMENTS – SEE WHAT YOU THINK!
Designing Intelligent Behavior Change Implementations for Digital Physical Activity Interventions

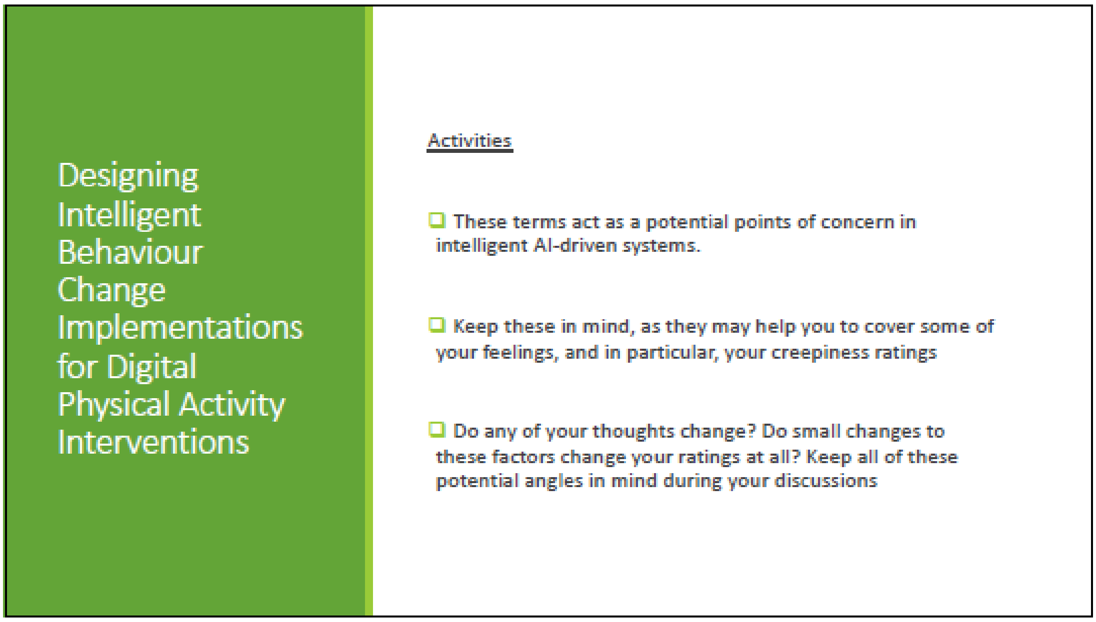
11


Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
Welcome All!
The experts have now returned to the study for the afternoon
The users here have been passing judgement on your implementation designs, specifically how ‘creepy’ they find them
All your personalisation efforts, intelligent design and use of data have factored into these decisions

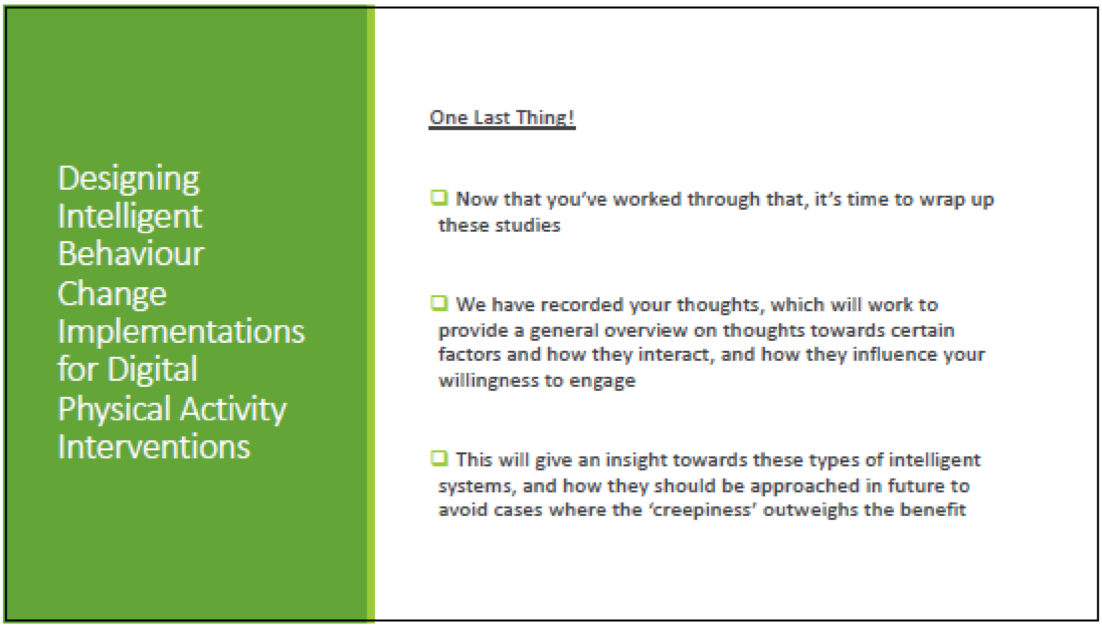
12


Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
Activities
Consider the following terms:
Trust
Reliability
Usability
Transparency
Causality
Fairness
Privacy
Efficacy
Autonomy

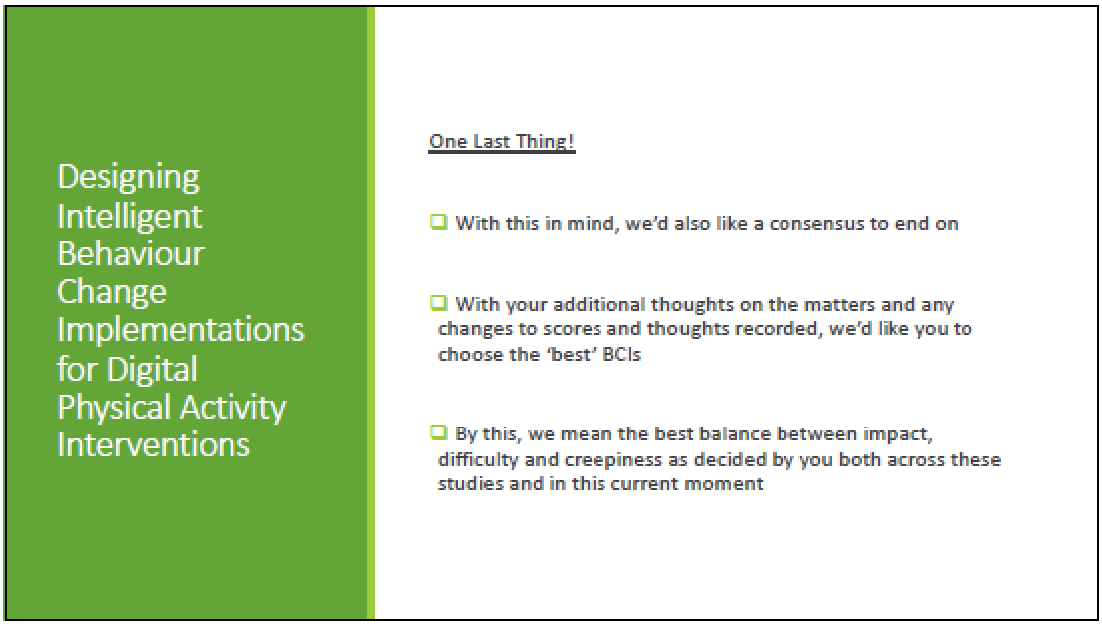
13


Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
Activities
These terms act as a potential points of concern in intelligent AI-driven systems.
Keep these in mind, as they may help you to cover some of your feelings, and in particular, your creepiness ratings
Do any of your thoughts change? Do small changes to these factors change your ratings at all? Keep all of these potential angles in mind during your discussions

14


Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
One Last Thing!
Now that you've worked through that, it's time to wrap up these studies
We have recorded your thoughts, which will work to provide a general overview on thoughts towards certain factors and how they interact, and how they influence your willingness to engage
This will give an insight towards these types of intelligent systems, and how they should be approached in future to avoid cases where the 'creepiness' outweighs the benefit

15


Designing Intelligent Behaviour Change Implementations for Digital Physical Activity Interventions
One Last Thing!
With this in mind, we'd also like a consensus to end on
With your additional thoughts on the matters and any changes to scores and thoughts recorded, we'd like you to choose the 'best' BCIs
By this, we mean the best balance between impact, difficulty and creepiness as decided by you both across these studies and in this current moment

16

B.2 Validation Study

B.2.1 Workshop Materials

ELD & VSD Presentations

Technique Name	Effect-Led Design	*Participants*	Designers, Stakeholders
Process Stage	Greenlighting : Scoping : Design Work : Evaluation		
Tools	Pen and paper, audio recorder, topic guides		
Purpose	To develop designs driven by outcome metrics, then refined through user analysis		
Strengths	- Concepts are developed wholly to aide outcomes - User values gathered are tailored to the system		
Weaknesses	- Nature of process means some concepts are unfeasible or overly abrasive in approach - Some unseen values may not be captured		
Output	- Recordings - Transcripts - Detailed concept designs and value discussions		

1

Effect-Led Design

Effect-Led Design, as the name implies, focuses on **system effectiveness** – Design choices complement system efficacy through use of **Behaviour Change Techniques** as key foundational pieces – Unique techniques comprising multiple approaches to enacting a change or improvement in behaviour.

Systems are intended to drive effect through two key tenets: Focus on **intelligent approaches** and **temporary flouting of end-user values**

These values are later introduced in the context to these high-effect concepts, to refine concepts in exact line with the needs of the users **for the specific focus area**

Concepts are designed and refined **specifically for the purpose of the behaviour and the values of the users involved** – Some systems can be less feasible and difficult to adapt for wider use – However, **it's arguably the optimal system for these users for this purpose**

Effect-Led Design – Concept Briefs

Effect-Led Design, in essence, works to **develop concepts in three distinct areas**:

Everyday – A concept that reflects commonly available systems, similar to what would be considered a 'typical application' in the target area

Extreme Efficacy – Flout user values and ignore user boundaries to an extent that resulting concepts are still usable, but unlikely to be popular or widely adopted

(cartoonishly) Evil – Ignore values and boundaries to the greatest extents, developing concepts that border of satire and would be deemed unacceptable to any potential users

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3

Effect-Led Design Process

The Effect-Led Design process breaks down into three distinct **stages**:

Conceptualise – The outlining of conceptual details, selection of behaviour change techniques and development of initial design concepts

Analyse – These concepts are analysed and discussed by end users, picking out problematic elements that negatively affect usability

Design – Designers and end users collaborate to refine the initial concepts into designs based on the user feedback and analysis

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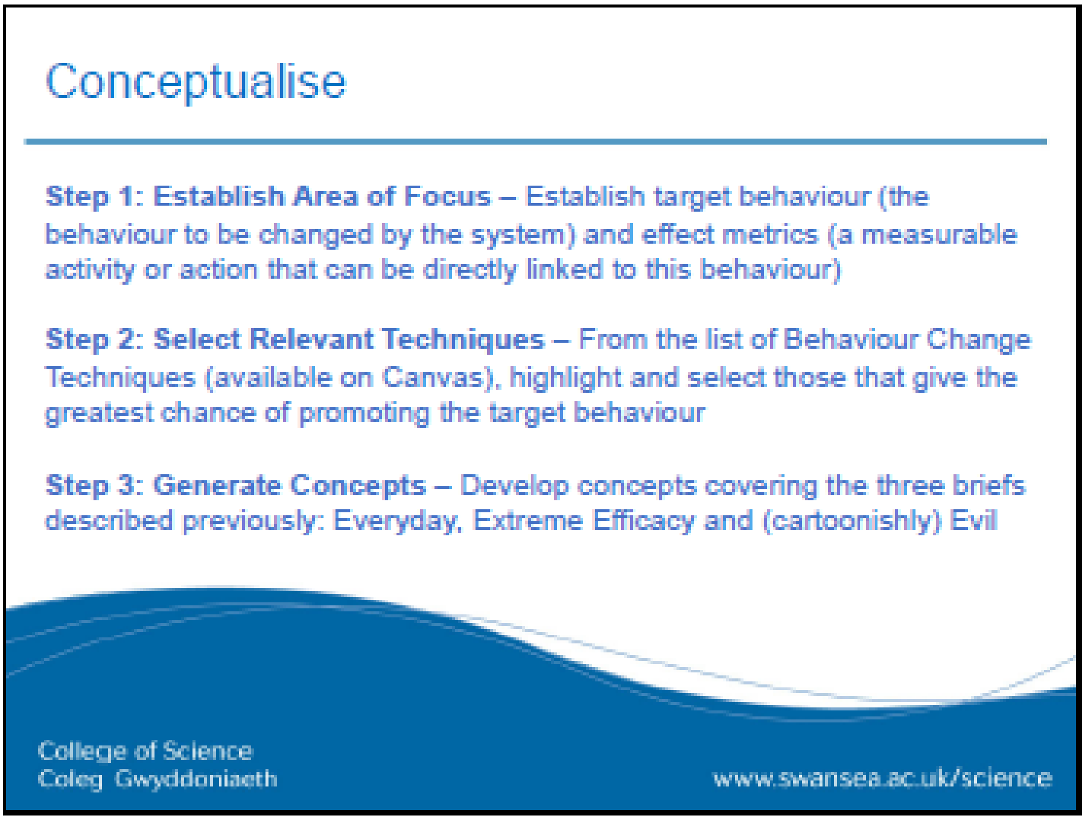
Conceptualise
Step 1: Establish Area of Focus – Establish target behaviour (the behaviour to be changed by the system) and effect metrics (a measurable activity or action that can be directly linked to this behaviour)
Step 2: Select Relevant Techniques – From the list of Behaviour Change Techniques (available on Canvas), highlight and select those that give the greatest chance of promoting the target behaviour
Step 3: Generate Concepts – Develop concepts covering the three briefs described previously: Everyday, Extreme Efficacy and (cartoonishly) Evil
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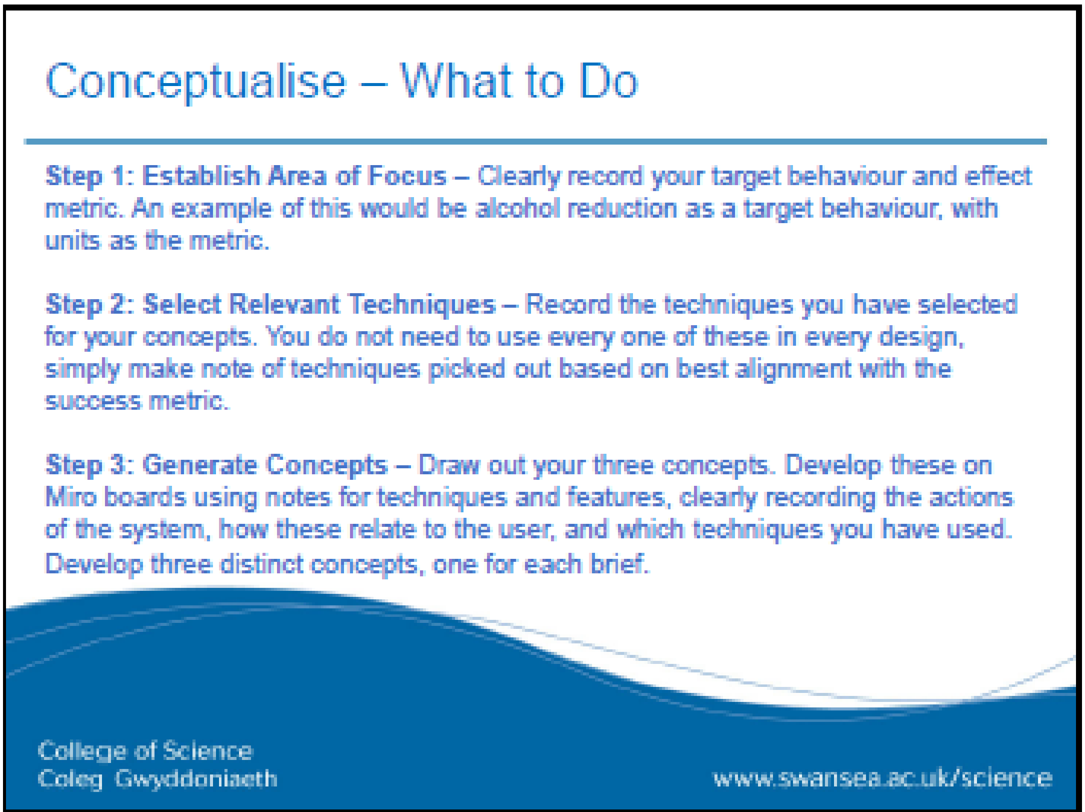
5


Conceptualise – What to Do
Step 1: Establish Area of Focus – Clearly record your target behaviour and effect metric. An example of this would be alcohol reduction as a target behaviour, with units as the metric.
Step 2: Select Relevant Techniques – Record the techniques you have selected for your concepts. You do not need to use every one of these in every design, simply make note of techniques picked out based on best alignment with the success metric.
Step 3: Generate Concepts – Draw out your three concepts. Develop these on Miro boards using notes for techniques and features, clearly recording the actions of the system, how these relate to the user, and which techniques you have used. Develop three distinct concepts, one for each brief.
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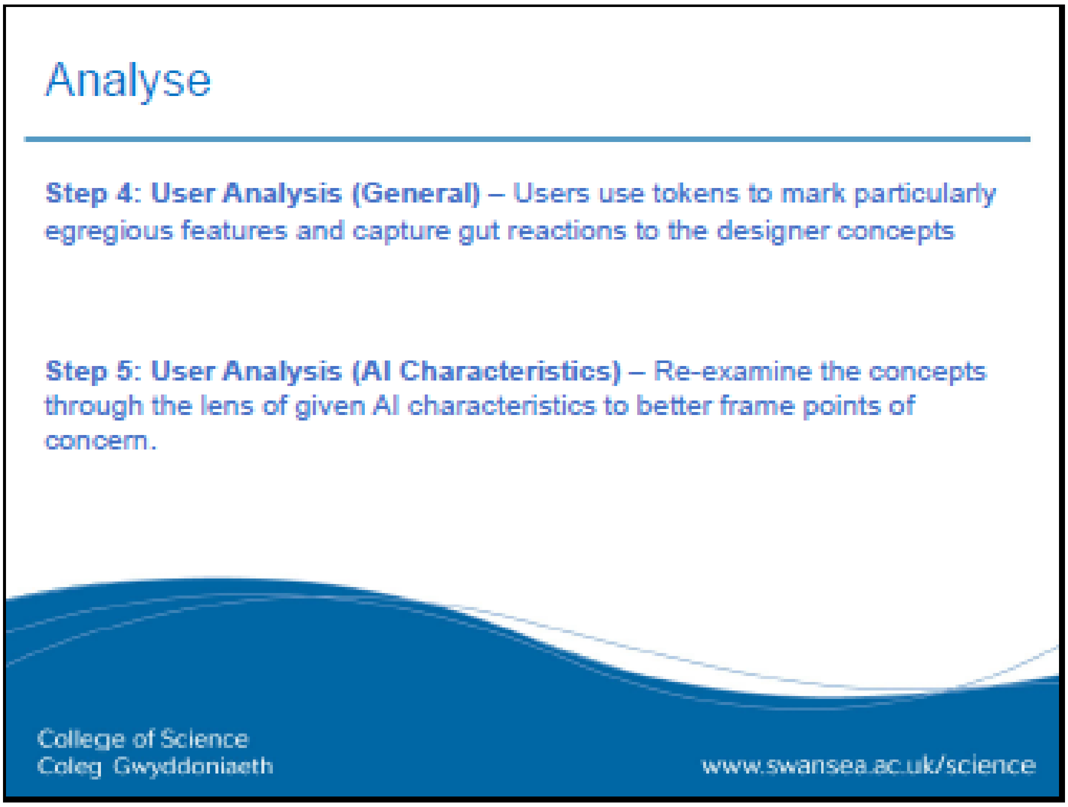
Analyse
Step 4: User Analysis (General) – Users use tokens to mark particularly egregious features and capture gut reactions to the designer concepts
Step 5: User Analysis (AI Characteristics) – Re-examine the concepts through the lens of given AI characteristics to better frame points of concern.
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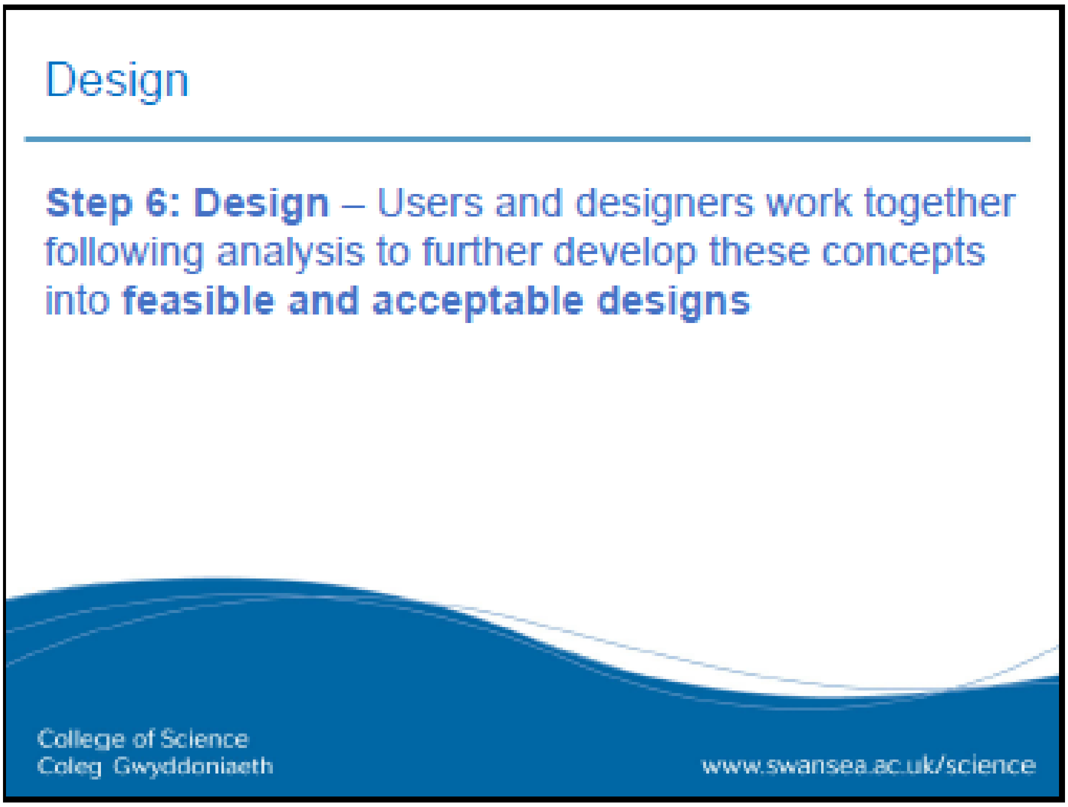
Design
Step 6: Design – Users and designers work together following analysis to further develop these concepts into **feasible and acceptable designs**
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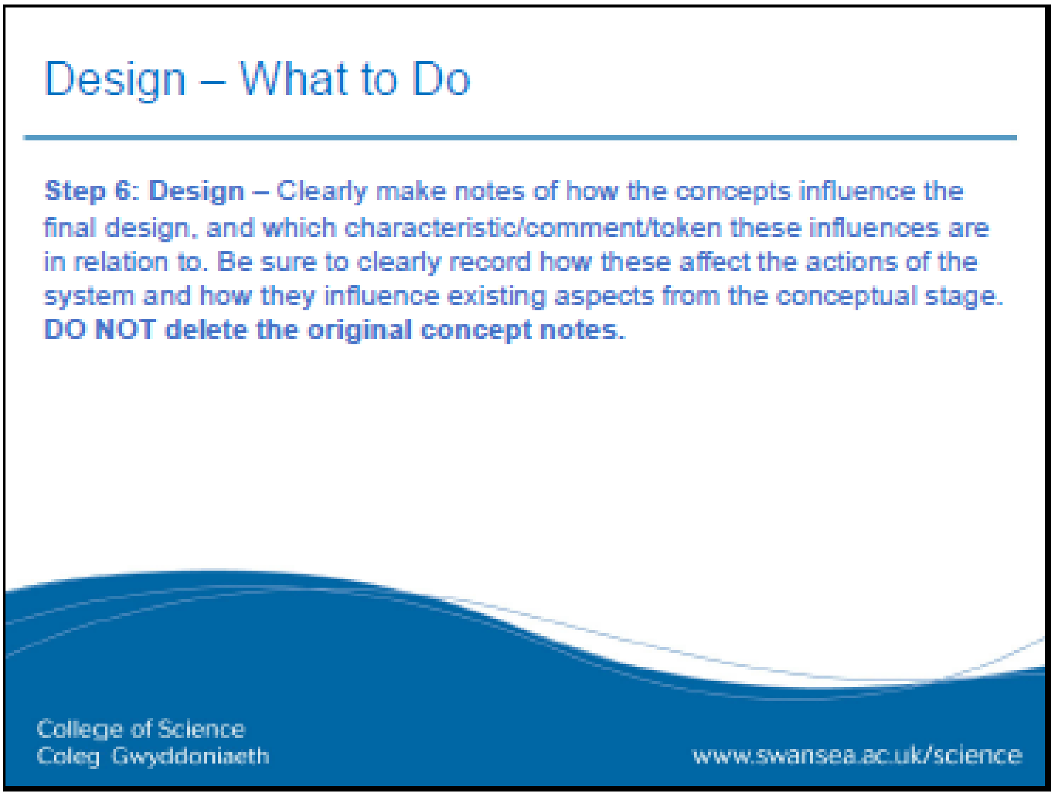
Design – What to Do
Step 6: Design – Clearly make notes of how the concepts influence the final design, and which characteristic/comment/token these influences are in relation to. Be sure to clearly record how these affect the actions of the system and how they influence existing aspects from the conceptual stage. **DO NOT delete the original concept notes.**
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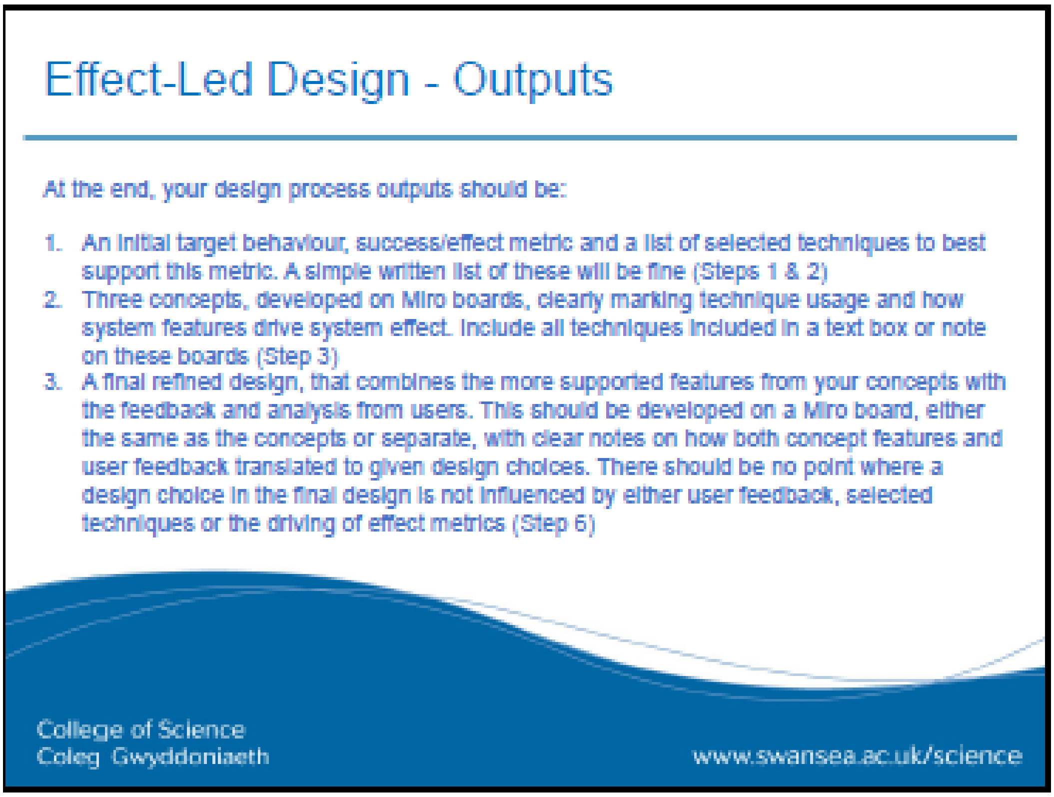
Effect-Led Design - Outputs
At the end, your design process outputs should be:
1. An initial target behaviour, success/effect metric and a list of selected techniques to best support this metric. A simple written list of these will be fine (Steps 1 & 2)
2. Three concepts, developed on Miro boards, clearly marking technique usage and how system features drive system effect. Include all techniques included in a text box or note on these boards (Step 3)
3. A final refined design, that combines the more supported features from your concepts with the feedback and analysis from users. This should be developed on a Miro board, either the same as the concepts or separate, with clear notes on how both concept features and user feedback translated to given design choices. There should be no point where a design choice in the final design is not influenced by either user feedback, selected techniques or the driving of effect metrics (Step 6)
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Working for the Other Group

As part of the workshop, you will be required to act as an end-user for students running the alternative design process.

In this case, you will act as users for Value Sensitive Design, where you will be required to act as participants in a focus group looking to discuss values for their eventual designs.

You will take part in a focus group where designers will be looking to elicit values from you which will then feed into design choices. Your involvement will not appear past this point, so please make a good effort as part of the focus group to ensure the other group is able to effectively carry out the remainder of their process.

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Technique Name	Effect-Led Design	*Participants*	Designers, Stakeholders
Process Stage	Greenlighting : Scoping : **Design Work** : Evaluation		
Tools	Pen and paper, audio recorder, topic guides		
Purpose	To develop designs driven by outcome metrics, then refined through user analysis		
Strengths	- Concepts are developed wholly to aide outcomes - User values gathered are tailored to the system		
Weaknesses	- Nature of process means some concepts are unfeasible or overly abrasive in approach - Some unseen values may not be captured		
Output	- Recordings - Transcripts - Detailed concept designs and value discussions		

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Technique Name	Value Sensitive Design	*Participants*	Designers, Stakeholders
Process Stage	Greenlighting : Scoping : Design Work : Evaluation		
Tools	Pen and paper, audio recorder, topic guides		
Purpose	To develop system designs built up primarily from stakeholder values		
Strengths	- Ensures designs satisfy necessary values - Systems are tuned to the needs of the stakeholders		
Weaknesses	- Can be sidetracked or diluted by conservative value taking - Possibility of over-engineering to specific stakeholders		
Output	- Recordings - Designs - Collections of user values		

1

Value Sensitive Design

Value Sensitive Design, as the name implies, focuses on stakeholder values – Design choices complement values through selecting approaches based on information gained through value elicitation

A system is designed to compliment the values of the user and, in turn, be most effective for the user in question – a design is the best-suited system for those users

Value Sensitive Design requires selecting effective compromises between values and technical aspects of the system – Designers must be careful not to sacrifice values in the pursuit of technical improvement

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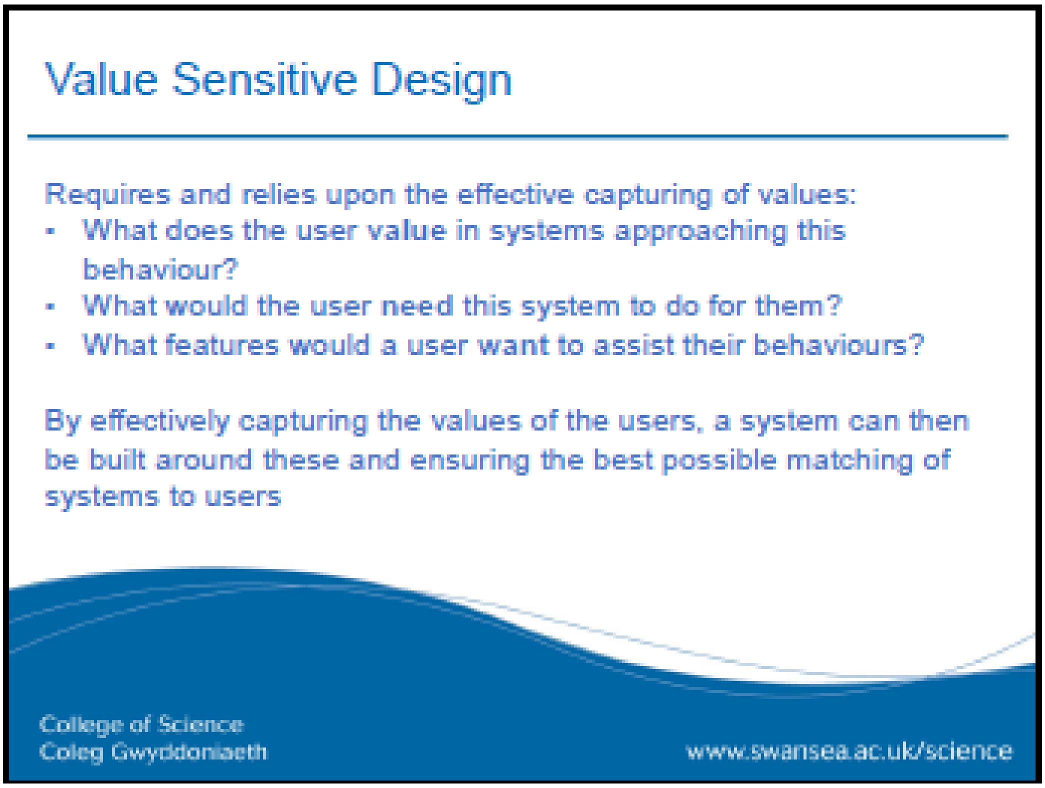
Value Sensitive Design
Requires and relies upon the effective capturing of values:
What does the user value in systems approaching this behaviour?
What would the user need this system to do for them?
What features would a user want to assist their behaviours?
By effectively capturing the values of the users, a system can then be built around these and ensuring the best possible matching of systems to users
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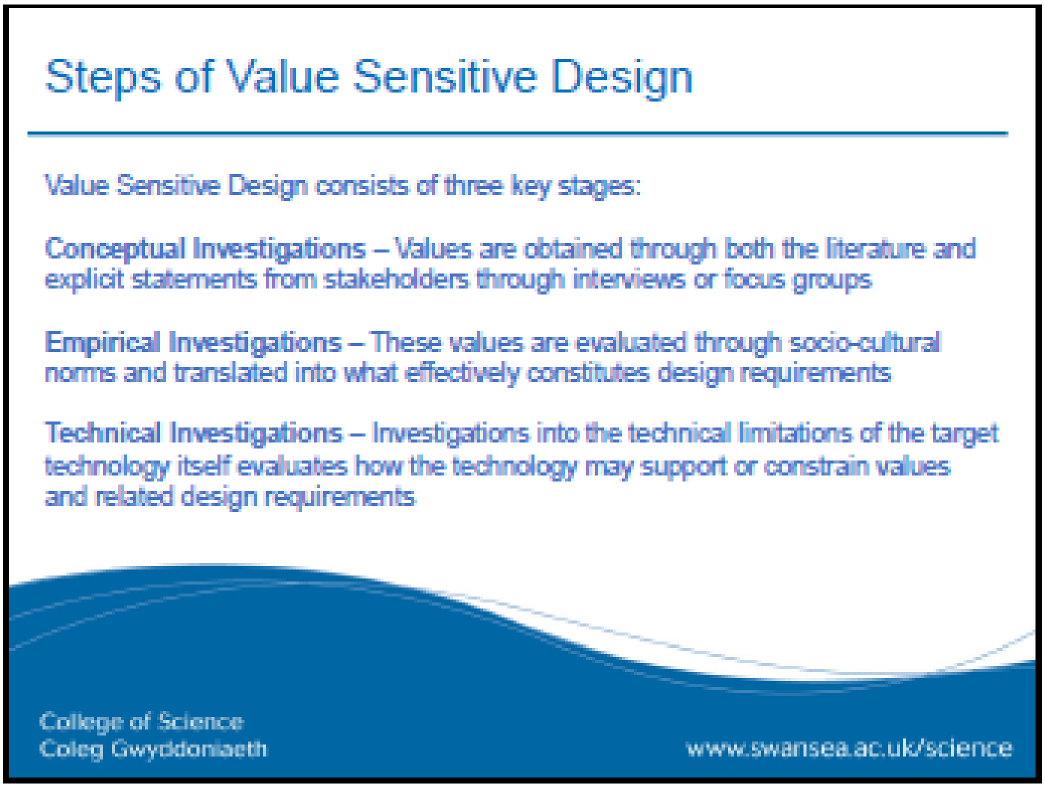
Steps of Value Sensitive Design
Value Sensitive Design consists of three key stages:
Conceptual Investigations – Values are obtained through both the literature and explicit statements from stakeholders through interviews or focus groups
Empirical Investigations – These values are evaluated through socio-cultural norms and translated into what effectively constitutes design requirements
Technical Investigations – Investigations into the technical limitations of the target technology itself evaluates how the technology may support or constrain values and related design requirements
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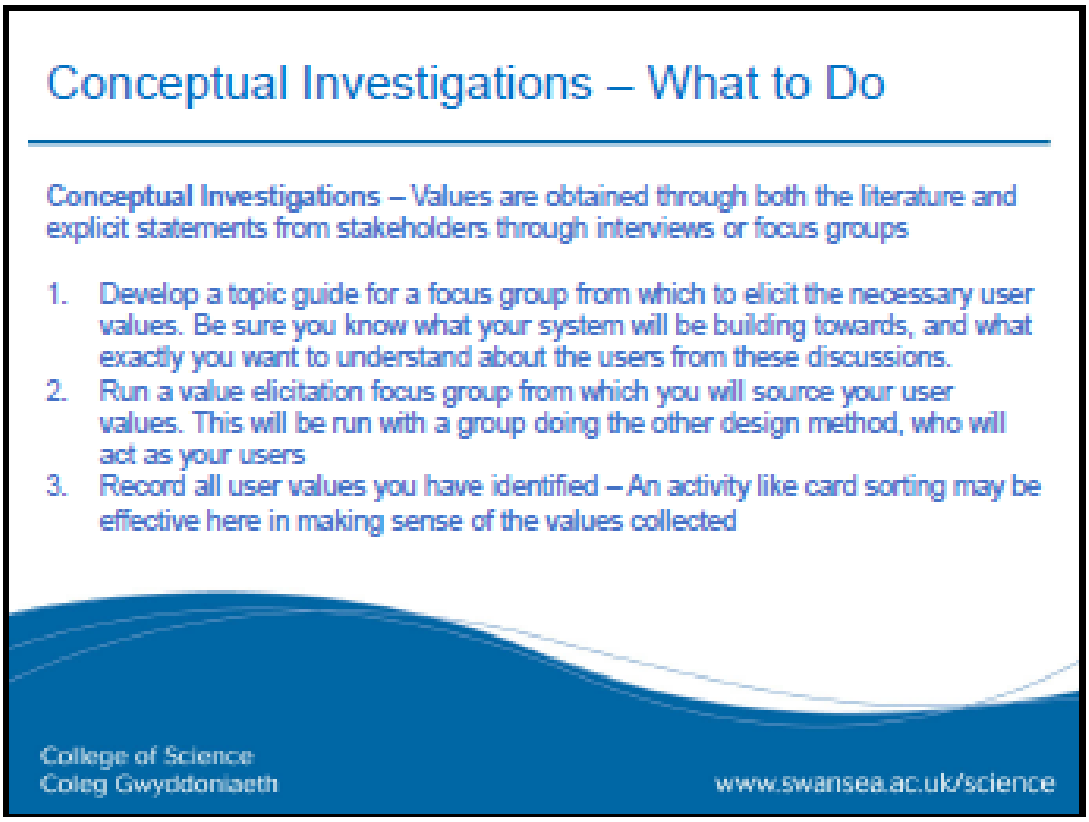
Conceptual Investigations – What to Do
Conceptual Investigations – Values are obtained through both the literature and explicit statements from stakeholders through interviews or focus groups
1. Develop a topic guide for a focus group from which to elicit the necessary user values. Be sure you know what your system will be building towards, and what exactly you want to understand about the users from these discussions.
2. Run a value elicitation focus group from which you will source your user values. This will be run with a group doing the other design method, who will act as your users
3. Record all user values you have identified – An activity like card sorting may be effective here in making sense of the values collected
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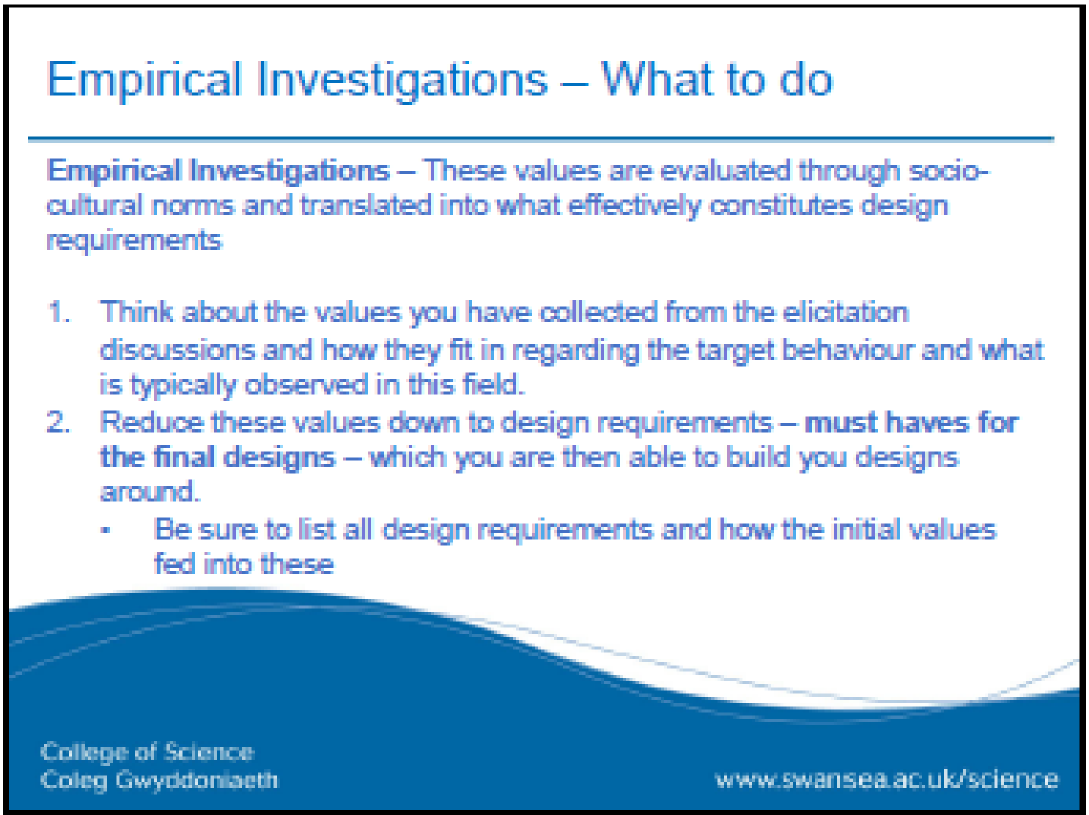
Empirical Investigations – What to do
Empirical Investigations – These values are evaluated through socio-cultural norms and translated into what effectively constitutes design requirements
1. Think about the values you have collected from the elicitation discussions and how they fit in regarding the target behaviour and what is typically observed in this field.
2. Reduce these values down to design requirements – must haves for the final designs – which you are then able to build you designs around.
• Be sure to list all design requirements and how the initial values fed into these
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6

Technical Investigations – What to do

Technical Investigations – Investigations into the technical limitations of the target technology itself evaluates how the technology may support or constrain values and related design requirements

1. Think about the target platform for your system – likely a mobile application – and how this may limit the values (and related value-derived requirements) in the process of creating designs
2. It is likely you will need to make some compromises with values to adhere to the technical limitations.
   - Be sure to record all observations on how the technology supports or constrains the designs, and any compromises or alterations you made following these being identified

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Value Sensitive Design – Make a Design!

Your final action should be to create a design to support the target behaviour while adhering to the value requirements outlined by the process.

Develop this design on a Miro board, marking important features and how these relate to the values collected as well as requirements and technical limitations. The process of using the design, as well as how elicited values feed into design decisions, should be made clear.

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Value Sensitive Design – Outputs

At the end, your design process outputs should be:

1. The initial sourced values, in the form of a list or possibly a card-sort of all collected (Conceptual)
2. How these were translated into value requirements, likely a follow from the card-sort making clear the progression from initial values (Empirical)
3. How technical investigations reflected these values, as well as any notable compromises or constraints, in the form of listed technical limitations and associated supported/constrained/compromised values (Technical)
4. A detailed final design, outlining how this design would work to support the behaviour, presented clearly on a Miro board with reference to requirements, technical constraints and values (Design)

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Working for the Other Group

As part of the workshop, you will be required to act as an end-user for students running the alternative design process.

In this case, you will act as users for Effect-Led Design, where you will be required to analyse and comment on designs, before working with the designers to develop a refined design idea from the concepts you view.

On a shared Miro board (containing the design concepts), make general notes on aspects of the system making clear what your comments are in relation to. Select a token to mark 'highly egregious' elements. You will then be asked to make comments in relation to specific characteristics, and once again should make clear what these are in relation to. These characteristics are: Trust, Reliability, Usability, Transparency, Causality, Fairness, Privacy, Efficacy and Autonomy.

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10

Technique Name	**Value Sensitive Design**	*Participants*	Designers, Stakeholders
Process Stage	Greenlighting : Scoping : **Design Work** : Evaluation		
Tools	Pen and paper, audio recorder, topic guides		
Purpose	To develop system designs built up primarily from stakeholder values		
Strengths	- Ensures designs satisfy necessary values - Systems are tuned to the needs of the stakeholders		
Weaknesses	- Can be sidetracked or diluted by conservative value taking - Possibility of over-engineering to specific stakeholders		
Output	- Recordings - Designs - Collections of user values		

11

Post-Workshop Questions

Group Number:

Please describe the design(s) you developed during the ELD process:

Design 1:

Design 2:

Design 3:

Please list the BCTs you used in your ELD concepts:

Design 1:

Design 2:

Design 3:

Outline how your designs changed following user discussions:

Design 1:

Design 2:

Design 3:

Please list any and all feelings/opinions, positive or negative, on the ELD process and its place in the wider world of design:

Group Number:

Please describe the design(s) you developed during the VSD process:

Design 1:

Design 2:

Design 3:

Please list the user values you focused on for your VSD designs:

Design 1:

Design 2:

Design 3:

Outline how user discussions shaped your eventual designs:

Design 1:

Design 2:

Design 3:

Please list any and all feelings/opinions, positive or negative, on the VSD process and its place in the wider world of design:

Group Number: Design Method:

Following the completion of the workshop, please submit this completed questionnaire alongside the workshop materials

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
We had a clear picture of the change in behaviour that we were designing for					
We had a clear, countable change in behaviour that we were designing for					
We selected our approaches to changing behaviour based on the degree of impact they would have on end-user behaviour					
We selected our approaches to change behaviour based on the degree of alignment with the end user's principles					
During the design process, we spent time thinking about how our designs aligned with the user's principles					
The playfulness of the design process made it easy to talk about a wide range of different ways to change behaviour					
The design process' focus on user's principles made it easy to talk about the ethical implications of our ideas					
We produced a final design that aligned with the user's principles					
The design focus on system impact limited the acceptability of the final design					
The design focus on stakeholder principles limited the final design's ability to change behaviour					

APPENDIX C

EXPERIMENTAL STUDY MATERIALS

C.1 Recruitment Materials

C.1.1 Emails for Recruitment Communications

Initial Contact

Do you want to earn £25 for running an app?
Help us change the world of wellbeing and fitness apps by taking part!
We would love your participation in a study we're running – All participants welcome, regardless of experience or knowledge of fitness apps.
Unfortunately, only Android users may participate.
Please email d.p.scott@swansea.ac.uk for further details.

Following Expression of Interest

Thank you for your interest in taking part!
Before we provide all the official documentation, we felt it best to provide some insight into what you'll be doing as part of this study.
My name is Darren Scott, a PhD Candidate at the University. The applications out there targeting boosting your fitness often struggle to maintain interest past the initial on-boarding process. Our aim is to develop a system that holds your interest and helps you with your active goals.
After installing the application and accepting the introductory screens, you will be ready to go. You are only required to work with the information presented and use it to try and increase step counts for a period of four weeks.
This application is unfortunately only open to users with Android devices. We are offering a £25 Amazon voucher upon completion of both the four weeks of application usage and a follow-up interview detailing your experience.
If you wish to take part in this study, please respond to this email with your intention to participate.

Following Confirmation of Interest

Thank you so much for your continued interest in taking part in the study.
While the application is prepared, could I please ask that you view the document attached to this email and either sign and return the attached consent form, or respond to this email with a sentence providing your informed consent to take part in this study.
Could you please also complete the survey at **https://forms.gle/2kVB9hV9LHwPgHFV8** to help us with analysis of collected data (please answer the same email used in this exchange)
If you have any further questions, do not hesitate to contact me on this email address.

Following Reception of Consent

Please find attached to this email the application file, as well as an instructional video that will guide you through the process of downloading and installing the application file such that you can take part. If you encounter issues during downloading that are due to incompatible versions of Android or other technical difficulties, you may retract your participation with no issue.
There is a known issue regarding excessive step figures during early use, if this is experienced, do not be alarmed, this is known to be a Day 1 issue and your system should be unaffected in following days.
You may encounter some minor technical bugs; a restart of the application should resolve most issues. If you encounter sustained technical difficulties, please contact me and I will attempt to resolve these.
Once again, if you have any questions or difficulties in installing the application, I will do my best to help you join this study in earnest.

C.2 Experimental Qualitative Data Questions

C.2.1 Fake Peer Questions

Initial Questions

- Did you find the system helpful and easy to use?
- Did you feel the system encouraged you to increase your activity and be more active in your general life?
- Did the comparisons, and how they changed, impact your behaviour?
  - Was this a positive or negative impact?
  - Did the changes in comparisons have a notable impact?
    - If so, how exactly did these changes affect you?
- Did the changes in social comparison targets motivate you to be more active?
- Do you feel like you improved your behaviour?
  - If so, did the app help or hinder this change?

Following Fake Peer Reveal

- Did you believe the peer data presented legitimate instances of social comparison?
- Were the peer values you received believable as step counts users could achieve in those intervals?
- How do you feel at this point now knowing the peer values were fabricated?
  - Did you have any inclination during the process that the values were not real?
- If you had been informed before the process that the values were fabricated, would you have agreed to use the system?
  - Would you have been encouraged by a social competition set-up where the competition is known to be artificially generated?
- Does the knowledge now of the fabricated peer change your thoughts looking back on your use of the system?

C.2.2 Technique Switching Questions

- Did you find the system helpful and easy to use?
- Did you feel the system encouraged you to increase your activity and be more active in your general life?
- Did the changes in techniques, and how they changed, impact your behaviour?
  - Was this a positive or negative impact?
  - Did the changes in techniques have a notable impact?
    - If so, how exactly did these changes affect you?
- Did the changes in behaviour change techniques motivate you to be more active?
- Do you feel like you improved your behaviour?
  - If so, did the app help or hinder this change?
- Did the changes in techniques affect your ability to maintain behavioural habits?
  - Did the changes affect the initial ability to become 'attached' to a technique?
- Did the techniques changing keep the process more interesting due to changing approaches?
  - Did this help avoid a technique or approach becoming 'stale'?

- Did you feel techniques you worked well with and that best motivated you appeared more frequently?
  - Additionally, did you feel techniques that did not motivate you and possibly demotivated you appeared less frequently if at all?
- Did you ever find a technique appeared too frequently even with the changing nature?
  - Did a technique you found interesting and motivating within the switching become less impactful due to being switched to more frequently?