A Data Science approach to behavioural change: large scale interventions on physical activity and weight loss

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I, Rodrigo Mazorra Blanco, confirm that the work presented in this thesis is my own. Where information has been derives from other sources, I confirm that this has been indicated in the work

Abstract

This PhD thesis is a quantitative investigation combining Behaviour Change Science with a Data Science approach in search of more effective large scale, multi-component behavioural interventions for health and well-being. There is limited evidence about how technology-based interventions (including those using wearable physical activity monitors and apps) are efficacious for increasing physical activity and nutrition. The relevance of this research is the systematic approach to overcome previous studies' limitations in method and measurement: restricted research about multi-component interventions, limited analysis about the impact of social networking, the inclusion of components without sufficient evidence about the components' effectiveness, the absence of a control group(s), small sample sizes, subjective physical activity reporting, among other limitations.

The research was done in conjunction with Tictrac Ltd as the industrial partner, and the UCL Centre for Behaviour Change. Tictrac Ltd builds platforms for the collection and aggregation of personal data generated by the users' devices and mobile apps. The collaboration with the UCL Centre for Behaviour Change has been instrumental to design, implement, evaluate and analyse behaviour change interventions that impact wellbeing and health.

The thesis comprises three areas of research:

1. Computational platforms for large scale behavioural interventions
To support this research, computational platforms were designed, built, deployed and used for randomised behavioural interventions with control groups. The interventions were implemented as experiments related to the behavioural impact on physical activity, weight loss and change in diet.

2. Behaviour change experiments
The two experiments use the Behaviour Change Wheel framework for behaviour change, intervention design and evaluation. A Data Science approach was used to test hypotheses, determine and quantify the effect of the fundamental intervention components and their interactions. The effective use of tracking devices and apps was determined by comparing the results of 'structured intervention' –vs- those of the control group.

Experiment 1: Large scale intervention in a corporate wellness setting
Multi-component behavioural intervention with: control group, self-defined goals, choice architecture and personal dashboards for physical activity and weight loss. The analysis covers network effects of social interactions, the role of being explicit about a type of goal, the impact of making part of team, among other relevant outcomes.

Experiment 2: Identification of critical factors of a technology-based intervention
Multi-component behavioural intervention with simultaneous target behaviours related to weight loss and physical activity, inspired by factorial design for the determination of critical factors and effective components. The analysis comprises: components' interactions (coach, challenge, team, action plans, forum), non-linear relationships (BMI, change in diet habit), five personality traits, among other relevant results.

3. Frameworks for future large scale interventions in behaviour change
The implementation of both experiments required an applied use of theoretical and practical principles for the design of the experimental computational platforms. As a result, two frameworks were suggested for future interventions: an implementation framework and a data strategy framework.

The main contributions to science of this research are described below.

Scientific contributions:

- Determined scenarios when multi-component interventions are efficacious for physical activity, weight loss and diet habits (nutrition) improvement using technology-based delivery mechanisms
- Multi-disciplinary approach for the validation of theory with data generated from experimental research, resulting in the advance of Behaviour Change Science
- Provided evidence about how a ‘structured intervention’ outperformed a control by conducting large-scale randomised research with control group
- Measurement of the impact of social ties and communications as network effects on physical activity & weight loss
- Discovery of the non-linear relationships of weight loss and initial BMI, as well as between weight loss and initial diet habits
- Characterisation of behavioural profiles for change potential and improvement related to weight loss
- Definition and implementation of a Data Science workflow for data capture, modelling, and definition of effective components of large scale interventions

Findings about Behaviour Change interventions:

- Identification of routines for the effective use of tracking devices and apps for behavioural change interventions
- Effective encoding of behaviour change techniques on intervention platforms that use activity tracking devices & apps
- Determination of evidence-based effective intervention components and their interactions by conducting Experimental research
- Definition of a ‘framework for the implementation of computational platforms for intervention’ operationalising behaviour change techniques, among other structural intervention components.

Impact Statement

This PhD thesis is an empirical study that uses the quantitative approach of Data Science for the analysis of the data generated from large scale behavioural interventions, contributing to the advance of Behavioural Change Science. The results of this study indicate pathways to impact future chronic health conditions via the identification of intervention principles and defining changes in routines for improving weight management and increasing physical activity.

As a multi-disciplinary approach, the investigation combines principles of: Behaviour Change Science, Computational Social Science, Digital Health, Human Computer Interaction, Complex Systems, and Experimental Research with a Data Science approach. The benefits of combining these fields of study result in validating decades of research with relevant data to substantiate the findings of previous investigations while contributing to the refinement of existing theories.

The behavioural analysis here performed, quantifies and tests some of the fundamental questions related to the efficacy of intervention components for physical activity and weight loss, confirming the relevance of simultaneous multiple components, being explicit about the type of goal pursued, the impact of social interaction and the use of computational platforms as an effective medium of delivery. On reflection, it was possible to observe through the analysis how the main theoretical principles of experimental design, intervention design and evaluation withhold to be true, while further work is still required in optimising the delivery.

This investigation is a unique collaboration between academia and an industrial partner enabling academic research within a commercial environment. As a result, the design and delivery of interventions reached more than 25,000 people, including the preliminary study and two experiments (in addition to the control group of 14,161 people). The feedback reports at the end of the interventions indicated that more than 30% of the participants (who completed the interventions) considered that the interventions helped them achieve their goal or their self-efficacy (self-belief and confidence) about reaching their goal the next time they try to achieve it.

This research had a direct impact on the strategy of Tictrac Ltd. (the industrial partner), resulting in the design of a new product and additional business from the use of the suggested frameworks for behaviour interventions that use computational platforms as a delivery medium.

The principles and frameworks used for intervention design, evaluation and implementation of the computational platforms used here, can be considered as transferable knowledge for other behaviour change interventions (particularly for those of large-scale). For example David Dunne an performance nutritionist and PhD student from LJMU has incorporated this practical knowledge for the design of interventions for peak performance in professional athletes.

The contributions of this work will benefit future behavioural interventions and the products that might deliver them, resulting in benefits for many stakeholders: future researchers, the service delivery practitioners of Behavioural Change Science and Digital Health, companies and product managers developing related products and foremost, the future recipient end users.

Acknowledgements

I would like to thank my principal supervisor Prof. Philip Treleaven for his patience, guidance, motivation and the freedom he provided for this multi-disciplinary exploration. I have great gratitude to Associate Prof. Carmen Lefevre, her constructive feedback enabled the correct application of Behaviour Change Science for technology-based, multi-component interventions. Dr Eric Topol (Director of the STSI) inspired me to do research related patient-centric digital health when we met in San Diego at the inception of this study. I am grateful to Prof. Licia Capra the Transfer Viva examiner and Associate Prof. Shi Zhou the second supervisor, they both provided the guidance and feedback that inspired the final structure of the thesis. Prof. Tomaso Aste always provided support on this academic journey. Associate Prof. Soong Moon Kang's advice was relevant to overcome the hurdles and to search for meaning within the analysis. Dr. Delmiro Fernández Reyes guidance was valuable to present all the results in a coherent structure.

I am very grateful to the collaborative work with Xiaoxi Yan and David Dunne and I look forward to continue doing relevant research with them. I wish them success, patience, clarity, resilience and persistence for the completion of their PhD's.

My appreciation goes to, Dr. John G. Dinsmore and Dr. Denise Gorse for being the examiners of this thesis.

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I would like to acknowledge Tictrac Ltd the industrial partner for providing the engineering capacity and the collaboration for the experiments of this thesis. I am very grateful to all the Tictrac team for their support. Martin Blinder suggested the opportunity for an academic collaboration in a commercial space, Jean Philippe Doumeng made it happen and Mark Donnelly enabled the completion of this project. The cooperation with James Pollock, Ludo Lacay, Oliver McCarthy and Michael Legal was instrumental for building the platforms and running the experiments: our conversations, questions and common trajectory inspired the completion of this investigation.

On a personal level, I appreciate the support from the UCL comrades especially from Adriano Soares Koshiyama, Leslie Kanthan, Pariya Salehi, Tharsis Souza, Bogdan Botrinca, Andy Smith and Peter Divos. A special thank you to the Refineryy team: Rob Stewart, Sam Lessani, Hirsh Pithadia, Afsaneh Mastouri. Also important to mention Sensei Ismail Hasan and all the Aikido friends, you played a key role in practical behaviour change experiments at the dojo and keeping life balance during these years of research.

I dedicate this Phd to my close family whom I love: Ximena my sister, Josefina my mother, Alvaro my father and Dr. Olya Kolchyna my sweetheart and life partner who traversed this academic adventure with me.

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Chapter
1. Introduction

The chapter describes the motivation for the PhD investigation about the identification of critical factors for multi-component technology-enabled interventions for behaviour change related to physical activity and weight loss. The main research objectives are identified, the main contributions are described and the structure of the thesis is presented. The chapter presents a brief overview about the so far unfulfilled promise of wearable devices for increasing physical activity and weight loss and suggests that a behaviour change intervention is required for the effective use of wearables.

1.1 Technology-based Behaviour Change

This research is an experimental investigation about the critical factors of technology-based behaviour change interventions, characterised by simultaneous multiple components that make use of wearables. This thesis challenges the position that wearables devices & apps for self-tracking are good for health outcomes on their own. However we support and consider pivotal the fact that behavioural sciences' literature related to the use of self-monitoring devices has shown that wearables can be effectively used for the improvement of physical activity and weight loss [1-5]. Behaviour Change Science requires mechanisms for cost effective interventions that can scale to improve public health [6], this is why mobile health technology and wearables require evaluation as possible mediums for scalable delivery of behaviour change. The multi-disciplinary work of Spring and collaborators [7-9] about multiple component interventions on behaviour change trials "Make Better Choices" 1 & 2 (respectively MBC1 and MBC2) inspired this PhD and the experimental investigation about the use of wearables for behavioural interventions.

As a result of making research questions about the effective use of wearables for behaviour change interventions [10] the core of the study was defined in the form of experiments that use computational platforms for behaviour change intervention delivery. This work can be categorised as part of a worldwide multi-disciplinary cost-effective approach to reducing the impact of physical inactivity, the world's fourth leading cause of death [11] and the pandemic dynamics of obesity [12].

Wearable devices and apps (*'wearables'*) improve the capacity to record, monitor and report information, but have limited efficacy on their own to change behaviours related to physical activity [5, 13, 14] and weight loss. Up to date (2017) there is only some evidence about the effectiveness of wearable devices and apps for positive sustained health outcomes [4, 9, 15-20].

At the inception of the research, in 2013, the rise of wearable devices [21] implied a promise of substantial improvement in health [22-25] and the use of the data generated for the same purpose. It is still expected [6, 26, 27] that medical and consumer grade wearables will be part of the transformation and re-engineering of health care [28] and health insurance [29] with low cost 24/7 monitoring. A structural approach is required for effective use of wearables enabling health management [30] that goes beyond just making use of self-monitoring devices.

In order to analyse the actual impact of the wearables and their use for behaviour change interventions a collaboration was established with the Tictrac Ltd. as the industrial partner. This collaboration resulted in the design and deployment of platforms that integrate intervention components with data streams generated by self-monitoring devices. The collaboration with the UCL Centre for Behaviour Change was instrumental to design, implement, evaluate and analyse behaviour change interventions that impact wellbeing and health. This research overcomes some limitations of previous studies in method and measurement [17, 18, 31-34]: small sample sizes, the absence of a control group(s), the inclusion of components without sufficient evidence about the components' effectiveness, subjective physical activity reporting.

1.2 Research Motivation

The main motivation for this research was to answer: "*How can behaviour change interventions make use of computational platforms for the effective increase of physical activity and weight loss, and re-contextualise wearable physical activity monitors and the data generated within the intervention?*" The answer to this question required an approach across many disciplines to determine the critical factors of technology-based behaviour change interventions, comprising multiple simultaneous intervention components.

This thesis incorporates multi-disciplinary principles of Behaviour Change Science, Computational Social Science, Digital Health, Complex Systems and Human Computer Interaction, converging into '*Experimental Platform Design*' as a construct for the validation of theory via experimental platforms. The Experimental Research comprises two experiments, each with an independent Data Science approach and a clear Data Strategy, to deliver '*Behavioural Analytics*' (see Figure 1.1).

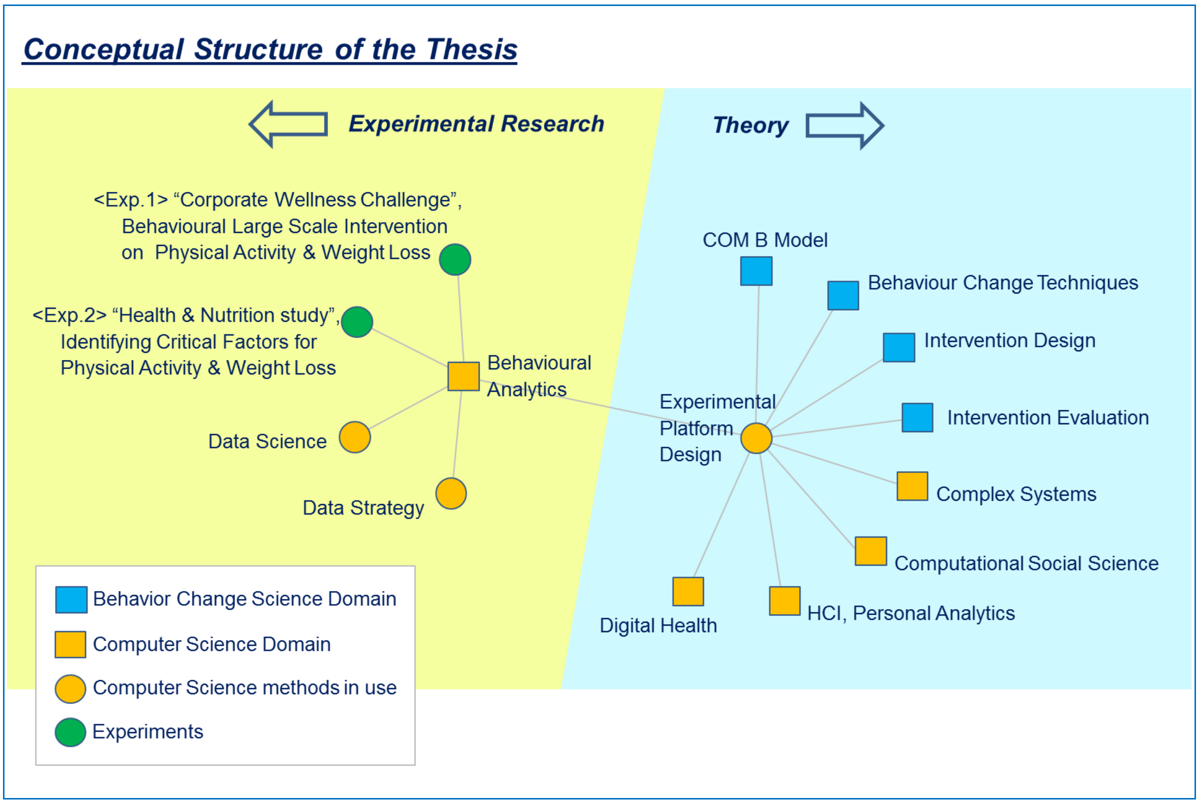

Figure 1.1 ***Conceptual structure of the thesis: science domains, and experimental platforms***

Behaviour Change Science provides the principles and theory for intervention design and evaluation. Although Behaviour Change Science is relatively new as a science, it has a long history across multiple disciplines [35] in which the work around behavioural interventions has been consolidating as a sounder scientific basis [36]. This research should contribute to the development of Behaviour Change Science by validating decades of research with relevant data to substantiate the findings of previous investigations and the refinement of existing theories.

The Experimental Research was defined with an underlying Data Science approach to optimise the cycle that begins with data collection, to modelling and evaluation, resulting in behavioural analytics that quantify and test some of the fundamental questions [17] related to the efficacy of intervention components for physical activity and weight loss.

In order to design and build the computational platforms for conducting the experiments, Computer Science was the domain of reference on specific fields like Complex Systems, Digital Health, Computational Social Science and Human Computer Interaction.

At the core of this PhD thesis (see Figure 1.2) resides the analytical complementarity of methods [37, 38] between: (a) Behavioural Sciences, with classical analysis and (b) Data Science analysis. Classical analysis is characterised for having a hypothesis driven approach that determines the data collection, data analysis and contributes to scientific knowledge. The Data Science analysis has a starting point the data acquisition (capture / access) at the same level as the initial hypothesis and the data mining techniques to be used. This is followed by the refinement of the hypothesis and the development and use of algorithms to contribute to scientific knowledge.

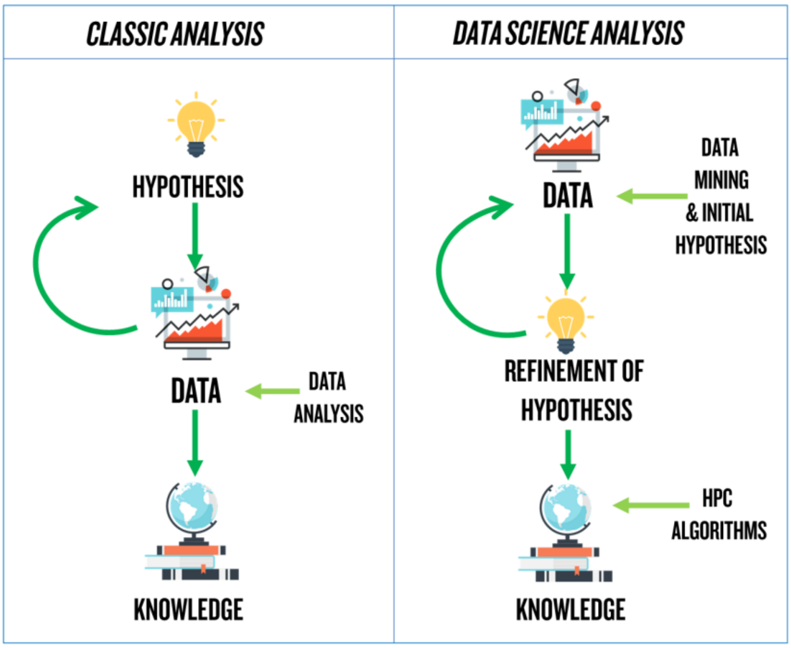

Figure 1.2 ***Analytical complementarity: classic analysis and data science analysis*** [37]

The relevance of this complementary approach for this thesis resides on the efficiency of design expressed as experimental platforms. The analytical combination can overcome complexity and operational constraints of large multi-components behaviour change interventions that require a tech-enabled delivery.

1.3 Research Objectives

This thesis sets out to achieve three main objectives.

1. **Identification of the critical components required for technology-based interventions that target behaviour change related to increasing physical activity and weight loss.**

   A wide range of apps are offered for physical activity and weight loss, although many of these apps have insufficient evidence-informed content [39] and their effective delivery capacity relies mainly on the individual responsibility [40]. There is evidence about the impact of mobile technology interventions on increasing physical activity [41], short-term weight loss [42] and moderate evidence for the medium term weight loss.

Technology based interventions [40] have the potential to reach large number of individuals cost-effectively. The potential of using smartphones (extensible to wearables) for behaviour change interventions has been identified since 2012 [43]. This is relevant for investigators because apps and wearables [44] can be used as effective research tools.

Bundled health behaviours have the potential to maximize the positive impact on public health [7]. There is a positive impact of targeting multiple behaviour changes in diet, activity [8] and weight loss [45, 46]. Multi-component interventions have been evaluated on behaviour change trials MBC1 and MBC2 [7-9] for addressing behaviours of suboptimal diet and inactive lifestyle. The results of the MBC1 inspired the research idea of integrating wearables with other coordinated components for intervention on a platform for research (idea which became this PhD).

The common ground between interventions for physical activity and weight loss determined which components were selected for the interventions of this thesis and the computational platforms that were built. Systematic review identified the most useful strategies for physical activity interventions [32] as: physical activity profiles, goal setting, real-time feedback, social support networking, and online expert consultation. For weight loss the five key components identified are [47]: self-monitoring, counsellor feedback and communication, social support, use of a structured program and use of an individually tailored program. The experiments were the context for evaluation of critical components for technology-based interventions, among those selected based on theory and evidence.

2. **Conduct experimental research on behaviour change, with a validation process using a Data Science workflow to quantify the effect of the intervention components and their interactions. This goal is inclusive of the determination of the effective use of self-tracking devices and apps.**

Change of behavioural intention can derive in behaviour change [48], hence it is possible to conduct experimental research on behaviour change. The interventions were implemented as experiments related to the behavioural impact on physical activity, weight loss and change in diet. The two interventions of this study were designed on the principles described by Michie and collaborators [49-54] providing a methodological background: ‘The Behaviour Change

Wheel' (BCW) with the underlying 'COM-B model' with the 'behaviour change taxonomy' of 'behaviour change techniques' (BCTs) and 'Behaviour Change Interventions Ontology' (BCIO). The intervention design process covered three stages as described in the BCW: 'understanding the behaviour', 'identifying the intervention options' and then 'identifying the content and the implementation options'. The APEASE criterion was used for intervention design, covering: affordability, practicability, effectiveness and cost-effectiveness, acceptability, side-effects / safety and Equity.

Implementation and evaluation were considered simultaneously during the phases of intervention design and implementation. The evaluation provided [52, 54] information about how the outcomes were achieved, which were the mechanisms of action and the impact of the different components of the intervention and their interactions.

A Data Science approach was used as the framework for data capture, data wrangling, exploratory data analysis, feature engineering, hypothesis testing and building models in the quest for the quantitative explanation of behaviour change using analytics. The findings are being divulgated with different media inclusive of this thesis. The Data Science workflows implemented had an industrial standard as described in Figure 1.3 [55].

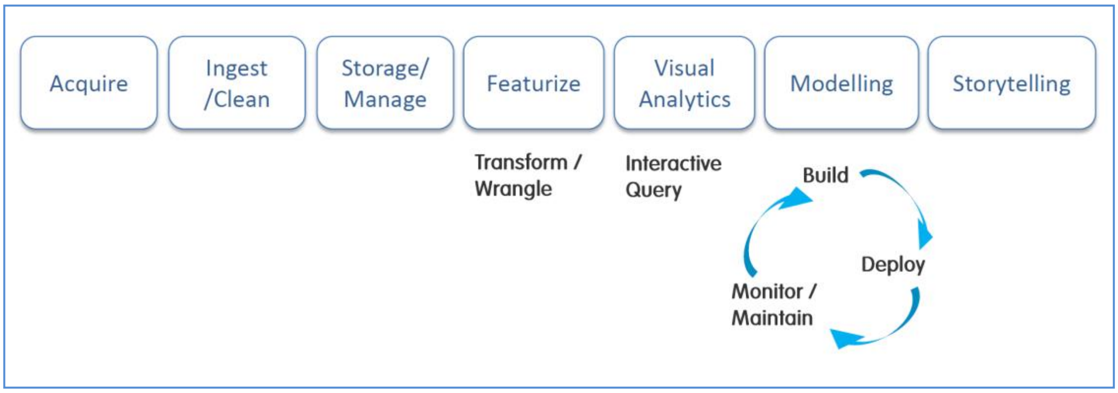

Figure 1.3 ***Data Science Workflow***

3. **Suggest theoretical and practical principles, in the form of frameworks, for the design and implementation of computational platforms for experimental research of large scale.**

The 'Preliminary Work: Capturing Long-Term Behaviours with wearables' (Appendix 1) proved the viability of the research as an ensemble of a Data Science workflow, wearables platform(s) and behaviour change analytics. Additionally, as a result of this work a series of 'suggested requirements' were determined for future interventions. These requirements were tested in Experiment 1 & Experiment 2, then consolidated as a part of this thesis as ‘frameworks’: (1) ‘Data Science approach to behavioural interventions’ and (2) for an ‘Implementation of computational platforms for intervention’. The frameworks are transferable knowledge to facilitate future behaviour change interventions, particularly those of large-scale. The ‘Suggested requirements’ are listed below.

- Incorporate the criteria of Behaviour Change Science for intervention design, implementation and evaluation as part of the computational platform.
- Encode behaviour change techniques in the UX/UI, content and product features for intervention components.
- Plan and design the re-contextualization of wearable devices as part of structured interventions.
- Include a Data Science workflow with an industrial standard with the capacity to ingest, process and wrangle millions of data points.
- Recruitment should target over-subscription of 300% the target sample size, this because the behavioural data generated from wearables has a Zipfian structure.
- Intervention duration (*further research required*):
  - For short term, optimise engagement at 6 weeks
  - For medium term, when using wearables do not extend beyond 5 months
- Define the behavioural analytics that require recording as interaction, engagement, performance, among others metrics.
- Optimise engagement by incorporating best practices for product design, UX / UI.
- Define the technical specifications required for the computational platform inclusive of all the components for intervention.

The absence in literature of any specific ‘framework for a Data Science approach to behavioural interventions’ validates the need for further work on this direction.

1.4 Contributions to Science

This study has scientific contributions and findings related to behaviour change interventions.

Scientific contributions:

- While previous studies have been concentrated on the analysis of single intervention components at a time (coach, action plans, goal setting, social support, food journals, support groups, competition, etc.), very limited research has been done on multi-component interventions delivered as computational platforms. This thesis analyses the impact of simultaneous multiple intervention components (inclusive of re-contextualised wearables) and contributes to literature by determining which components and their interactions are critical factors for physical activity improvement and weight loss.

- The study of large scale interventions is limited in literature, primarily because it requires a budget proportional to the size of the intervention and the alignment of multiple stakeholders to make it happen. This research allows the validation of previous and new findings on large scale interventions related to physical activity and weight loss. It is a contribution by providing evidence about how a 'structured intervention' outperformed a randomised control.

- There is limited literature related to how the underlying social structure behind communication affects an intervention's effectiveness. This thesis contributes by measuring the impact of social ties and communications as network effects on physical activity & weight loss.

- Very limited research has been done on the behavioural profiling with regards to the change potential of participants in an intervention. This thesis contributes with the discovery of the non-linear relationships of weight loss and initial BMI, as well as between weight loss and initial diet habits. These non-linear relationships characterise behavioural profiles of potential for change and improvement related to weight loss. The research contributes as well with the evaluation of personality traits as indicators of the implied probability for changing diet habits and exercise habits.

- This thesis provides the framework for a 'Data Science approach to behavioural interventions' (DSABI) that can be adopted by the stakeholders responsible of delivering and evaluating interventions. This framework enables a data-driven approach designed to be complementary to the theoretical constructs of behaviour change interventions.

Findings about Behaviour Change interventions:

- This study has practical implications for practitioners of Behavioural Change Science, Behavioural Digital Health and Digital Health dedicated to the service delivery: it demonstrated how computational platforms can be used as relevant mediums for behavioural interventions with routines for the effective use of wearables. Following these findings, practitioners might be motivated to design and implement cost effective interventions as digital environments that can scale for public health improvement.

- Revisions of previous studies highlight limitations in: method, measurement, small sample sizes, absence of control group(s), subjective physical activity reporting, and inclusion of components without sufficient evidence about their effectiveness. This thesis fills in the gap by evaluating interventions of large sample sizes, with control groups of larger or similar size. The interventions' components selection was based on sufficient evidence about their effectiveness. Physical activity reporting was done automatically with the integration of wearables to provide measurements directly from sensors. These improvements should give reference points for future experimental researchers.

- This thesis provides a detailed description of a framework for the 'Implementation of computational platforms for intervention' (ICPI). As a framework it encompasses the practical and effective encoding of behaviour change techniques on intervention platforms and the use of routines for effective use of self-tracking/monitoring devices & apps. This framework can be directly adopted by different stakeholders within the industry of digital health products or any other sector that may benefit from embedding interventions as part of technology-based products and the respective designs for efficacious UX/UI.

1.5 Structure of the Thesis

The remainder of this thesis has the following structure:

- Chapter 2 presents background information, discussion of related works and review of the most relevant literature for this study: 1) behaviour change interventions; 2) corporate wellness interventions; 3) caloric deficit; 4) personal informatics in human computer interaction; 5) complex networks in computational social science; 6) current limitations of technology-based interventions for behaviour change; 7) applied statistics: OLS models, factorial design; 8) applied network analysis. A reader might choose to skip this chapter and refer to the literature review or the specific methods when required while reading the different chapters of this thesis.

- Chapter 3 is dedicated to the description of the computational platforms built for the experiments, delivering the intervention components, enabling and capturing participants' interactions, data collection, data consolidation along with data filtering. The 'preliminary work' and the two platforms used for Experiment 1 and Experiment 2 are discussed.

- Chapter 4 aims to achieve the first and second objectives of the thesis by evaluating a large scale multi-component intervention in a corporate wellness setting, Experiment 1. The analysis explores the effectiveness of different intervention components of a "Corporate Wellness Challenge" delivered as a digital environment that integrated a web-app, user interaction on a platform, wearables and a challenge with independent team and individual modalities. The self-motivated targeting of positive behaviour change (related to physical activity and weight loss) and the large scale of the intervention make this experiment unique. The relevant large number of participants on the experiment justifies the search for significance of: being explicit about a type of goal, making part of team (or not) on a competition, among other components discussed in the chapter. The assessment of the experiment includes the comparison of a 'structured intervention' –vs- a control sample of end-users with wearables under no predefined context. The control sample was at least as large as the sample of those in the experiment with wearable devices, validating the role of the 'Challenge effect'.

- Chapter 5 is a continuation of chapter 4, as the analysis of network effects on Experiment 1. Network analysis is used for the measurement of the impact of social interaction on behaviour change related to physical activity and weight loss. The assessment of the results is done by exploring the determinants of social structure of the affiliate/association networks as a product of base characteristics.

- Chapter 6 provides further results related to the first and second objectives of the thesis by identifying the critical factors of intervention present in Experiment 2: The 'Health & Nutrition Study', an intervention for academic research with the approval of the UCL Research Ethics Committee. As a technology-based intervention, simultaneous multiple intervention components (inclusive of re-contextualised wearables) are analysed to determine which of these are effective as interactions or independently. The intervention was inspired with a factorial design to implement multiple simultaneous experiments. Participants were randomly allocated to different digital environments defined as distinct combinations of intervention components. Besides the findings related to most effective bundles of intervention components, unique non-linear relationships where discovered between weight loss and BMI as well as between weight loss and the initial diet habit. As part of the assessment, the chapter comprises as well the evaluation of the probability of change for diet habits and exercise habits using personality traits as indicators, introducing the concept of behavioural profiling for change potential at the individual level.

- Chapter 7 aims to achieve the third objective of the thesis by suggesting two frameworks that can be directly adopted in the future by different stakeholders who might deliver a behavioural intervention on a platform. The frameworks were ideated as a result of the 'preliminary work', tested live for Experiments 1 and 2, and then refined in this chapter. The first framework provides a ‘Data Science approach to behavioural interventions’ that can be adopted for delivering and evaluating interventions, while enabling a complementary approach to the theoretical constructs of behaviour change interventions. The second framework enables the ‘Implementation of computational platforms for intervention’: it encompasses the practical encoding of behaviour change techniques on intervention platforms and the use of routines for effective use of self-tracking/monitoring devices & apps.

- Chapter 8 contains the conclusions of the PhD thesis, makes a critical assessment of the experiments’ results and the frameworks and suggests future work.

- The thesis finishes with the Appendices and a list of references.

Chapter

2. Background & Literature Review

The purpose of this chapter is to introduce the key concepts and methods of behaviour change interventions, corporate wellness interventions, caloric deficit, personal informatics in human computer interaction, complex networks in computational social science, applied statistics (OLS models, factorial design) and applied network analysis. The chapter also presents the current limitations in technology-based interventions for behaviour and the state-of-the-art literature review for each of the topics.

2.1 Behaviour change interventions: related work

A "Behaviour Change Intervention" (BCI) is defined [54, 56] as "*a product, service, activity or structural change, intended to achieve behaviour change. It can be specified in terms of the content of the intervention and the way this is delivered.*" This section covers the principles behind BCI, inclusive of two subsections about 'Intervention design' and 'Intervention Evaluation'.

Behaviour Change Science requires mechanisms for cost effective interventions that can scale to improve public health [6]. The required use technology for this purpose should use principles and theory for intervention design and evaluation, comprising techniques and methods that have a scientific basis in Behaviour Change Science (described in this section).

The effort of consolidating the practice around behaviour change interventions into a science began by defining and agreeing on the terms for describing the techniques used for the interventions [49]. The revision about how interventions work and the study of the mechanisms that lead to changes of behaviour was the pathway to the formulation of an agreement about the 'core components' of interventions. The resulting theory provided as well as guidelines for designing interventions has led to further developments within the theory. The constructive process of this work (2009) [49] refined the nomenclature of techniques, the identification of the theoretical underlying principles and an ontology of terms used.

The COM-B model was proposed for understanding behaviour and designing interventions [50, 51], in which Capability, Opportunity and Motivation are factors underlying a Behaviour (Figure 2.1). Quoting the authors [51] "*Capability is defined as the individual's psychological and physical capacity to engage in the activity concerned. It includes having the necessary knowledge and skills. Motivation is defined as all those brain processes that energize and direct behaviour, not just goals* *and conscious decision-making. It includes habitual processes, emotional responding, as well as analytical decision-making. Opportunity is defined as all the factors that lie outside the individual that make the behaviour possible or prompt it*." The model also described how capability and opportunity have the potential to modify the motivation. Because the output behaviour affects the components of the model in a feedback loop, it is possible to use the COM-B model [50] to design interventions.

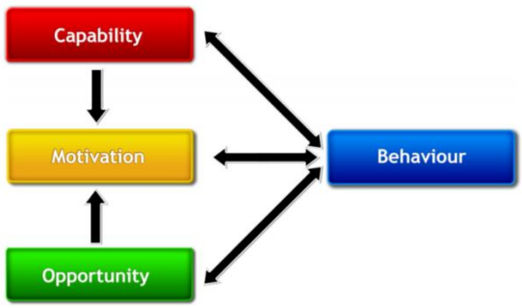

Figure 2.1 ***The COM-B Model*** [50]

A behaviour intervention requires the understanding of the users' perspectives as social and material contexts. When a behaviour change has been conceptually defined, the COM-B is used for the assessment of the underlying 'behaviour system' with intrinsic components that may lead (or not) to the objective 'target behaviour'. In the case of interventions, 'target behaviours' are defined as those key specific desired behaviours to which a behaviour change intervention is aimed at. A target behaviour requires specificity on 'who' needs to do 'what' in which context ('where', 'when', 'how often'). Classical examples in the literature of target behaviours are smoking cessation, medication adherence or complying with norm or policy.

Michie, Stralen and Wood [50] proposed a new framework in 2011 'The behaviour change wheel' as a method for designing and characterising behaviour change interventions (*also presented as a book in 2014* [51]). The behaviour change wheel (BCW) has at the core the 'COM-B' model as a 'behaviour system'. As a result of the synthesis of the 19 frameworks [50] to classify interventions (health, environment, culture change and social marketing) 9 intervention functions and 7 policy categories were further described and consolidated in the BCW. Interventions and policies correspond to the second and third ring of the BCW respectively, (see Figure 2.2).

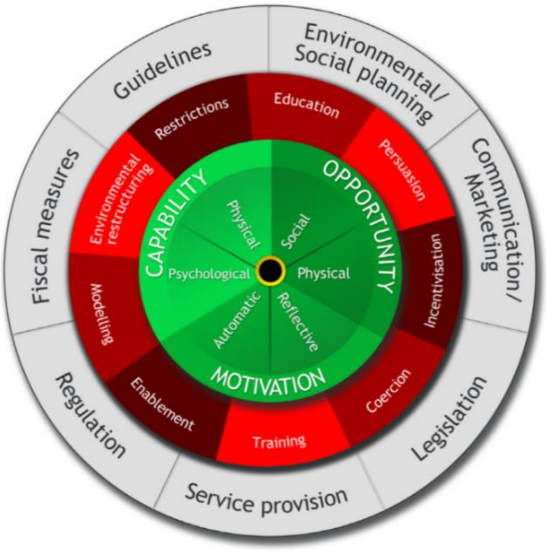

Figure 2.2 ***The Behaviour Change Wheel*** [51]

In 2013 the systematic review presented by Michie and a wide group of collaborators, produced a hierarchical 'Behaviour Change Taxonomy' [53], (*now a common reference in literature*) as a standardized taxonomy set of 'Behaviour Change Techniques' (BCT's) for interventions [49, 53]. The set of BCT's used in this research for Experiments 1 & 2 comprises of the following:

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- Goal setting: outcome & behaviour
- Action planning
- Habit formation, (goal setting)
- Self-monitoring of behaviour
- Feedback and monitoring
- Social Comparison
- Comparison of behaviour
- Review behaviour goal
- Feedback on outcomes
- Monitoring of an outcome
- Valued Self-Identity
- Framing / Reframing
- Information about health consequences

Among the latest developments in Behaviour Change Science field is the Human Behaviour-Change Project (HBCP) [54] which aims to develop and evaluate a BCI Knowledge System, and contribute to the reduction of the current waste in research. The HBCP initiative has as background the Lancet series "Research: increasing value, reducing waste" [57] and the REWARD statement (REduce research Waste And Reward Diligence) and supporting its campaign [58].

The HBCP addresses the need for development of a BCI ontology (BCIO) [54] as means to organise, classify research and generate inferences in which terms, relationships and entities are defined within a common ontological resource enabling the alignment of guiding principles for future work. This work addresses the consolidation of the current knowledge fragmentation of Behaviour Change Science, achieving results similar to those in Gene Ontology for the unification of Biology [59], with an on-going ontology development program [60, 61].

The result of this ontological work will bring more clarity about entities and relationships in BCI's. As described by the authors (Figure 2.3, as a network diagram [54]) the BCIO has so far (2017) two main groups of associations defined around 'BCI evaluation' and 'BCI scenario'.

Group 1, around 'BCI evaluation', comprising:	'BCI evaluation report', 'BCI study', 'Method', 'Effect', 'Risk of bias features'
Group 2, around 'BCI scenario', comprising:	'Outcome (behaviour)', 'Intervention', 'Context', 'Exposure', 'Mechanism of action', 'Outcome (behaviour) value'

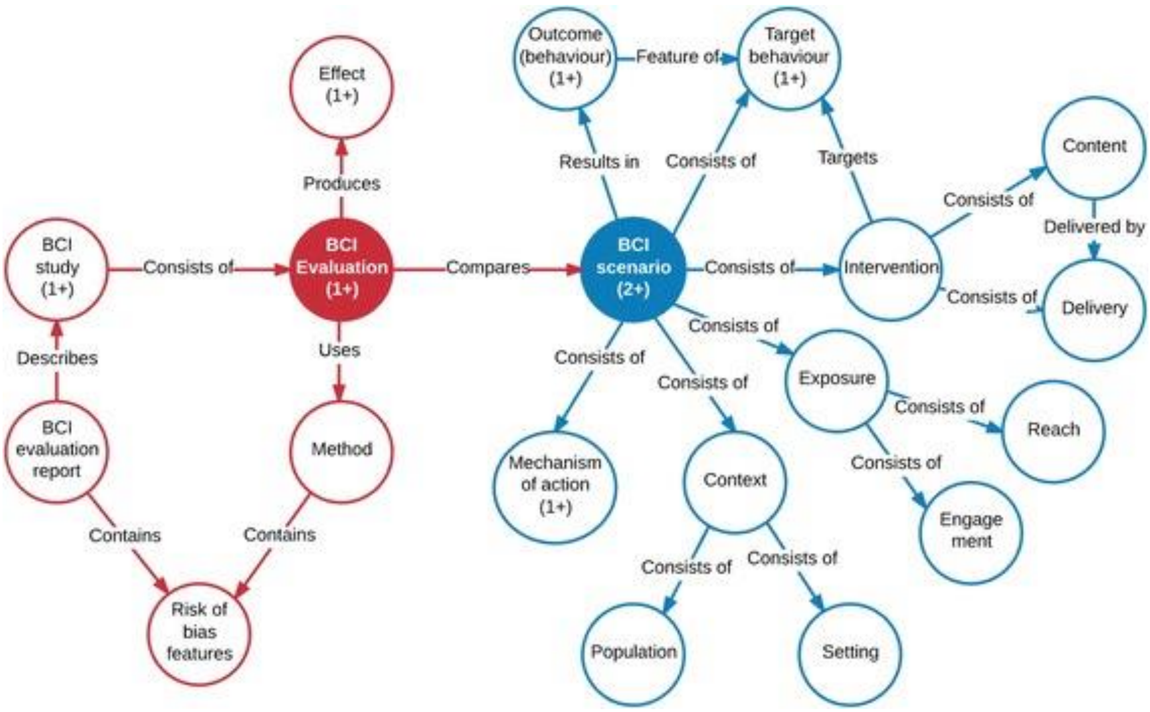


Figure 2.3 ***Human Behaviour-Change Project (HBCP)*** *[54] which "Key upper-level entities and examples of relationships to be captured in the BCIO. (Numbers in brackets refer to the number of entities required if not 1)"*

The inherent causal connections are explicit on Figure 2.4 (same article [54]), in which it can be seen how an outcome is a function of: an intervention for a target behaviour; when behaviour change takes place via certain mechanisms of action, given the intervention brings exposure to a population on an specific context(s) with setting(s). This methodological relationships' structure, as addressed by BCIO, will be used on this PhD thesis.

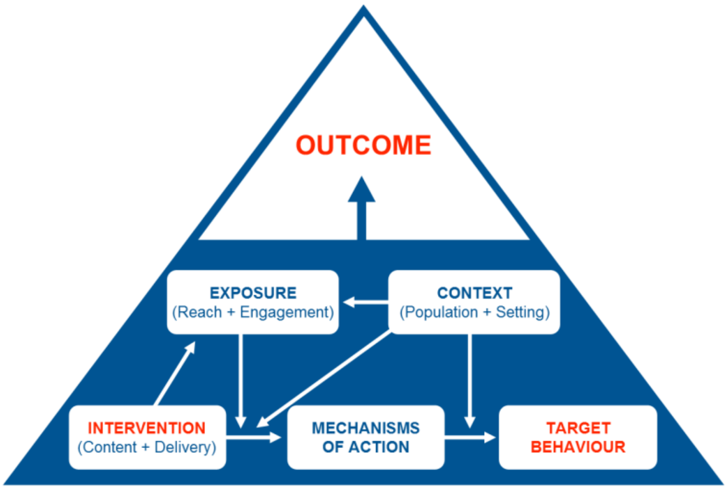


Figure 2.4 ***HBCP*** [54], *"Upper-level entities in BCI scenarios, and their causal connections"*

2.1.1 Intervention design

An intervention should have an emphasis on the autonomous motivation of the receiver of the intervention, with a focus on creating lifestyle compatible habits. By determining the key behavioural issues (from the user point of view) it is possible to define the distinctive intervention features that are required. The intervention design process (BCW [51]) covers three stages: understanding the behaviour, identifying the intervention options and then last identifying the content and the implementation options. The intervention design process is summarized in Table 2.1 below.

Table 2.1 *Three stages of the intervention design process*

Stage 1:	<u>Understand the behaviour</u>	1. Define the problem in behavioural terms 2. Select target behaviour 3. Specify the target behaviour 4. Identify what need to change
Stage 2:	<u>Identify intervention options</u>	Identify: 1. Intervention functions 2. Policy categories
Stage 3:	<u>Identify content and implementation options</u>	Identify: 1. Behaviour change techniques 2. Mode of delivery

The intervention designer will be following a behaviour change intervention design workflow (Figure 2.5) that stages: the likelihood that the behaviour will be implemented, cross spill over to other related behaviours, intervention functions and the combination of BCTs to use in order to 'code' (express the BCT's in the process and medium) in the intervention.

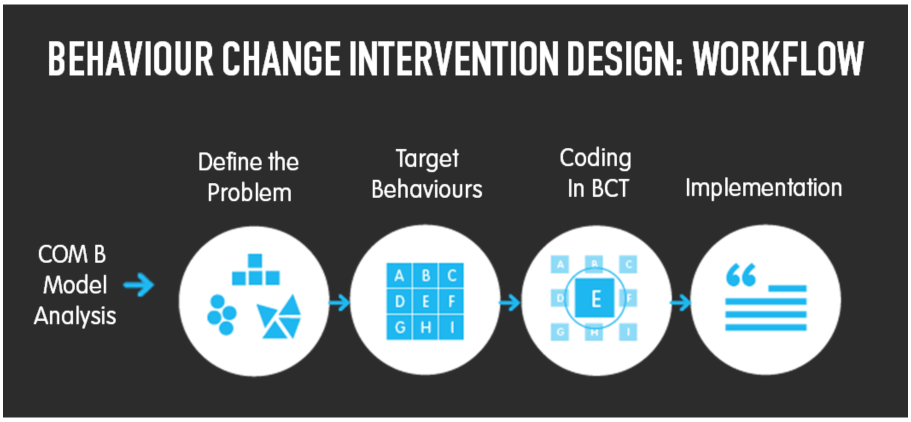


Figure 2.5 ***Behaviour Change Intervention Design: Workflow***

The APEASE criteria [51] enables the implementation. The acronym summarizes fundamental criteria for intervention design viability: Affordability, Practicability, Effectiveness & cost-effectiveness, Acceptability, Side-effects / safety and Equity. The definitions follow:

<u>Affordability</u>:	• An intervention should be delivered within an acceptable budget in order to reach those for whom it would be relevant.
<u>Practicability</u>:	• An intervention is considered practicable if its delivery can be executed using the means fit for purpose for a target population.
<u>Effectiveness & cost-effectiveness</u>:	• Intervention effectiveness refers to the effect impact when measured against the expected objectives in real world scenario. • Cost-effectiveness accounts for a cost-based comparison aiming at the choosing the best option between alternative interventions.
<u>Acceptability</u>:	• The intervention should be considered appropriate by the relevant stakeholders.
<u>Side-effects / safety</u>:	• An intervention should not produce unwanted side-effects or have unintended consequences.
<u>Equity</u>:	• An intervention might have implications for existing disparities reducing or increasing them. In this sense the standard of living, wellbeing, health and other aspects between different sectors of society should be considered.

2.1.2 Intervention evaluation

Interventions require evaluation in order to determine if the resulting outcomes match the purpose for which the intervention was designed. As described by The Medical Research Council's guidance for evaluating complex interventions [52], evaluation provides information about how the outcome was achieved, the nature of the mechanics of the intervention for success and failure and the impact of the different components of the intervention. A "Behaviour Change Intervention Evaluation" is defined

[54] as "*A comparison between two or more BCI scenarios focusing particularly on estimating the differences in outcomes between these scenarios*".

The evaluation design should encompass the coverage of the whole intervention, inclusive of baseline and follow-up periods (within the remit of the research conditions). For this reason during the intervention design stage it is relevant to have a clear understanding of the evaluation methods to be used and their implementation. There are several reasons supporting this, to name three: first, BCTs and their effectiveness measure will be matched to the outcomes; second, the implementation mechanics and monitoring logistics require an evaluation plan in place; third, identifying the evidence base will required.

The methodological background for the intervention evaluation of this research is provided by the COM-B model, the BCW, the BCTs used in the interventions and the BCIO. This background substantiates the form of the experiments by providing the methods of intervention, intervention design and intervention evaluation. Michie's Behaviour Change framework (COM-B model, BCW, BCT's) is used [51, 54] in the evaluation of the behaviour change interventions for:

1. Content identification for the intervention
2. Determining the functions of the BCTs as instrumental part of the intervention
3. Understanding the processes of change and the theoretical foundations of the intervention and the results obtained
4. Assessment of intervention delivery with regards to its original purpose
5. The evaluation of other behaviour change frameworks using the BCW as a benchmark

From the quantitative point of view the state of the art for the evaluation for multicomponent behavioural interventions is using factorial experimental design (also in this section) based on widely used engineering methods for development, optimization and evaluation [62].

2.2 Corporate wellness interventions: related work

Corporate wellness interventions (CWI) and programs are created by employers to promote good health and a healthy workplace culture [63]. It is expected that such programs should result in the reduction of absenteeism, improve productivity, reduce medical claims, support the values and culture at work related to healthy habits, improve employees' health, wellbeing and facilitate the identification of health related problems [64] of the target population. Participation in CWI's are associated with lower absenteeism rates and higher job satisfaction. '*Corporate wellness interventions*' are also denoted as '*corporate wellbeing interventions*', '*corporate wellness*', '*wellness* *interventions*', '*employee health promotion*', '*worksite health promotion programs*', '*organizational wellness program*', among other related terms. The main reference term that will be used on this thesis is '*corporate wellness intervention*' (CWI).

There is very little evidence or conclusive results about the effectiveness of corporate wellness programs for the purpose of employees' health improvement. The systematic review [65] done in 2008 by Berg et al. indicates that across 20 studies it was possible to determine the limitations of the studies and implications for interventions, but it was not possible to demonstrate convincingly the associated health improvements.

There is an explicit need in corporate organizations for the design and analysis of effective corporate wellness interventions for multiple risk factors [66] such as obesity, poor nutrition, physical inactivity, stress, insufficient sleep; in addition [67] to other common risk factors like cigarette smoking and risky drinking of alcoholic beverages. All these risk factors contribute to chronic disease prevalence [67] and also affect employees' wellbeing and work ability.

There are many uncertainties regarding the determinants of participation in worksite health promotion programs [68] and there are open questions about the relevant drivers for retention and engagement, since they affect program effectiveness. It is known that there is more attrition among those participants with unhealthy lifestyles.

The systematic review by Roebrek et al. [69] identified that participation in corporate wellness interventions was higher when an incentive was offered or when the programme had multiple target behaviours and was made of multiple components. Female workers had a higher participation than men, although this difference was not present when the intervention was defined as access to a fitness centre. Typically the participation level was under 50% and further research is required to determine how to increase participation and reach many employees. Health related determinants (obesity, hypertension, cholesterol levels, fitness, health risk levels, etc.), affect participation in different ways without clear patterns. The only statistical significant associations reported, were those related to higher participation among white-collar or those workers with secure or full-time contracts. In contrast, there was lower participation among workers with shift work. Workers who were married/cohabiting displayed a significant higher participation. Demographics like age, education and income had no effect on participation. Not all the studies analysed had information regarding educational level and income, which are important since unhealthy lifestyles are more common on lower socio-economic groups.

Corporate wellness has been permeated by digitized health promotion practices [13, 40] with the promise [22-25] of delivering better results with the use of wearables and computerized interventions [70-72]. It is relevant to determine how it is possible to make effective use of wearables on corporate wellness interventions since they would be cost/effective and entice low cost monitoring 24/7. Experiment 1 as part of this PhD thesis, is an empirical approach to make this happen via a digital environment for a behaviour change intervention (as a CWI targeted at increasing physical activity and weight loss).

2.3 Caloric deficit, weight loss and physical activity: related work

Obesity is developed [73] by a positive energy imbalance ('caloric surplus'). This excess energy leads to weight gain, and in the absence of a structured exercise program, this weight gained is stored as body fat. The inverse dynamic leading to weight loss is a negative energy imbalance ('caloric deficit') which also has a feedback loop as the body displays passive compensatory effects. The feedback loop modulates the effectiveness of many weight loss interventions and is the basis for matching energy intake and energy utilization to optimize results.

To lose weight, [74] 'caloric deficit' should take place in order to reduce the body mass (BM). This negative balance can take place in the body by different combinations of dietary restriction and/or increased energy expenditure. The study by Strasser et al. showed that independent of the method for weight loss, it is the negative energy balance alone the key factor behind weight loss. These authors reviewed a wide range of studies [74] and derived to the conclusion that exercise activity alone can reduce BM slightly (as a result of increasing energy expenditure). However, it is the combination of diet and physical activity training that delivers significant BM reduction (by decreasing energy in and increasing energy out) while improving obesity-associated risk factors. When diet is combined with aerobic training there is the additional benefit of improving physical fitness.

Dietary caloric restriction might not be enough for the maintenance of a body composition [75] with reduced body mass (weight loss), due to a variety of factors. Higher protein intakes (2.3-3.1kg of FFM) during weight loss and maintenance is the most important dietary factor for muscle mass retention in individuals who are following a hypocaloric diet, with resistance training being the most overall important factor [76]. Any lean mass that is lost over time will lower energy expenditure and can negatively impact muscle strength and function. Over time, these losses can contribute to the development of sarcopenia [77]. There are a number of additional advantages to maintaining a higher protein intakes during weight loss and maintenance such as improved satiety, high thermic effect of food (TEF), lower grehlin levels, and improved gluconeogenesis [78]. Outside of increasing physical activity to help protect and maintain muscle mass to reduce age related degenerative disease risk factors, increasing total levels of physical activity to improve absolute levels of fitness can lead to an improvement in health status over time and reduce cardiovascular disease risk factors.

There is an underlying complexity [75] of physiological factors (genetic, hormonal) and societal factors (family, environmental, socio-economic) that should be considered for interventions that encompass behavioural management strategies for diet and physical activity. The sustained change in body mass will depend on the levels of a body composition continuum and the levels of a physical fitness continuum.

Measured on the level of the body composition continuum are the risks of disease associated with the individuals' level of body fat [75]. Risk increases as body fat levels increase and decrease towards the extremes of being severely under fat or severely over fat. The risks are minimised when body fat levels are within a healthy range. Extremes at each end of the continuum are both high risk. Extremely low levels of body fat are associated with nutrient deficiencies, immune suppression, fertility issues, hormonal imbalances and in some instances poor bone health. Extremely high levels of body fat increase risk of diabetes and cardiovascular diseases. On the levels of fitness continuum, the risk of disease decreases as an individual goes from active to highly active and increases as they become more sedentary and inactive.

The 2-years study by Sacks et al. showed that there is benefit to a reduced-calorie diet for weight loss [79] regardless of the macronutrients emphasized by the diet (with reported energy intakes and physical activity that were similar among the different dietary groups analysed), supporting the "calories in, calories out" paradigm. Most of the weight loss occurred in the initial 6 months and all the groups of the study on average regained body weight slowly. A total of 23% of the participants continued to lose weight beyond 6 months up to the 2 years. At the 2 years timepoint, 31-37% had lost at least 5%, 14-15% had lost at least 10%, 2-4% had lost 20kg or more. Attendance to the counselling sessions had a strong association with weight loss, implying that attendance to counselling could be considered a proxy for commitment to achieving weight loss and engagement to the intervention. Continued contact with the participants was also associated with less weight regain post-weight-loss. These findings point to behavioural factors as the main drivers for weight loss, rather than macronutrient metabolism. Also the discussion provides space for considering the benefit of tailoring diets for personal and cultural preferences to increase the possibility of long-term success.

Hall et al. [73] described a framework for the regulation of body weight as "*A fundamental principle of nutrition and metabolism is that body weight change is associated with an imbalance between the* *energy content of food an energy expended by the body to maintain life and perform physical work*". The framework has the underlying balance/imbalance of a biological system described by the energy balance equation ($E_S = E_I - E_O$), which complies with the first law of thermodynamics, (conservation of energy). The terms are defined as: E_S is the rate of change in body, E_I is the chemical energy from the food and fluids consumes and E_O aggregates any work performed in addition to radiant, conductive and convective heat lost.

The balance between intake and utilization will be expressed in body weight which includes body water. Excess energy ('caloric surplus') is stored in different ways [73]: lipids as the largest source of stored energy in the form triglycerides as the major fuel reserve (present in the adipose tissue) and glycogen from carbohydrates in the form of intracellular glycogen in the muscular tissue and the liver.

For the purpose of this PhD Thesis the experimental interventions will have a behavioural approach (as suggested by Hall et al. [73] and with the considerations highlighted by Clark [75]) targeting behaviours related to negative energy imbalance ('caloric deficit') sustained through time, hence possibly enabling body fat reduction. This might be achieved experimentally by combinations of diet restriction and energy expenditure as described in Table 2.2:

Table 2.2 ***Combinations of diet restriction and energy expenditure***

No change on the intake • (*same energy input*)	Increasing exercise • (*increased energy expenditure*)	
Reduction on the intake • (*reduced energy input*)	Maintaining the exercise level • (*same energy expenditure*)	
Reduction on the intake • (*reduced energy input*)	Increasing exercise • (*increased energy expenditure*)	*A combination of both, matching the intake to the exercise demand.*

2.4 Personal informatics in human computer interaction: related work

Human Computer Interaction (HCI) is an interdisciplinary field studying the practical and theoretical challenges of the use of computers by humans. Within this research HCI will be considered from the point of view of '*Personal Informatics*', as background reference for building platforms for interventions like the ones designed and used for Experiments 1 & 2.

'Personal informatics' (PI) was defined in literature by Li et al. (2010) [80] as "*systems (…) that help people collect personally relevant information for the purpose of self-reflection and gaining self-knowledge. There are two core aspects to every personal informatics system: collection and reflection. Effective personal informatics systems help users collect the necessary personal information for insightful reflection. Personal informatics goes by other names, such as "living by* *numbers", "quantified self", "self-*surveillance*", "self-tracking", and "personal analytics"*. Li's definition condenses problems common to different groups (corporate, academic and amateur) involved in the development of self-tracking [81] with electronic and computational means motivated by the growth of wearables into mass markets. The honest comment in the abstract of Li´s article [80] highlights the relevance and broad space for research at the time of publication (2010): "*However, there is no comprehensive list of problems that users experience using these systems, and no guidance for making these systems more effective*". Which explains why personal informatics was first described as a field of research by Li as part of his PhD [82] at Carnegie Mellon University.

Personal informatics comprises core HCI problems studied by many authors [81-106], to name few relevant branches: effects of personal informatics on user's behaviour and daily lives, tools for self-knowledge, analysis of personal records, mechanisms for data collection (manual (active) and automated (passive)), effectiveness of different user interfaces and visualizations (UI), underlying considerations for theoretical models for user's experience (UX), HCI dynamics, technological integrations, among many others.

Wolfram described 'personal analytics' in his blog (2012) [92] making reference to his experience finding meaning in a personal dataset collected for more than 20 years, which contains his own: keystrokes, emails sent and received, phone usage, steps, hours awake, among other personal and behavioural data. Wolfram highlighted [92] how different timelines present in his dataset helped him look back at his own history and self-reflect. To implement personal analytics at large scale Wolfram suggested that it would be required [96]: data science ('*the whole cluster of technologies'*), many sensors, plumbing infrastructure for communicating all the input devices into a repository and access to such data repository for analysis.

The Quantified Self (QS) movement [107, 108] is built using personal informatics systems and as such on the principles of ubicomp by 'self-quantifiers' who are making the effort of understanding themselves through digital profiles that they track and create. The principle of self-tracking is at the core of QS, has populated the HCI research field for the last years [81] and has grown (similar to the PI research) as wearables have been released in the market and smartphones have become a common tool to power self-quantification apps.

Rooksky et al. [98] provide a very rich qualitative and critical approach to personal tracking with relevant findings that have ethnographic relevance ("*open discussion of what people want, do, and experience when using personal trackers*") and display the common self-selection bias present in the use of wearables and self-tracking devices. The authors remind the reader that personal tracking is not new (consider diaries/journals to track and manage activities or for self-reflection). They mention that research in this area has been predominantly focused on individual, research-supplied technologies and there are fundamental questions open about what self-tracking is, quoting them: "*What people decide to track using consumer products, what trackers they decide to use, and how they use them over days, weeks, months and potentially lifetimes remains understudied*".

For the critical assessment of personal informatics, (quoting here references from Rooksky et al. [98]): Simon [109] highlights how problematic it is to assume that people will postpone and calibrate rationally an action until there is a "*newfound understanding*"; which is in contradiction with Li et al's technology-centric-model comprising 5 stages: 1) *Preparation*, 2) *Collection*, 3) *Integration*, 4) *Reflection* and 5) *Action* in which people "*choose what they are going to do with their newfound understanding of themselves*". In direct questioning to this underlying rational assumption, there is also a base to support that rationalisation is rarely achieved: Pollocks et al. history of enterprise systems [110] and Berg's analysis of decision support in healthcare [111].

Rooksky et al. [98] Introduced the concept of *'lived informatics'* characterizing a state of affairs, in contrast to Li's '*personal informatics*'. The contrast is highlighting a radical view indicating that PI should be done over the range of the activities experienced / lived, overcoming the problem of assumed rationalized data collection and subsequent expected rational decision making. Rooksky et al. studied the main use cases of wearables for self-tracking and found interesting characterisations relevant for any future work in or using personal informatics (listed below with additional 'implications' for further work, commented by the author of this PhD thesis *as underlined text*).

- People do not organize activity trackers logically, instead they interweave them. Users might have multiple trackers with the same functionality. Trackers are used crossing invisible boundaries of different irreconcilable personal digital profiles (messaging services, social networks, web applications). *Implies: design for interweaving, beyond integration*.
- Surprisingly, tracking is often collaborative and social and not necessarily personal, especially when used to tell stories about the trackers themselves or for comparison (social currency?), as well as means for documenting life (i.e.: paraphrasing "*how many steps / km/ miles from the station to my parents' house? Although I know the area*") that could have social value as life-stories. *Implies: the reconsideration of tracking as social tracking*.
- There are different styles of tracking: directive tracking (implies goal driven tracking, i.e. to lose or maintain weight or a training program), documentary tracking, diagnostic tracking, collecting rewards (i.e. Vitality health insurance) and 'fetished tracking'. *Implies: the meaning of data has a contextual and motivational component*.

- Self-tracking could switch from documentary tracking to goal tracking seamlessly. *Implies: adaptability for the re-contextualization of meaning in self-tracking*.
- Tracking information is primarily interpreted and used with reference to daily and short term goals and decision making, dealing with current life challenges' prospective, with a notion of "*dwelling*" [112] and "*a praxis of living*" [113]. *Implies: the permeability of design to the nature of every day, in a lifetime experience*.
- Personal Informatics might have limitations if there is an omission of the natural characterisations and use of technology displayed by people in everyday life and to action on their future's outlook. *Implies: understanding as a requirement, of the natural characterisation of personal tracking as a personal experience*.
- Activity trackers are interweaved with an infrastructure, requiring a phone or a web app to make sense of the data. *Implies: understanding the end-user and the access to pertinent infrastructure for increasing the odds (relative probability) of usage and effective use for intervention*.
- Tracking could be related to self-appreciation processes like self-esteem or self-pride achieving milestones like running a marathon, achieving a bicycle speed, raising 'x' amount for charity, etc., reminiscent of technology as an experience [114]. *Implies: an assessment of the unexplored/latent motivation behind self-tracking*.
- There are different types of persons and related motivations: "*a stats person*", "*not a data person at all*", "*into games*", "*not a games person at all*", in which each person in his/her own way appropriated the activity tracking. *Implies: the assessment of motivational signatures to optimize the delivery capacity*.
- There was no clarity about the underlying personality traits, behaviour change took place in different ways, across multiple technologies in use and with different motivational guidelines. *Implies: the need for assessment of personality's traits to adaptively tailor the UX/UI for an optimised delivery capacity*.

Khovanskaya et al. [93] conclude that personal informatics represent applications built on top of the ubicomp infrastructures (data gathering and data mining) that facilitate self-reflection. The authors highlight the need for understanding the wide scope of the data collected for the creation of models that explain human activity. Supporting Khovanskaya et al. [93] and Elsen et al. [81], there is a need to overcome the short-comings of personal informatics that match the unfulfilled promise of wearables on the improvement of health [22-25, 106]. Similarly, Videnova (with her *'(...) Rapid Ethnography'*) [115] and others [95] challenge the status quo of personal informatics suggesting the possibility of other type of relationships between users and personal data, in alignment with Rooksky et al. [98].

These open questions are an invitation to the reformulation of personal informatics systems and the ‘meaning’ and ‘value’ for the recipient end-users.

The literature review done by a team of the UCL Interaction Centre (UCLIC) [100] has identified 3 streams in PI: 1) Psychological stream, need for self-reflection, 2) Phenomenological stream, how self-tracking technologies are being used, 3) Humanistic Stream, a reflective and critical point of view on technology-centric PI. The UCLIC authors suggest future research on PI by exploring the underrepresented social and cultural dimensions, combining methods and sensing techniques and translating knowledge to leverage the design of personal informatics.

To conclude this subsection, Rapp et al. suggested (2016) seven design strategies for PI [102]: *(1) Remind and motivate the act of self-reporting; (2) Give users the power over their data; (3) Leave users free to help each other; (4) Mirror the user; (5) Provide tailored reports, goals and suggestions exploiting narrative forms of presentation; (6) Give the user the opportunity of reliving her/his data; (7) Sustain user motivation in the whole user journey by levering both extrinsic and intrinsic motivations.”*

2.5 Complex networks in computational social science: related work

The study of networks, in the form of mathematical graph theory [116] goes back to Leonhard Euler. Euler provided the first proof of network theory in August 26, 1735 when he presented [117] the paper “*Solutio Problematis ad Geometriam situs Pertinentis*” (‘A problem relating to the geometry of position’) to the Academy of Sciences in St. Petersburg [118] (published in 1741).

Euler´s article referred to the “seven bridges of Könisberg problem”, which required to devise a path to cross the seven bridges of the city once and only once (see 2nd section of Figure 2.6). The bridges over the Pregel river (‘a’,’b’,’c’,’d’,’e’,’f’,’g’) connected islands ‘A’ and ‘D’, with mainland sections ‘C’ and ‘B’. Euler translated the problem into a mathematical structure ‘graph’ with two entity types: “vertex” (node) far any land mass and “edge” (link) for any bridge, (3rd section of Figure 2.6).

Euler proved no solution was possible, regardless of the choice of route and developed analysis techniques ensuring mathematical rigour. If there was 1 bridge less on the initial problem, there would be a solution.

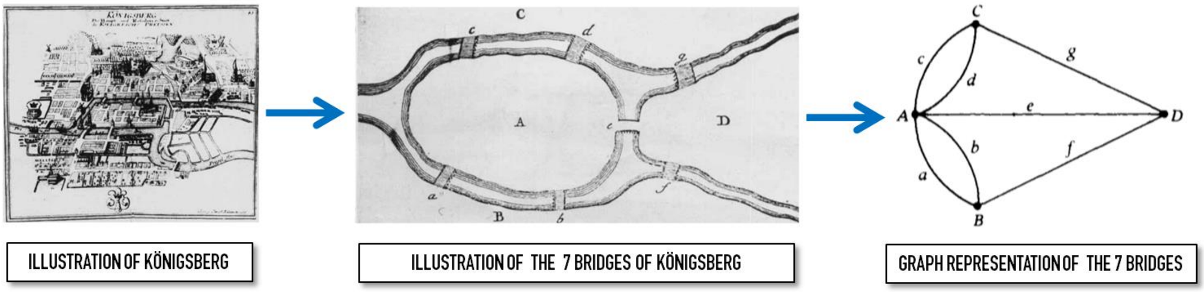
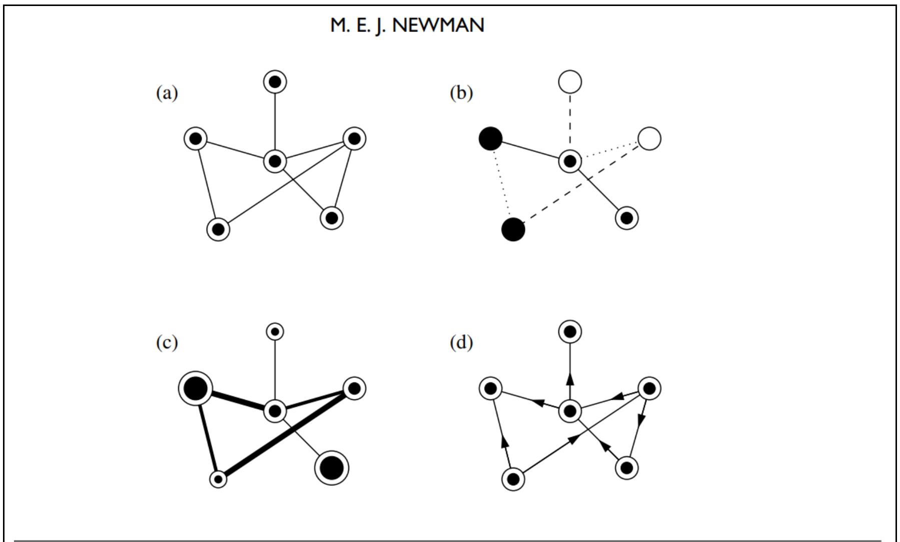


Figure 2.6 ***The first network graph representation by Leonhard Euler*** [117, 118].

In social sciences there has been an extensive study of networks [116]. This because, social networks are the most parsimonious way to analyse social structure i.e. by reconstructing the ties (edges) between individuals (vertexes) to address centrality [119], connectivity and the strength of weak ties [120]. The related background development [121] has as main contributors the sciences of sociology, psychology and anthropology, respectively: Simmel, *patterns of interaction* (dyads, triads) [122]; Moreno, *sociogram* [123]; Lévi-Strauss, *structuralism* [124]; (to name few of the most relevant). The study of social networks has methods and applications for analysis (for reference [125, 126]).

There are different types of networks, to illustrate three types of them see Figure 2.7 with examples of connected graphs from Newman's [116] paper: (a) undirected network, (b) with discrete types of vertices and edges, (c) with different weights for vertices and edges and (d) directed network (digraph) with directions per edge.



Examples of various types of networks: (a) *an undirected network with only a single type of vertex and a single type of edge;* (b) *a network with a number of discrete vertex and edge types;* (c) *a network with varying vertex and edge weights;* (d) *a directed network in which each edge has a direction.*

Figure 2.7 ***Examples of various types of network****, [116] Fig.1.4*

There are more types of graphs, for example those partitioned in natural ways, when disjointed described as *disconnected graphs*. When there are more than two different types of vertices, with edges between the different types defined as *bipartite graphs*. When the graph has groups of common membership they are *affiliation networks*. Graphs that represent change in time (vertices and edges appearing or disappearing) are known as *temporal networks*. Graphs of graphs, defined as *multiplex*.

The reach of complex networks in computational social science is broad [127]. With the development of computational capacity and communication networks, the scale of analysis has grown substantially by enabling data gathering and analysis to create larger scale network graphs, growing in size permanently [116]. It is now common to see studies with millions or billions of nodes. The change of scale required the development of the statistical properties of graphs like path lengths and degree distributions to characterize the structure and behaviour of networked complex systems. The properties of these complex systems are defined in network metrics to characterise each network.

For a broader reference about networks refer to "*Networks: an introduction*" by Newman [128], "*Lectures on complex networks*" by Dorogovtsev [129] and "*Basic Graph Theory*" by Jungnickel [130]. For the purpose of this thesis, the following list of terms (Table 2.3) covers those required for this thesis: *network metrics*, *degree*, *diameter*, *cluster*, *complex networks*, *one-mode projection* and *social network analysis (SNA*).

Table 2.3 ***Some definitions of terms of network analysis***

***Network Metrics*:**	Also known as *graph metrics*, are used to describe the structure of the graph or the relationships between its components or structural form. To name few: *degree, centrality, connectedness, betweenness,* among others.
***Degree*:**	Number of edges connected to a vertex.
***Diameter*:**	Is the length (number of edges) of the longest geodesic path between any two vertices on the network.
***Cluster*:**	Is defined as tightly knit, highly bonded subgroup [131].
***Complex Networks*:**	Are considered in the network theory as networks with a non-trivial structure / topology like those that take place in real systems.
One-Mode projection:	The one-mode projection of a *bipartite network*, with two types of vertices, is a process in which mathematically the network is project on one of the two types of networks, preserving the structure on only one type of nodes.
Social Network Analysis: (SNA)	Uses graph theory to examine and understand the relationships of social nature that encompass, people, group, affiliations, among others. With mathematical, empirical, sociological developments and applications.

Centrality [119, 132] is a fundamental metric of SNA. Different centrality measures can be used to capture the complementary aspects of a node's position in the network [133]. Different "theories" are implied in the use of different measures of centrality: degree, closeness and betweenness. Respectively, each centrality metric can be considered as: activity, independence and control. These sociological implications should be considered for network analysis modelling.

Scale-free networks are defined as those networks with a power-law degree distribution. The relevance of determining the large-scale properties of complex networks resides on the capacity to report the underlying self-organization dynamics. Barábasi et al. [134], showed how large networks self-organize into a scale-free state when growth and preferential attachment (characteristics of real networks) are incorporated to random networks. Power-law distributions have been defined in a broad range of real networks [116], as cited by Newman: network of citations between scientific papers, the internet, metabolic networks, telephone calls graphs, network of human sexual contacts, among others. Other functional forms of degree distributions are exponentials in networks: power grid, railway networks, some collaboration networks, among others with exponential cut-offs.

SNA has enabled the study of distributed leadership in networks, research has shown that decentralization of leadership was not significantly related to superior team performance [135]. Although, comparatively certain kinds of decentralized structures of leadership do support better team performance, given the structural characteristics. SNA has also been used for the identification of different leadership networks. Hoppe et al. proposed in 2010 a leadership network classification framework [131]: 'peer leadership network', 'organizational leadership network', 'field-policy network' and 'collective leadership network'. A leadership network might display one of these single classes' structure or a hybrid structure. New SNA findings could be expected from methodologies to exploit crowd-sourced sensor data, like the work on 'community similarity networks' (CSN) [136], because CSN are effective in presence of population diversity and operate via similarity networks.

Centola's 2010 study on spreading behaviour on-line [137] has relevant findings for health interventions' design. His findings show that individual adoption of health behaviours improved by reinforcing signals originated from clustered social ties. Additionally, the individual-level effect translates into a large-scale diffusion, characterised by faster spreading and broader reach in clustered networks (control consisted of random networks). Highly clustered networks display redundant linkage, which is effective for promoting behaviour diffusion. The redundant ties do not benefit simple contagion (information or disease). The implications of these findings imply that health behaviour intervention (i.e. diet improvement, increasing physical activity, condom use, etc.) may benefit from contextual, redundant proximity that could take place at large work-based networks or in residential networks. Hence contextual linkage should be accounted for, when the behaviours to diffuse are complex (costly, difficult, imply contravention of social norms, etc.).

The visualization of Social networks is non-trivial, especially as complexity scales [138] and information is encoded in different ways. To illustrate with an example, see the network to depict the spread of obesity as an epidemic, as studied in the Framingham Heart Survey social network [139], (*Multimedia resource showing the network evolution, accessible via: http://bit.ly/2lHt9ks*).

Freeman [140] provides a good reference for the visualization of social networks to help investigators understand network data, with guidance about how to communicate information and findings in pictorial images. There are different tools for visualization of network systems, discussing them is beyond the scope of this work. Anyhow, see Ognyanova's resources [141] for creating, manipulating and visualizing network graphs, as a reference for practitioners and non-practitioners of network analysis in R [142, 143].

2.6 Current Limitations in Technology-based Interventions for Behaviour

Currently there is a broad development and use digital behaviour change interventions (DBCIs) for health. There is a need for providing guidelines and recommendations related to the design, evaluation, development and implementation of effective and cost-effective DBCIs for health behaviours. These requirements motivated the international workshop that took place in London September 2015 (condensed in the article authored by Michie et al. [144]). The authors identified that recommendations are required: (1) for identification of the scientific principles that result in effective, safe DBCIs; (2) to support effectively key disciplines, health care professionals, patients and the public; (3) to advance research methods and techniques related to DBCIs and (4) to cover aspects related to regulation, ethics and information governance; There are relevant areas of development of DBCIs, (continuing with the list of items): (5) identification of mechanisms of action; (6) the best practices for the effective implementation of the DBCIs; (7) the use of data science techniques, machine learning, Bayesian statistics (as part of Computer Science and Engineering) and (8) addressing "effective engagement", sufficient to achieve the intended outcomes. There is a great potential for testing and advancing the theories of behaviour change by making use of the data and results of DBCIs. Further benefits will come from evaluations of DBCIs that include all the development cycle and consider tuning the design for generalizability. The adequate use of new implementation designs with rich data streams should benefit future DBCIs and the advance of science. The active role of researchers and intervention designers is crucial for the purpose of the development of future DBCIs, behaviour change theories and the implementation of health related interventions.

Lewis et al. and other authors [17, 18, 31-34] have described the need for overcoming limitations in behaviour interventions related to physical activity (PA) and weight loss (WL). These limitations include, but are not exclusive to: need for large randomized controlled trials, use of terms without common meaning, limited use of evidence-based components, subjective physical reporting, exploration of social networking and the practical application of ground theory. The critical evaluation of intervention studies done by Lewis et al. [17] defined three emerging areas of research for physical activity interventions: "*(1) interventions targeting sedentary behaviour; (2) examining the efficacy of technology-based physical activity interventions; and (3) dissemination of physical activity interventions*". These emerging areas have limitations and require future research (see Table 2.4 summarizing Lewis et al. [17]).

Table 2.4 ***Three emerging areas of research for physical activity by Lewis et.al*** [17], ***their limitations and future research required.***

Emerging Areas	***Limitations of these studies***	***Future studies***
Research has focused on decreasing sedentary behaviour [145] and increasing PA.	"(…) *small sample sizes, a lack of randomization, short-term intervention, lack of racial/ethnic diversity, and subjective measures*"	"(…) *use common terminology, explore optimal replacement behaviors for sedentary behaviors, examine long-term outcomes, include large randomized trials, and consider the lifespan*", and settings different from workplace.
Growing evidence about the efficacy of technology-based PA interventions [32, 43] characterised by innovation related to integration of platforms and devices.	"(…) *measurement and methodological limitations. Large-scale, randomized studies that include long-term follow-up* (…)".	"(…) *include evidence-based components, have consistency in physical activity reporting, explore the use of social networking, examine innovative apps, improve physical activity monitoring, consider the lifespan, and utilize a theoretical framework*".
Few evidence-based PA interventions that have been disseminated with the RE-AIM framework (Reach, Effectiveness, Adoption, Implementation, and Maintenance) [146].	"(…) *Public health impact is dependent on the extent to which efficacious physical activity interventions are disseminated with fidelity into real world settings, maintained, and institutionalized*".	For "(…) *significant public health impact, researchers need to step up their efforts to improve the dissemination of physical activity programs, and consider eventual dissemination in all stages of the research process*".

Dealing with effective weight loss is complex, quoting Poncela-Casasnovas et al. [147] "*It is well established that weight loss increases in proportion to the number of contacts with an interventionist and that reducing the total number of sessions to less than 12 over a six-month period compromises* *the efficacy of weight-loss treatment. Multiple treatment sessions are costly, however, and time-consuming for patients. More scalable, less burdensome treatment modalities are thus needed to reach the enormous population that needs help with weight loss*". For the purpose of increasing the potential for public health it is required to implement technology-based interventions. Gold et al. [148] provided evidence in 2007 about the superior effectiveness of an on-line weight management (OWM) structural behaviour weight loss led by a therapist, when compared to a commercial weight loss application without the same domain expertise behind.

OWM programmes have the potential of facilitating weight loss at low cost [149] although internet support is not close to in-person therapist support for long-term maintenance (of weight loss). For OWM, Krukowski et al. identified [150] that the use of app features related to the 'feedback' factor (progress charts, physiological calculators, journals) is a good predictor for weight loss during the treatment period. While the 'social support' factor (chats, and biographical information) was the best predictor during maintenance.

In 2017, Spring et al. concluded that [151] "*Abbreviated behavioural counselling can produce clinically meaningful weight loss regardless of whether self-monitoring is performed on paper or smartphone, but long-term superiority over standard of care self-guided treatment is challenging to maintain*". The authors analysed three different diabetes prevention programs (DPP) with weight loss as an outcome: (1.) and (2.) combining face-to-face and telephone treatment with two different mediums for self-monitoring (either on smartphone or on paper) and (3.) a self-guided intervention. The self-guided intervention performed worse than the other two DPP. The higher yields using technology or paper support the potential of interventions of this kind, as cheaper solutions than full DPP lifestyle interventions. The findings also confirm similar results indicating that mobile technologies can enhance engagement and self-monitoring in weight loss interventions. Although, it is relevant to mention that the use of self-monitoring technologies does not translate directly into weight loss.

Christakis et al. support the hypothesis of social contagion as the underlying epidemic signature of obesity described by the Framingham Heart Survey social network [139]. The study by Cohen-Cole and Fletcher [152], suggests that the spread of obesity is related to the environment in which individuals live, they do not rule out the person-to-person spread of obesity and indicate that environmental factors can cause the appearance of social network effects. Leahey et al. [153] found evidence that social influences can also be associated with weight loss intentions and BMI in young adults, via social contacts and normative beliefs. In 2015 Poncela-Casasnovas et al. examined the potential of two mechanisms of action in OWM (i) social contagion and (ii) social support [147].

Poncela-Casasnovas et al. where motivated by the limited literature about social contagion for weight loss in contrast to the strong evidence about social support, they hypothesized that (i) weight loss may spread by a contagion process and (ii) social support can be influential via other behaviours non-related to weight change. The findings of Poncela-Casasnovas et al. indicate that there is a significant correlation in their sample between weight loss and: initial BMI, adherence to self-monitoring and social networking. Greater embeddedness within the network was the factor with highest statistical significance for weight loss.

The simulations done by Bahr et al. [154] suggest that individuals tend to cluster on their BMI levels and propose that traditional weigh management fails due to targeting overweight and obese individuals when there are no considerations about the surrounding cluster (the impact of the individual's surrounding social network). Bahr et al. also highlight how long term benefits are higher for 'dieting with friends of friends', than 'dieting with friends'. The underlying result highlights the value of influence, via social forces, on long-term weight management. These findings are aligned with: those of Christakis [139], the evidence found by Leahey et al. [153], the results of Poncela-Casasnovas [147] and the analysis by Cohen-Cole [152].

With regards to the use of self-tracking for health and to mention few researchers, Miyamoto et al. [15] addressed the fact that tracking health data is not enough, although the use of tracking data with a health component, does increase awareness. Bloss et al. [16] indicated that there is some evidence of improvement in health self-management and little evidence of differences in health care costs or utilization as a result of their use. Katrin et al. [4] highlighted that interdisciplinary work is required for long-term engagement and to provide optimal support. Piwek et al. [30] highlighted how consumer health wearables provide promises about health management that require a more structural approach than just making use of the wearables.

There are two main fundamental problems related to using wearables in healthcare [155]: first, the meaningful use of wearables and second, the challenge of adoption. Reifferscheid has been exploring [155, 156] the problem of meaning in wearable devices by addressing how data mining and analytical techniques provide relevant meaning and understanding. Although the 'problem of meaning' is relevant and data mining can provide better understanding of the data and the individual, it is intertwined in non-trivial ways with the problem of long-term adoption [157] that requires an approach that encompasses all the related stakeholders. Reifferscheid exemplifies a relatively naïve approach (common to many authors in literature [1, 158-161]), in which there seems to be a direct translation of business analytics [162] into human behaviour for health, wellbeing and clinical informatics. 'Reifferscheid's type' of analyses have relevance, although they have four limitations as underlying assumptions (discussed before): (1) expected rational decision making (see Rooksky et al. [98]), (2) does not take into account the need for individual responsibility for effective use of wearables [40], (3) is built on the unfulfilled promise of wearables for the improvement of health [22-25, 106] and (4) assumes certain type of relationships between users and personal data (the nature of these assumed relationships is and should be challenged [95, 115] for further studies), that not always address what is relevant, for whom, when and in which format of communication or interaction.

Bort-Roig et al.'s systematic review (2014) [32] about influencing and measuring physical activity (PA) with smartphone technology, highlights how most smartphone strategies tend to be ad hoc and not theory-based. As well they identified different strategies related to the encouragement of PA, among them the most effective are: physical activity profiles, goal setting, real-time feedback, social support networking, and online expert consultation.

Up to date there is only some evidence about the effectiveness of wearable devices and apps for positive sustained health outcomes [4, 15-19]. The systematic review by Schoeppe et al. of interventions that use apps for the improvement of diet, physical activity and reducing sedentary behaviour [18], indicates how apps should gather more usage statistics for the identification of factors related in some way to intervention efficacy. The authors highlight that it is required to optimise the number and combination of app features, behaviour change techniques and ideal contact intensity with participants for the optimisation of intervention efficacy. Measuring should encompass multi-component interventions, delivery modes and using larger sample sizes. Tailoring interventions should target specific groups, take into account socio-demographic and psychosocial factors to help identify the relationship between engagement and intervention efficacy.

To overcome the limitations related to multi-morbidity the work of Dinsmore et al. is a reference for the design of behaviour interventions in which patients have more than one health condition [163, 164] and technology components are used.

2.7 Models & Techniques

This section covers the models and techniques used for explanatory analysis or predicted probability (most of them are explanatory only). The models and techniques are used to evaluate and analyse the behavioural change interventions of: the preliminary work, Experiment 1 and Experiment 2. The chapter comprehends three sections:

1. Ordinary least squares (OLS) models: OLS with interactions, OLS with nested variables, OLS with interactions & nested variables, generalized additive models (GAM) and logistic probability models.

2. Factorial design: an alternative to multiple single factor experiments, produces simple effects of each factor, the interaction effects between factors and the main effects (prevalent at all levels of a factor).

3. Applied network analysis: a description of a bipartite network, followed by a one-mode decomposition to produce the projected network. This section uses the mathematical notion of network analysis.

2.7.1 Ordinary Least Squares (OLS)

The references for this section are covered by statistical text books and papers [165-172] comprising: statistic methods for categorical data analysis, generalized linear models (GLM), generalized additive models (GAM), applied regression analysis, and maximum likelihood estimation of logistic regression. The analysis was done in R [142, 143] libraries [173, 174]. Models fitted using the standard ordinary least squares (OLS) method take the following form for N observations and p dependent variables,

$$y_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \epsilon_i \text{ , } where\ i = 1, \ldots, N, \tag{2.1}$$

In which y_i is the outcome (i.e. change in weight) and x_{ij} is the jth independent variable for the ith user, and β_j is the regression coefficient for each independent variable. The error is assumed to be independent and identically distributed (*i.i.d.*).

The constraint for the model is set at $\sum_j \beta_j = 0$ for each categorical variable such that for binary variables, they are coded as (1,-1). The regression coefficients β_j will give the overall effects (or overall deviations from the outcome) of the variables (i.e. let x_j = sex (female = 1, male= -1), then β_j is the difference of the mean outcome of females from the grand mean, and -β_j is the equivalent difference for males).

The following subsections explain different variations of the OLS. These include addition of special terms such as interaction and nested variables; the general additive model (GAM), which is a generalised form of OLS to accommodate non-linear relationship; and subgroup analysis base on variable of interest and variations of these cases.

OLS with interactions

The *OLS models with interactions* capture the effect of two factors interacting with each other. In these cases, the models are fitted as in eq 1 with the additional terms $\alpha x_{ji} x_{j'i}$, where $j \neq j'$, and α is the interaction coefficient for pairs of dependent variables, $x_{ji} x_{j'i}$.

OLS with subgroups

Further subgroup analysis can also done by fitting independent models to users with different Degree levels. For n_l users of degree level l (l=*Low*,*High*), the following model is fitted.

$$y_{li} = \beta_{0l} + \beta_{1l} x_{1li} + \cdots + \beta_{(p-1)l} x_{(p-1)li} + \epsilon_{li} , i = 1,2, \ldots , N_l , \quad \textbf{(2.2)}$$

where *p-1* are the number of explanatory regressors excluding Degree itself.

OLS with nested variables

The OLS with nested variables, are models fitted using the standard ordinary least squares (OLS) method (eq 1). The following example illustrates the OLS with nested variables.

An example from Experiment 1: A situation in which a nested variable is required is the case of experiment 1 in which for one of the factors (i.e. factor A = Team), there is a nested factor (i.e. factor B = Captain), in which B only occurs as one level of A and there can be no interaction. This nested relationship gives the following model for factor A: $Y_{ijk} = m + a_i + b_{j(k)} + \epsilon_{ijk}$. This equation describes that each data value is a grand mean (the sum of a common value) which is the level effect for Factor A, Factor B's level effect is nested within Factor A, and the residual.

Generalized Additive Models

The weight change model used for the analysis of Experiment 2 is fitted using generalized additive model (GAM) which is a flexible generalization of the standard ordinary least squares (OLS) models. A GAM model replaces the linear form $\beta_j x_{ji}$ by smooth functions $\beta_j f_j(x_{ji})$,

$$y_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_j f_j(x_{ji}) + \beta_p x_{ip} + \epsilon_i , where\ i = 1, \ldots , N \ . \quad \textbf{(2.3)}$$

The non-parametric function can hold an estimator like a thin plate spline smoother. The GAM are suitable for the exploration and understanding of a dataset facilitating the visualization of the relationship between of the dependent and the independent variables, when the latter are non-linear in nature. The analysis was done using GAM [173] models in R [142].

Logistic Regression Models

Logistic regression models were used for the analysis of Experiment 2 to capture the impact the *change in diet habit* and the *change in exercise habit*.

A logistic regression (LR), also known as a logit model is part of the generalised linear models (GLM) in which the dependent variable (outcome) is of categorical form. Categories that have more than two classes are referenced as multinomial or ordinal logistic regression. For the outcomes '*delta diet*' and '*delta exercise*' are dichotomised for the purpose of fitting a LR. In GLM the linear components are mapped to a function of the dependent variable. The LR function is the logit transformation of the outcome's probability. This is also the log-odds of the outcome analysed [172]. The equation is of the form

$$\log\left(\frac{\pi_i}{1-\pi_i}\right)=\sum_{j=0}^{j} x_{ij}\beta_j\,, \quad i = 1,2,\ldots,N; \;\; j = \text{number of independent variables}, \tag{2.4}$$

where π_i represents the probability of the outcome for the *i*-th observation. For the *j*-th variable X_{ij} there is a coefficient β_j. The LR assumption is that the predictor variables X_{ij} have a linear relationship to the log-odds of the outcome. The LR aims to estimate the $j+1$ unknown β parameters. The β parameters are estimated by determining the maximum likelihood estimates (MLEs) of the parameters. The values that optimize the likelihood function are the MLEs values for β. The likelihood function has the form

$$L(\beta \mid y)=\prod_{i=1}^{N}\pi_i^{\,y_i}(1-\pi_i)^{1-y_i} \tag{2.5}$$

where y_i is the outcome of interest (defined as 1 or 0) for the *i*-th observation. The LR has the advantage of a straightforward implementation with highly interpretable results. Additionally, once the LR model has been validated it can be used to estimate the predicted probability of the outcome by solving for π_i.

2.7.2 Factorial Design

Conventional intervention evaluation [175] comprises designing and implementing an intervention that is then evaluated with a randomized confirmatory trial, taking into consideration a single variable or factor that is refined through additional iterations of the evaluation (experiment). The single factor analysis has the limitation of leading very slowly to an optimized intervention process (if it leads in this direction at all). Although randomized confirmatory trials are a golden standard, the further intervention design and evaluation based on the results of single factors analysis might not be randomized and hence might be subject to introducing a bias through the iteration process.

Factorial design is an alternative [176] that consists of a set of multiple single factor experiments and produces as a result the simple effects of each factor, the interaction effects between factors and the main effects (prevalent at all levels of a factor). Therefore factorial design produces three types of information that make it more efficient than conventional experimental designs. Factorial design is relevant for behavioural interventions evaluation as a method that can analytically combine the different components of the intervention program and the delivery of the program (as a component(s)). Randomized confirmatory trials do not allow the isolation of the program component and delivery mechanisms; therefore there is a case for using an approach from the family of factorial design.

For factorial design each factor has discrete values or levels. A full factorial design takes into considerations all the combinations of the levels for each factor. An experimental run includes all the possible combinations. Each one of these combinations is considered a 'condition'. For the randomised confirmatory trials these combinations are denoted 'treatments'. As an example consider a factorial design experiment that has 3 variables / factors, each one with 2 levels, in this case the experiment would have 8 conditions / treatments ($2 \times 2 \times 2$ or 2^3), including all the combinations for all the factors.

Factorial design is of great value for randomized confirmatory trials (RCT) in which different interventions and their inherent treatments require study and analysis. The power of factorial design for RCT resides in the fact that in a single experiment it is possible to achieve the same result as conducting 'n' experiments for 'n' interventions. Factorial design is efficient from the resource point of view and the requirement of a smaller number of subjects when compared to those required by 'n' traditional experiments.

The complexity of analysing and implementing all the conditions might be a limitation to factorial experimental design. Because all the conditions a full factorial design might not be required or it might not be reasonable to implement, it is possible to choose strategically a subset of the conditions

[175] in order to study and estimate the effects of some of the conditions by taking into account some assumptions of the investigator. When a factorial design uses a subset of the conditions it considered as a 'fractional factorial design', and they have been used extensively in engineering and agriculture. The reduced design can still provide the main effects for the independent variables providing a interesting characteristic for research and analysis.

In this research, Experiment 2 is an attempt of factorial experimental design for evaluating the behavioural change interventions as quantitative processes that are the state of the art of Behaviour Change Science [175].

2.7.3 Applied Network Analysis

The description of the one-mode decomposition for a bipartite network will illustrate how applied network analysis can be done for SNA. This section uses mathematical notation to describe networks and the one-mode decomposition of a bipartite network. (*Read this subsection in conjunction with '2.5 Complex networks in computational social science: related work'*).

For practical references about bipartite networks and their decomposition see Shizuka's lab notes [177] and Ognyanova's resources [141]. Network analysis can be done with different software packages and tools, the analysis and graph representations for this thesis were done in Python [178] with NetworkX [141] and R [142, 143] using IGraph [179].

A Bipartite Network used for Social Network Analysis

A bipartite network was created from the communication interactions between participants on Experiment 1's platform. The interaction dynamics captured consisted of participants making postings on digital boards. The digital boards had been assigned to teams or to participants strictly (if a participant was part of a team he/she would not have an individual board).

For the creation of the bipartite network two types of vertices were defined: '*participant vertices*' and '*digital board vertices*'. The edges came about from the links made between a participant and a board via postings. The edges' weight was defined as the number of postings made on each link. The resulting bipartite network created ('*Bipartite Network*' in Figure 2.8) represents the dynamics of communications.

The bipartite network was then transformed via one-mode decomposition by projecting a network of two types of vertices (*participants, boards*) into a '*projected network*' which only has one type of vertices (*participants*) on the projected network graph ('*Projected Network*' in Figure 2.8). The majority of postings were made by participants on their own digital boards, which implies that after the one-mode transformation they appeared as disconnected vertices.

The disconnected single nodes of participants were filtered out from the projected network to produce the final '*affiliation network*' graph ('*Filtered: Affiliation Network*' in Figure 2.8). The affiliation network has as a result only those participants who interacted in some collective form with 2 or more people, revealing the inherent social structure of those who communicated between each other. The baseline characteristics of each individual are assigned to the nodes and preserved for further analysis. The process is now described step by step using mathematical notation.

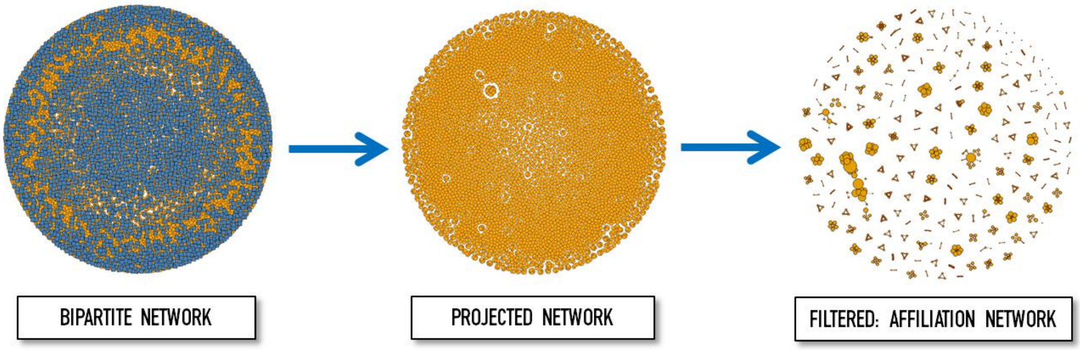


Figure 2.8 ***From a bipartite network to an affiliation network, via a one-mode decomposition***

Creating the bipartite network, product of participants' postings into walls:

1. ***There are two types of nodes***:

   Type 1, a wall $W_{i,j}$:

   Nodes Type 1 have i as the *type of wall* is and where j is the *type of id*. There are two *types of walls*: team wall ('*Tw*') or individual wall ('*Iw*'). In addition, to two *types of id*: team id ('*tid*') or individual id ('*iid*').

$$i = \in \{Tw, Iw\} \quad \textbf{(2.6)}$$
$$j = \in \{tid, iid\}$$

   When the wall is owned by a team '*R*' ('*R*' is the unique *team id*), the wall is denoted $W_{Tw,R}$. When the wall owner is an individual '*u*' ('*u*' is the unique *user id*), the wall is denoted: $W_{Iw,u}$.

   Type 2, a participant $P_{x,y}$:

   Nodes Type 2 have x as the *type of participant* (if a participant is part of a team or not) and y is the *user id*. Two *types of participants*: team member ('*Tm*') and individual participant ('*I*').

$$x = \in \{Tm, I\} \qquad \textbf{(2.7)}$$

When a participant is part of a team 'R' with a unique user id 'u', the participant is denoted $P_{R,u}$. If she/he participates as an individual with a unique user id 'u', the notation for the participant is $P_{I,u}$.

2. ***The links*** (undirected): Between an individual and a wall, created when a participant $P_{x,y}$, makes a post on a wall $W_{i,j}$, defined by an edge ($P_{x,y}$, $W_{i,j}$).

Obtaining the Projected Network, results of one-mode decomposition on the Type 2 nodes:

1. ***Nodes***: For any participant P_y in which y is the *user id*, the node will be denoted as P_u for a participant with a unique user id u. The information about P_u ('team member of…', 'individual participant', etc.) is assigned as a data descriptor to node P_u.

2. ***Links***: Every link is the implicit connection between any 2 participants (P_A, …, P_B) because at least one of the following is true.
   - Both participants (P_A and P_B) made a post on the same wall (W_l), which is part of the bipartite network.
   - The participants P_A posted on the wall W_B of the other participant P_B, or vice-versa P_B posted on the wall W_A. (Walls are either individual or team walls).

   As a result P_A and P_B will be connected by the edge (P_A, P_B).

3. ***Weight***: The weight of every link will be the sum of all the postings made to a wall or walls that connect directly P_A and P_B. This will be the weight w of the edge (P_A, P_B).

Obtaining the Filtered Affiliation Network, results from filtering the projected network:

1. ***Filtering***: All those nodes P_u in which the largest path has a distance ≥ 2 are preserved to create the *filtered affiliation network*. As a result, only the nodes that are connected to more than one node remain in the final network graph, as part of an *affiliation group* with a social structure of at least three people.

Chapter

3. Computational Platforms for Intervention

This chapter covers: the description of computational platforms for intervention built for this investigation, a review of the preliminary work for capturing behaviours of runners, the blueprint of a CPI, an overview of the 1st and 2nd platforms built. These two platforms were used for Experiment 1 and Experiment 2.

This research for more effective technology-based interventions required the design, built, development and implementation of computational platforms for interventions. The platforms were designed following a clear behaviour change intervention design. The ideation process comprised as well: intervention evaluation, product viability, data strategy, data analysis plan, communication & recruitment plans and project management involving all the required partners. As it will be explained on this chapter, it was instrumental for the investigation to design and build platforms, since they enabled running the interventions and the subsequent data analysis, far beyond the point of platforms' decommission.

3.1 Description of a computational platform for intervention

The blueprint for computational platforms for intervention (CPI) was a necessary bi-product of the preliminary work (see Appendix 1) in which a hybrid solution was used combining modules of different parties. It was determined on this preliminary work that a CPI should incorporate: (1) the applied principles of Behaviour Change Science for the design, development and deployment, (2) a Data Science workflow with an industrial standard with the capacity to ingest, process and wrangle millions of data points and (3) principles of product management, since engagement affects the data generation, therefore the best practices for product design, UX / UI are required.

3.1.1 Preliminary work: capturing behaviours of runners

The hybrid solution for the 'preliminary work' (Appendix 1) was limited as it was not designed for the specific purpose of behavioural interventions and produced a relative small amount of data given the high potential of data streams from wearable devices. As a global experiment aiming to capture, model and explain the behavioural change on the cohorts of experimental subjects ('runners') present on the experiment, the platform had to capture and consolidate data streams of wearables and required front-end for UX/UI.

The wearables data aggregation and automated data mining layer of the platform was built by Tictrac (the industrial partner of this research) as a back-end development with some automated data mining services delivered via API. The overlaying front-end app UX / UI was designed and built by another technological provider.

The analysis of the preliminary work and user testing was relevant to measure the variance between devices tracking the same activity (or measurement), reported as well by Lee et al. [180]. This analysis enabled the identification of routines that make effective use of tracking devices and apps for target behaviours (ie. steps count and weight measurement). As a result, if was decided to aggregate self-tracking data on a daily basis and present it as weekly averages; this to standardise the data formats coming from multiple devices.

The use of the CPI for the preliminary work was fundamental to calibrate the analysis requirements for future experiments, define a data strategy beforehand, create a framework for the implementation of a CPI and the determination of a data science approach for behavioural interventions.

3.1.2 Blueprint for a computational platform for intervention

A blueprint for a 'computational platform for intervention' was defined for future experiments, see Figure 3.1. It was determined that from the structural point of view, the CPI should have a single sign-off and integrate: back-end, front-end functionalities, automated data-mining capacity, analytics and data pipes enabling data analysis. As well a product management directive should govern the UX/UI. The platform has the capacity to integrate wearables data via API's. The self-tracking wearables (with yellow background) are produced digital traces of the physical world, where a user actually runs in the park with the sun above her/his head while a ubicomp mechanism records the distance, number of steps and average speed.

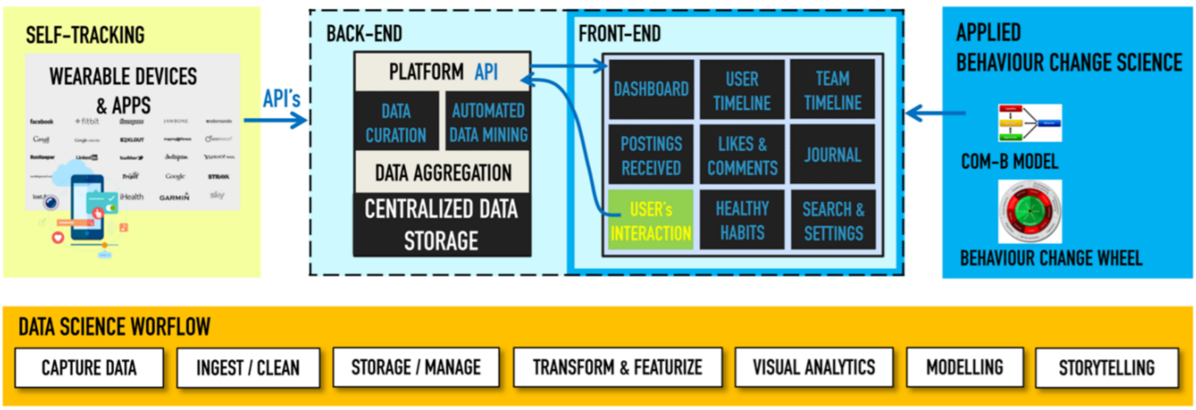


Figure 3.1 ***Blueprint for a computational platform for intervention***

In this blueprint CPI, the data is pushed from the wearables via API's into the platform, curated and stored on a centralized data repository. The data of the 'running event' is then pushed/ or called from the back-end to the front-end where the user sees her/his information on a dashboard, using the output of an automated data mining process. In this UX-UI interface the users have the capacity to interact with other platform members.

3.2 1st Platform: large scale intervention in a corporate wellness setting

Experiment 1 was a large scale intervention in a corporate wellness setting in the form of a 'Corporate Challenge' with an interactive platform designed with the CPI blueprint (Figure 3.1). The behaviour change intervention was delivered via a CPI consolidating the Corporate Challenge UX/UI and self-tracking data streams on personal dashboards (Figure 3.2). The front-end was functional across smartphones and multiple web browsers. The back-end had a dedicated infrastructure stack and connected all the data streams of different wearables via API, besides capturing platform interactions via analytics. The platform had three functional structures in place: (1) an on-boarding process, (2) the services provided and (3) the data pipes for data analysis.

<u>On-boarding</u>:

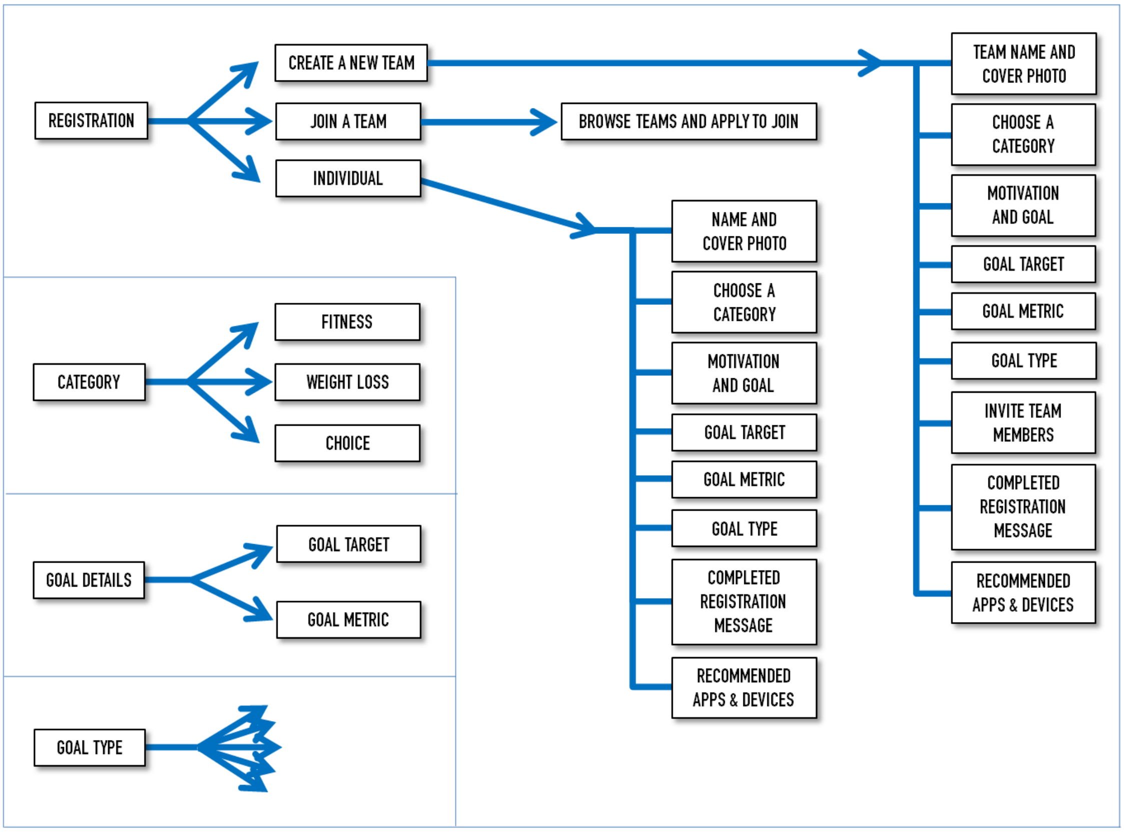


Figure 3.2 ***Experiment 1, On-boarding UX / UI: the user's journey for registration***

The on-boarding process was open during the 2 weeks of the registration period (see Figure 4.1) and was a key piece of the platform's UX / UI because it had an impact on engagement as the first interaction with the platform. The engagement was required to for the 4.5 months of intervention. On this user's journey the participants were exposed for the first time to behaviour change techniques related to 'Goals & Planning'. The on-boarding process was fulfilling the job of assisting the participants in the determination of which challenge competition they would be participating: as a team / individual on any of the three categories (Fitness, Weight Loss, Choice). Figure 3.2 describes the on-boarding navigation for a participant completing the registration.

<u>Services provided</u>:

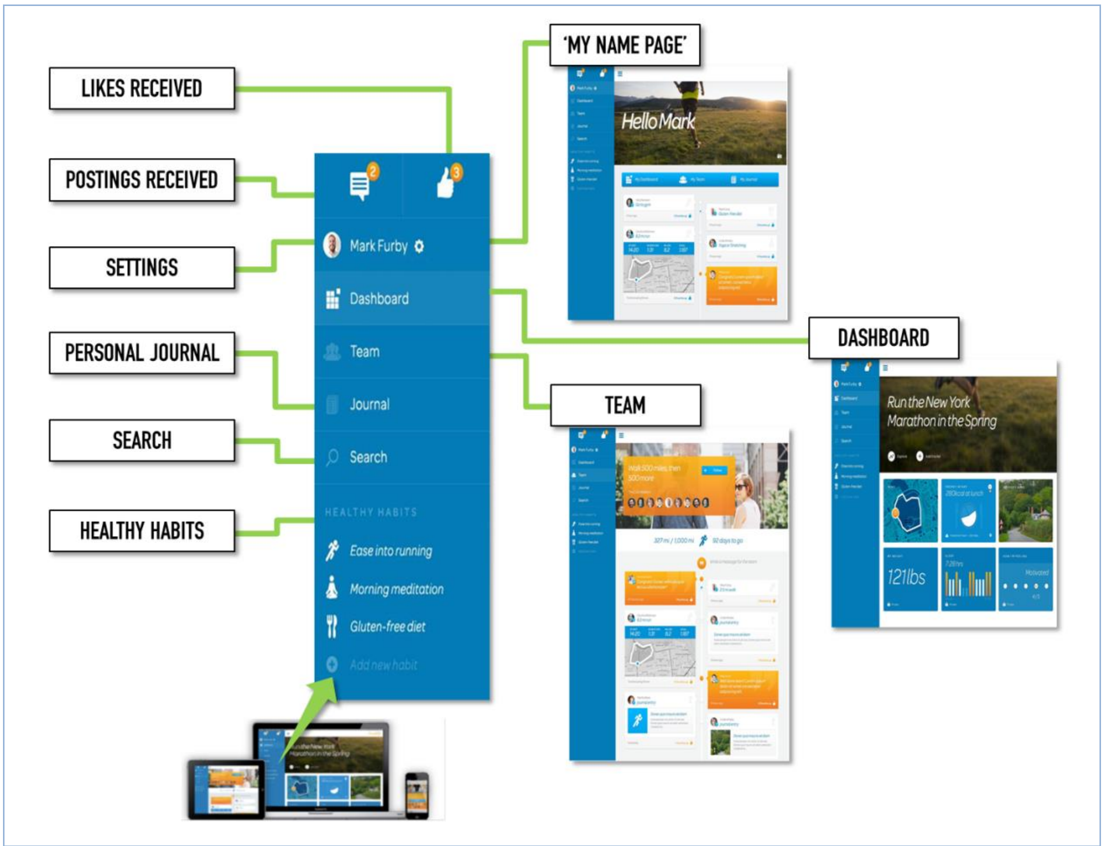


Figure 3.3 ***Experiment 1: Services provided UX / UI, the platform's experience, the menu bar***

The participants were introduced to the services and mechanics of the platform once the on-boarding process was completed. The services offered by the platform for each participant (Figure 3.3) where accessible from the menu of the front-end application and covered the following:

- ***Personal timeline 'My Name page'***: timeline events and communications of the participant
- ***Dashboard***: with all the aggregated data from the wearable devices synced
- ***Team timeline***: contains all the interactions of a the team of the participant
- ***Postings received***: the messages received on the 'digital wall' of the team or individual

- ***Likes received***: collection of the ‘thumbs up’ received
- ***Personal journal***: a place to record thoughts or insights on the intervention’s journey
- ***Search***: a useful tool to find someone or something
- ***Healthy habits***: habits the participant is working on
- ***Settings***: There is always a default setting to amend

The ‘postings received’ were published on ‘personal electronic wall’, which was a social interaction mechanism. The participants also had the capacity to post on other users’ or teams’ walls. The platform also provided automatic notifications to comply with the communication plan required for the intermediate stages and to follow other people or teams.

3.3 2nd Platform: identifying critical factors for an intervention on weight loss

The ‘Health & Nutrition’ study was an intervention experiment with an academic research focus packaged in a CPI with a web app interface consolidating lessons from the previous experimental platforms. This platform used the CPI blueprint, had connection capacity for self-tracking wearables, and an independent infrastructure stack. The Health & Nutrition intervention’s platform was built for the specific purpose of this research project and combined the skeleton of an old product design from Tictrac (the industrial partner) with additional features required for the study.

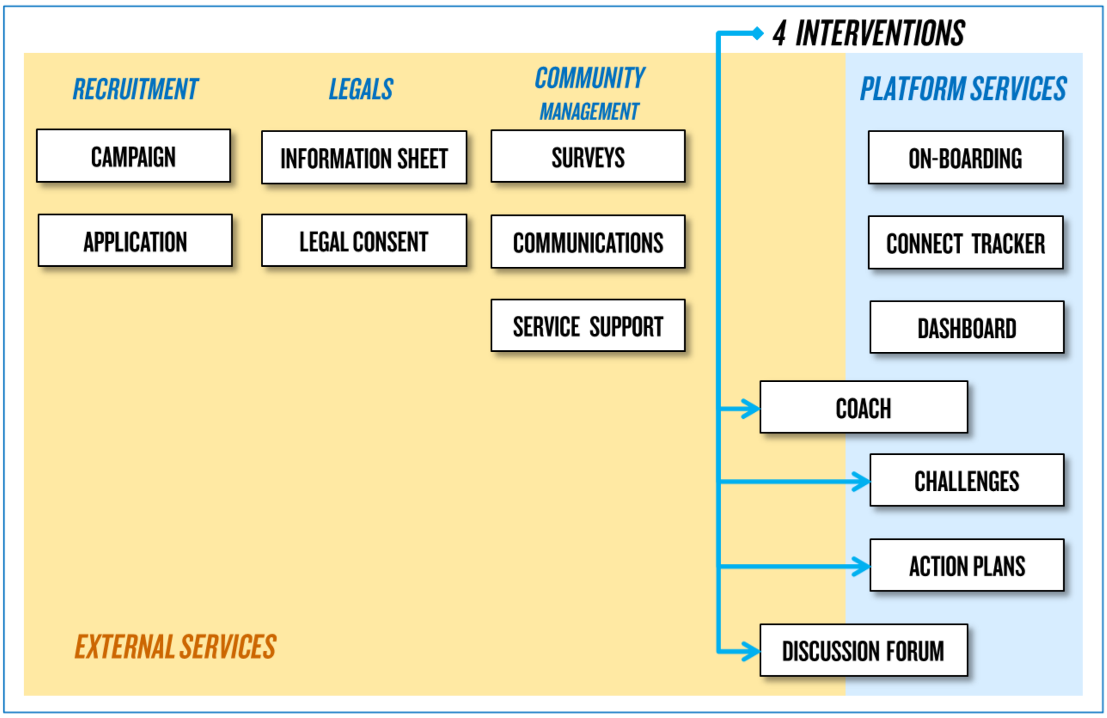


Figure 3.4 ***Experiment 2: functional components & platform stack***

For Experiment 2, five fundamental functional components had to be in place: *recruitment, legals*, *community management*, *four interventions* and the *platform services*. Figure 3.4 represents these functional components on the left side of the diagram. Some of these functional components required independent workflows due to the time and budget constraints. The 'platform services' (on the sky blue background), were implemented on an independent CPI stack. The services that had to take place out of the platform completely or partially are the 'external services' (over the ochre background). The data collection outcome from the external services was integrated manually to the database of the platform stack.

All the functional components ceased their operation once the intervention was completed, with the exception of the centralized data storage and data aggregation that was kept as an archive and used for data analysis. The five functional components of the Health & Nutrition study's platform are described below.

1. Recruitment:

With the notification of ethical approval from the UCL Research Ethics Committee a digital campaign was launched by the intervention team via multiple channels and external services to reach out.

2. Legals:

As continuation of the recruitment process, it was required to expose the eligible individuals to the 'Information Sheet' and then process the signature of the 'Legal consent' for each participant.

3. Community Management:

The interaction with more than 400 participants required a community management process for engaging with the participants (surveys, announcement of key dates and service support).

4. Four Interventions:

The 'Health & Nutrition' study used four interventions for behaviour change: *coach*, *challenges*, *action plans* and *discussion forum*. With the objective of integrating the four interventions within the platform stack services', the UX / UI was patched to reduce the friction produced by external services.

- The *coach* intervention required the use of an external booking system to make coaching appointments and the use of google forms to record the coaching sessions.
- The *challenges* and the *action plan* where provided as existing product features of the platform stack and adjusted as required.
- The *discussion forum* used a third party plug-in as a hybrid implementation.

The four interventions were deployed using a factorial design (Figure 3.5) aiming at balanced combinations of the interventions to recycle the control groups among the population of the study. The factorial design required a process for random allocation of the participants into the different combinations of interventions and the corresponding UX/UI.

	Combination Name	16 combinations								Size
1	1	AP_TT	+	Team	+	Coach	+	Forum		28
2	2	AP_TT	+	Team	+	Coach	+			25
3	3	AP_TT	+	Team	+		+	Forum		27
4	4	AP_TT	+	Team	+		+			23
5	5	AP_TT	+	Individual	+	Coach	+	Forum		27
6	6	AP_TT	+	Individual	+	Coach	+			27
7	7	AP_TT	+	Individual	+		+	Forum		27
8	8	AP_TT	+	Individual	+		+			29
9	13	Expert	+	Team	+	Coach	+	Forum		29
10	14	Expert	+	Team	+	Coach	+			27
11	15	Expert	+	Team	+		+	Forum		27
12	16	Expert	+	Team	+		+			26
13	17	Expert	+	Individual	+	Coach	+	Forum		34
14	18	Expert	+	Individual	+	Coach	+			25
15	19	Expert	+	Individual	+		+	Forum		26
16	20	Expert	+	Individual	+		+			25
Total		AP_TT	213	Team	212	Coach	222	Forum	225	432
		Expert	219	Individual	220		210		207	

Figure 3.5 ***Experiment 2: factorial design: the 16 combinations of four*** *interventions (coach, challenge type, action plan, forum)*

<u>5. Platform Services</u>:

The platform services consolidated a product design skeleton with the 2 add-ins for the coach and forum. The menu was the UX/UI axis for the front-end consolidation of services (Figure 3.6). The on-line services offered on the platform are explained below:

- ***Timeline***: personal timeline with self-tracking records, partial results of the walking challenge, facts and tips generated by the platform, among other information cards.
- ***Trackers***: section dedicated to connecting and managing self-tracking data streams generated by wearables and apps.
- ***Coach***: Those participants who had access to coaching sessions (up to 3 sessions per participant) had to book their appointments through the booking system via an external link.
- ***Action Plans***: two types of action plans were offered for the participants. Some participants had access to an action plan designed by a professional performance nutritionist ('Expert's tips'). The other participants had access to 2 action plans designed by Tictrac's team ('Lose Weight', 'Healthy Eating').

- ***Challenges***: With a connected wearable for steps count, the users had access to participate on a 'Walking Challenge'. The random allocation assigned them either to a 'team challenge' or to an 'individual challenge'.

- ***Forum***: The discussion forum was offered to some participants only and it was curated by the performance nutritionist regularly (6 of 7 days a week).

- ***Dashboard***: The dashboard consolidated all the visual analytics of the data collected via self-tracking wearables and apps under one roof.

- ***People***: This product feature facilitated finding other people in the study's platform.

- ***Information Sheet***: A link with access to the description of the study.

- ***Instructions manual** & **Connect your tracker***: webpages to facilitate the understanding of the intervention and the product features.

- ***On-boarding***: The process on the platform of giving access to a participant. There was an invitation process and an on-boarding interactive sequence.

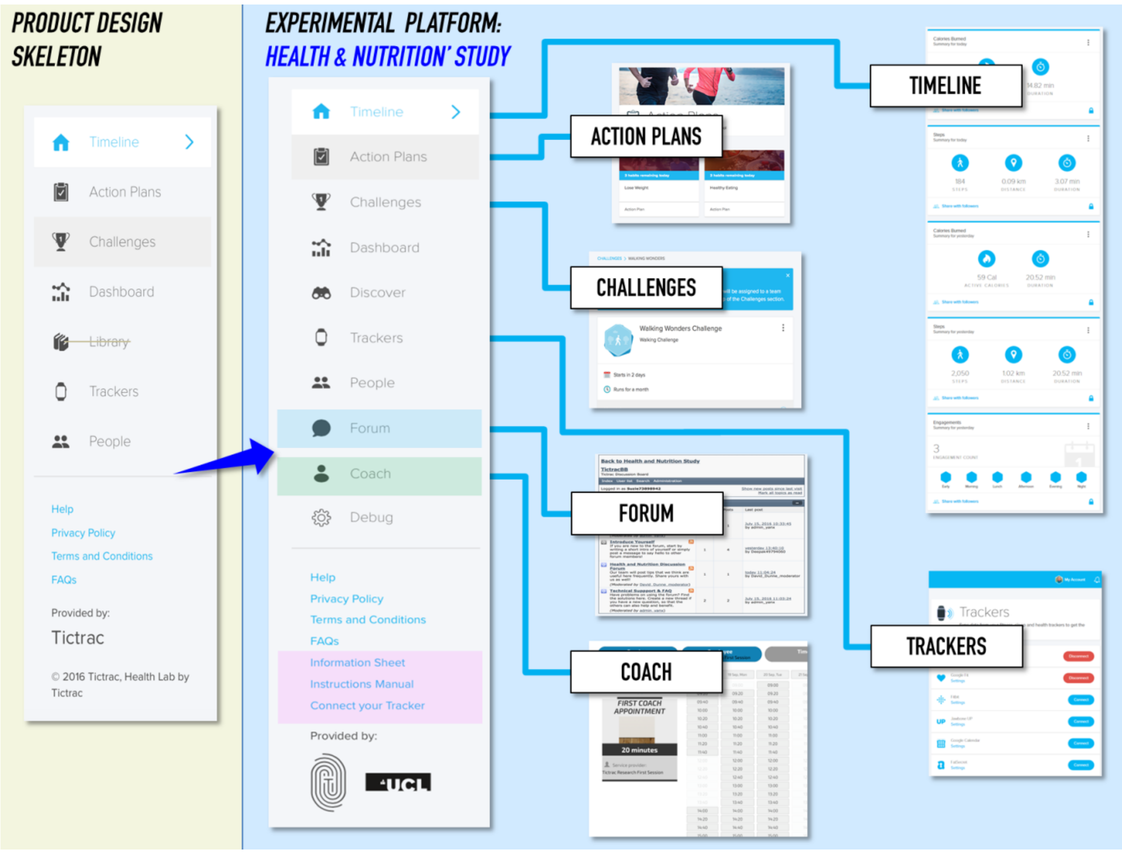


Figure 3.6 ***Experiment 2: factorial design: Services provided UX / UI, the menu bar***

Chapter

4. Large Scale Intervention on a Corporate Wellness Setting, *(Experiment 1. PART 1)*

> *Experiment 1 was a large scale multi-component intervention in a corporate wellness setting. As technology-based behaviour change intervention with a control group, the 'Corporate Wellness Challenge' was designed for the evaluation of intervention components' effectiveness for increasing physical activity and weight loss. The intervention was delivered on a computational platform integrating: social interaction (to measure network effects), 3 types of challenges with independent team and individual modalities (to measure the impact of competition and teams), self-monitoring (using wearables), goal setting (the impact of being explicit about a goal), progress monitoring, among other features. The chapter covers: research motivation and objectives, methodologies, dataset description, results, discussion, conclusion and further work. The analysis of social interaction is in Chapter 5.*

As a 'large scale intervention in a corporate wellness setting', the 'Corporate Wellness Challenge' (Corporate Challenge) was a behaviour change intervention with the aim of increasing physical activity and weight loss. The Corporate Challenge was delivered to a big United States corporate client of the Tictrac (the industrial partner). This research was possible thanks to the unique opportunity of doing academic research in a commercial environment.

The delivery was via a digital environment integrating multiple intervention components on a computational platform. The Corporate Challenge was designed on the evidence that participation in corporate wellness interventions was higher when the programme targeted multiple behaviours and had multiple components or when an incentive was offered [69]. The target participants of the intervention were all employees of the corporate client. The intervention took place for a period of 4.5 months (*from mid-February 2015, until the beginning of July 2015*) and there were 24,797 participants using a platform built specifically for this purpose. Chapter 4 and Chapter 5 cover the entirety of the analysis of this intervention (the *structured intervention* that is compared to an unrelated *control*).

4.1 The need for better corporate wellness interventions

As discussed in the literature review, there is limited evidence about the effectiveness of corporate wellness programs (CWP) for the health improvement of employees, Berg et al. [65]. Currently there are many uncertainties related to the participation on CWP [68] with open questions about retention and engagement. At the same time there is an explicit need in corporate organizations for effective corporate wellness interventions that address multiple risk factors ([66] *obesity, poor nutrition, physical inactivity, stress, insufficient sleep*, in addition to [67] *smoking and drinking*), because these risk factors contribute to employees' chronic disease, wellbeing and work ability.

In response to the requirement for better corporate wellness interventions (CWI) [13, 72, 181] Experiment 1 was an empirical approach to make better CWI's. Experiment 1 was designed with: the theoretical frameworks of behavioural change science, a data science workflow, deliberate use of personal informatics, mechanics for social interaction, the intention of making effective use of wearables and digitized health promotion practices delivering actual results [70-72] and not only promises [13, 40]. Additionally, the Corporate Challenge comprised what was the state of the art in corporate wellness challenges at the moment in time (2014 - 2015) when it was designed, deployed and delivered: multi-goal, multi-challenge, with incremental stages, simultaneous individual or team competitions, choice architecture and goal-oriented experience [63, 64, 66, 68, 70, 71, 182-208].

4.2 Experiment motivation & objectives

The research motivation for the Corporate Challenge was to do experimental research on behaviour change in a corporate wellness setting. The investigation comprises a technology-based behavioural intervention with the re-contextualisation of self-tracking wearables as effective and integrated components. The intervention was defined with a data science approach to determine the critical components for increasing physical activity weight loss. There are seven research objectives to Experiment 1, for the improvement of corporate wellness interventions:

- Assessment of the effectiveness of a multi-component technology based intervention for behaviour change on a corporate wellness setting
- Evaluation of intervention components
- Assessment of the impact of social interaction as network effects and social structure
- A control group analysis as the comparison of 'structured intervention' –vs- a control group
- Assessment about being explicit on a motivation for increased physical activity & weight loss
- Assessment of the impact of base characteristics on the intervention outcomes
- Re-contextualisation of wearable devices as effective intervention components

4.3 Chapter structure

The following Sections of the chapter cover experimental design, datasets, and findings in the form of the relevant results of the analysis of the Corporate Challenge:

- Analysis of the effect of being explicit about a specific goal ('fitness' or 'weight loss' motivation) to achieve changes in physical activity and weight loss.

Followed by the discussion comprising:

- A control group analysis highlighting the ‘challenge effect’, as a result of the comparison between a ‘structured intervention’ –vs- a control group for increasing physical activity and weight loss
- The analysis of the ‘team effect’
- The analysis of females and males and their outcomes on physical activity and weight
- The impact of adherence to the intervention on physical activity ad weight loss

The chapter finishes with conclusion and further work. The following chapter 5 will cover the network effect analysis to assess the impact of social interaction.

4.4 Research Methodology

The Corporate Challenge was designed as a multi-component intervention for corporate wellness using the principles of behaviour change science for intervention design and intervention evaluation. With the objective of overcoming some of the limitations of previous research, the Corporate Challenge was defined with a large control group and the use of self-tracking wearables re-contextualized for behavioural intervention.

4.4.1 Experimental design

By design Experiment 1 was defined for the identification of critical components for technology-based interventions, having as a starting point those selected based on theory and evidence. The intervention was designed with the most useful strategies identified in literature for physical activity [32] and weight loss [47] in the form of self-monitoring, physical activity profiles, goal setting, real-time feedback, social interaction, social support, a structured program and individually tailored components of the program.

The trial design followed the requirement of Tictrac´s client to create a Corporate Challenge for well-being in a corporate context for an intervention period of less than six months. The target behaviours were those related to increasing physical activity, weight loss, whilst also providing a space for other self-defined target behaviours. In a series of interactions between Tictrac’s client, the Tictrac team and the UCL researchers it was determined that the best delivery mechanism was a platform application that could integrate wearables. For this reason the trial design was oriented to the validation of a digital environment as an intervention space for the Corporate Challenge population. The trial design team selected leader-boards (team / individuals) combined in an app with a dashboard as the base (Figure 3.3) of the intervention functions that would carry behaviour change techniques, delivered as part of an altruistic competition: the ‘Corporate Challenge’.

The Corporate Challenge was designed with choice architecture, enabling the participants' to make selections with regards to: (1) *Modality of challenge*: as an 'individual' or as a member of a 'team' (each team had a team-selected 'captain'); (2) *Category*: 'Fitness', 'Weight Loss' or 'Choice' (an open category) and (3) Definition of the goal: 'target goal', 'goal type' and 'goal metric'. The challenge had stages of partial completion defined as four 'check-ins'. In order to be considered 'eligible to win' individual participants had to complete the four check-ins. Teams required the completion of the four check-ins by at least three team members. The check-ins surveys were used for self-reporting progress. By the end of the intervention (check-in 4), the participants also self-reported if they had been successful / or not in achieving the goal they selected at registration. The altruistic prizes of the Corporate Challenge were charity donations from the Employer on behalf of each one of the winning teams and winning individuals (for all the categories and modalities of the challenge) as described in Table 4.1.

Table 4.1 ***Corporate Challenge modalities and categories of competition***

Category	**Individual Participants**	**Teams**
Fitness	• *Individual, Fitness Category*	• *Team, Fitness Category*
Weight Loss	• *Individual, Weight Loss Category*	• *Team, Weight Loss Category*
Choice	• *Individual, Choice Category*	• *Team, Choice Category*

Experimental design was done with considerations for intervention evaluation. The intervention timeline (Figure 4.1) had a baseline, registration, four check-ins and follow-up period.

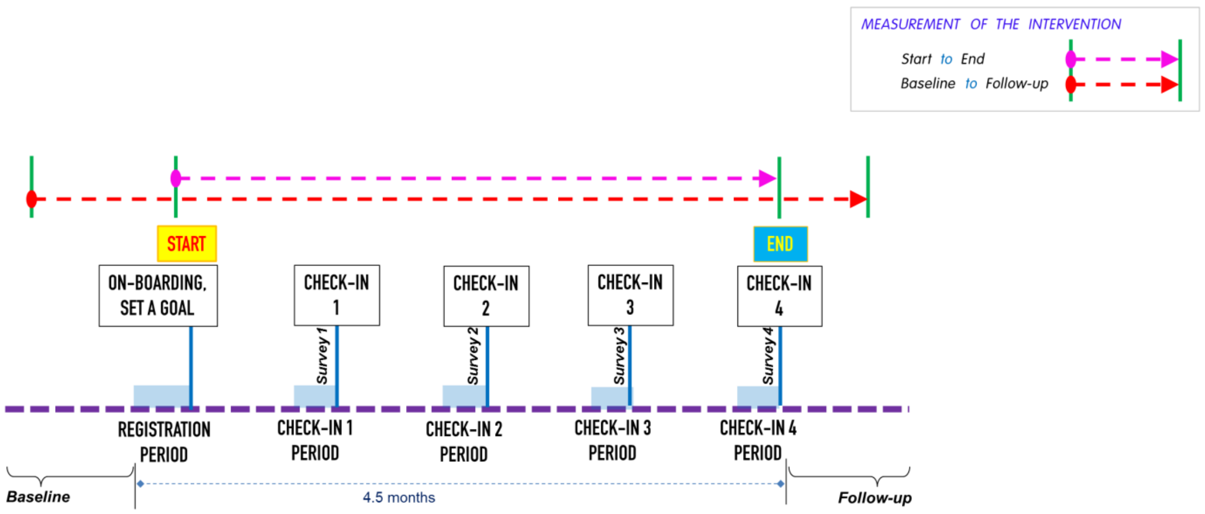


Figure 4.1 ***Diagram of the Corporate Challenge intervention***

Two measurements were defined for the intervention evaluation: (1) ‘start’ to ‘end’ of the intervention (magenta dotted line) and (2) ‘baseline’ to ‘follow-up’ (the red dotted line). The intervention evaluation was done ‘start’ to ‘end’, because this period had substantially larger sample sizes.

The registration survey was coded in the app on-boarding process (see Figure 3.2). The additional 4 surveys (check-ins) were designed to verify alignment to the selected goal, monitoring of progress, self-motivation and habits related to physical activity and food intake. The last survey had a broader set of questions (more qualitative) to assess the impact of the Corporate Challenge on the individual and his immediate network (work, friends and family).

4.4.2 Datasets

Experiment 1, ‘Large scale intervention in a corporate wellness setting’ has a rich dataset in many ways. The uniqueness on the dataset resides on an amalgamated combination of: 4.5 months of intervention captured as platform activity (via live analytics) and surveys, with multiple streams of self-tracking data; data from 24,797 participants; self-tracking data for 7,092 of the participants across 74 self-tracking metrics; base characteristics of the intervention’s population; comparison between a ‘*structured intervention*’ and a control group with similar demographic characteristics; and a control group of 14,161 additional individuals with self-tracking data. Because Experiment 1 was observational the power was not calculated in advance.

The population of registered participants was balanced (12,256 females, 12,453 males and 90 that did not identify as either) with an average age of 45.93 (standard deviation of 10.18). From the organizational point of view the population was very concentrated on the managerial employees (management: 19,408, all the other divisions: 5,391). For the analysis, demographics and base characteristics of the population of corporate wellness intervention are disclosed partially due to data protection. Wherever it was required, the segmentation indexes were modified for anonymization.

After exploratory data analysis (EDA) two self-tracking metrics were selected for physical activity *daily steps count* and *weight* (referred as ‘steps’ and ‘weight’, respectively). The EDA process indicated that only the ‘Fitness’ and ‘Weight Loss’ categories’ samples should be included in the research analysis because the ‘Choice’ category sample was small and very heterogeneous (from the point of view of the goal types, goal metrics and goal targets) which does not make it comparable to the other two, which are more homogeneous on their own.

The following Figures 4.2 and 4.3 are representations of the available data for the intervention evaluation of the Corporate Challenge. The datasets are explained using trees of Venn diagrams.

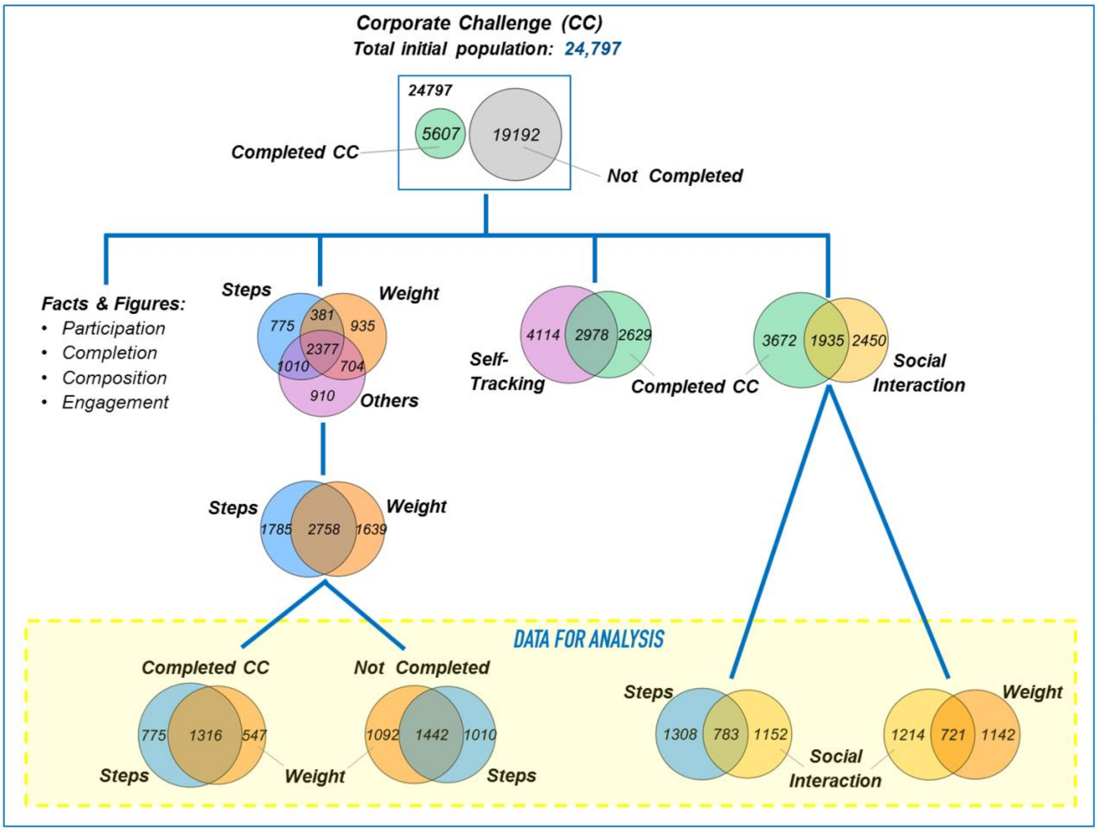


Figure 4.2 ***Dataset 1: Experiment 1, Corporate Challenge***

The tree of Venn diagrams in Figure 4.2 has four levels from top to bottom as a data inventory:

- ***Level 1***, the universe of all the population of the Corporate Challenge, with 2 disjoint circles representing those who completed the intervention and those who did not.

- ***Level 2***, has four branches, left to right:
    - *First branch L2*: 'Facts & Figures' with analytics product of the exploratory data analysis.
    - *Second branch L2*: three intersected circles which represent 7,092 participants with self-tracking data for steps, weight and all the other metrics combined.
    - *Third branch L2*: the intersection has 2,978 participants who completed the intervention and had self-tracking data (of 7,092 participants with wearables connected to the platform).
    - *Fourth branch L2*: at the intersection there are 1,935 participants with social interaction data and that completed the Corporate Challenge

- ***Level 3***, there were 6,182 participants who are tracking only steps and weight.

- ***Level 4***, inside the yellow box are the figures for number of participants and subsets where the data analysis was conducted.

- *First & Second branch L4*: participants with steps and weight data, split between those who completed the Corporate Challenge and those who did not (2,638 and 3,544 respectively).
- *Third & Fourth branch L4*: split of participants with steps and weight data, with the intersections for those who also had social interaction data

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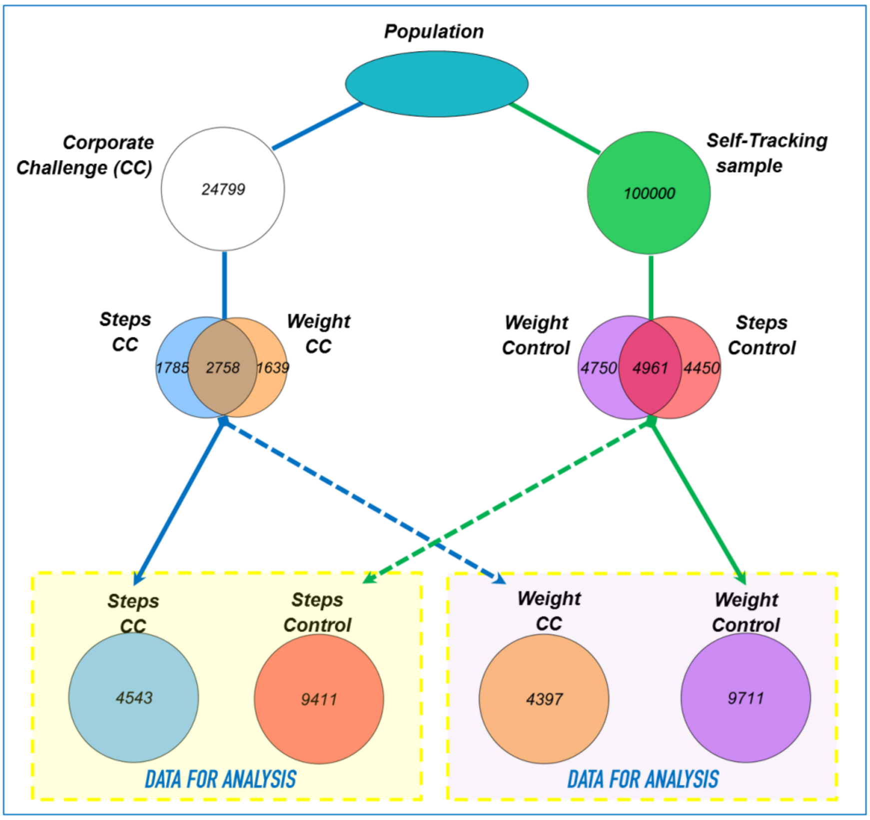


Figure 4.3 ***Dataset 2, with control group: Experiment 1, Corporate Challenge***

Figure 4.3 represents the dataset for a comparative analysis with a control group. This dataset is used in the discussion to evaluate and compare a 'structured intervention' (the Corporate Challenge) with a control group.

The control group consists of a sample of 14,161 individuals from an anonymised 100,000 population with self-tracking data, provided by Tictrac as part of the industrial collaboration for this research. The control group (14,161 individuals) comprehends people who: are avid users of wearables and apps and collect this data as synced data streams of self-tracking data of steps counts and weight. The control group was made of people who were not part of the intervention, and randomly selected to have a balanced proportion of females and males, at least 18 years old and not older than 75. They had to have self-tracking data during the same period of time, in a similar geography. The goals and motivations of each participant of the control group are unknown and uncertain. There is a self-selection bias in the composition of this sample, since people who collect self-tracking data tend to be active and are exposed to the long-term feedback effect of collecting their own data.

The data used for analysis is represented in the yellow and violet boxes 'Data for Analysis' (see below). For the physical activity analysis (steps) there are 4,543 in the Corporate Challenge and 9,411 in the control group. For the analysis of change in weight (%), there are 4,397 in the Corporate Challenge and 9,711 in the control group. As it will later be described on this chapter, the models for analysis use sub-sample sizes that are balanced.

4.5 Analysis and Results

The results generated by the Corporate Challenge are broad and unique. This section covers the analysis of the impact of being explicit about a specific goal (motivation) to achieve changes in behaviour that can be measured as changes in physical activity and weight loss. A wide range of wearables and apps were used to capture physical activity measured in daily steps count, these were self-selected by the participants and connected to the platform.

4.5.1 Being explicit about 'fitness' and increasing physical activity

This subsection is aimed at determining if it makes sense to be explicit about 'fitness' to increase activity level. As mentioned above, 'being explicit' in the context of this intervention is defined as the decision of a participant to be part of the 'Fitness' category. The outcome variable is the '*change in daily steps count*' (aggregated as a weekly average of daily steps counts). The change in daily steps count ('*change in steps*' or '*steps change*' indistinctly) was selected as the dependent variable to measure activity level for the following reasons. Daily steps count is a good proxy to determine how sedentary the lifestyle of an individual is. The change in steps can be measured with self-tracking data and is one of the most common metrics captured by wearable devices and apps. The 'count of daily steps' is generally more precise than the 'distance walked' typically calculated algorithmically by wearables or smartphones. The change in steps has the advantage of being comparable across females and males.

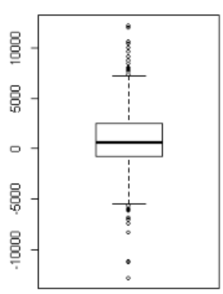
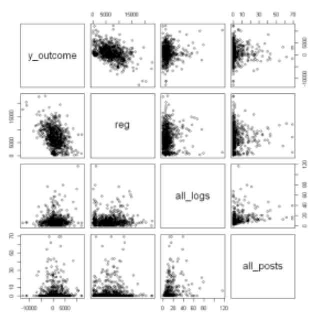
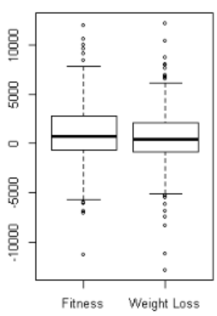
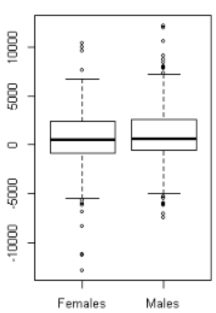
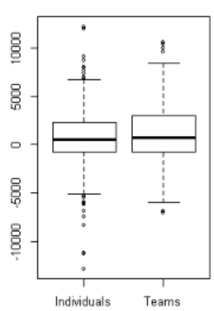
During the EDA other dependent variable candidates (*running, cycling and swimming*) were assessed to measure the change in activity level, they were not selected due to the following reasons. These other candidate metrics were not representative enough of all the population of the intervention, and the research was aimed at more general results. A follow-up intervention on these metrics would be too specialized and therefore limited in the future population reach of participants. The data collection on these metrics was less stable than steps towards the end of the Corporate Challenge. None of them displayed the well distributed characteristic of the change in steps.

The analysis goes through the revision of four explanatory models to ensure consistency of the results: '*Full dataset model'*, '*Balanced dataset model'*, '*Individuals dataset model'* and '*Teams dataset model'*. Each one of these models corresponds to a data subset of the dataset with 4,543 participants who collected self-tracking daily steps count data. The subsets were created by using the following criteria.

- The '*Full dataset model'*, taking a random sample of the 'Fitness' category to get a balanced sample of 818, split 50:50 (409, 409) for both categories ('Fitness' and 'Weight Loss').
- The '*Balanced dataset model*' is a subset of the '*Full dataset model*' balanced sample for modality: 'Team' or 'Individual'.
- The '*Individuals dataset model*' is a subset of the '*Full dataset model*' filtered for 'Individuals' exclusively.
- The '*Teams dataset model*' is a subset of the '*Full dataset model*' filtered for 'Teams' only.

The Full dataset model has as potential predictors: (1) 'Category', *Fitness* or *Weight Loss*, (2) 'Registration', the initial average daily steps count (physical activity metric) when they enrolled, (3) 'Sex', *Female*, *Male*, *Other*, (4) 'Modality', *Team* or *Individual*, (5) 'All logs', total times the participant logged-in to the platform, (6) 'All posts', total number of posts on the platform boards and (7) the interaction 'Registration:Sex'.

Table 4.2 ***Change in steps, Full dataset: Matrix plot***

Y_outcome	Continuous variables	Category	Sex	Modality
				

We assume the explanatory variables are not correlated as further confirmed by the matrix plot for the Full dataset model, see Table 4.2 (for all the four models, see Table Appendix 2.2). The dependent variable *change in steps* is normally distributed across the 4 models. The normal distribution for the y_outcome (*change in steps*) remains within each category.

Table 4.3 ***Change in steps, 4 models: Results table***

Full dataset model

Predictors	*B*	*CI*	*p*
	Dependent Variables y_outcome		
(Intercept)	2491.1	2070.6 – 2911.7	**<.001**
Category	345.3	157.0 – 533.5	**<.001**
Registration	-0.3	-0.3 – -0.2	**<.001**
Sex	442.2	81.2 – 803.1	**.0**
Modality (team)	-13.4	-247.5 – 220.6	.9
All logs	28.2	9.5 – 46.9	**.0**
All posts	-17.3	-42.5 – 7.9	.2
Registration:Sex	-0.1	-0.1 – -0.0	**<.001**
Observations		818	
R^2 / adj. R^2		.179 / .171	
F-statistics		25.143***	

Balanced dataset model

Predictors	*B*	*CI*	*p*
	Dependent Variables y_outcome		
(Intercept)	2630.3	1962.5 – 3298.2	**<.001**
Category	485.7	185.4 – 786.0	**.0**
Registration	-0.3	-0.4 – -0.2	**<.001**
Sex	592.0	-23.7 – 1207.8	.1
Modality (team)	104.0	-223.7 – 431.7	.5
All logs	30.0	1.5 – 58.4	**.0**
All posts	22.9	-8.5 – 54.2	.2
Registration:Sex	-0.1	-0.2 – -0.0	**.0**
Observations		316	
R^2 / adj. R^2		.235 / .217	
F-statistics		13.497***	

Individuals dataset model

Predictors	*B*	*CI*	*p*
	Dependent Variables y_outcome		
(Intercept)	2298.2	1833.7 – 2762.8	**<.001**
Category	298.5	75.9 – 521.0	**.0**
Registration	-0.2	-0.3 – -0.2	**<.001**
Sex	456.7	37.6 – 875.8	**.0**
All logs	21.4	-8.8 – 51.7	.2
All posts	-98.9	-193.1 – -4.6	**.0**
Registration:Sex	-0.1	-0.1 – -0.0	**.0**
Observations		577	
R^2 / adj. R^2		.153 / .144	
F-statistics		17.176***	

Teams dataset model

Predictors	*B*	*CI*	*p*
	Dependent Variables y_outcome		
(Intercept)	3034.4	2230.5 – 3838.4	**<.001**
Category	393.8	34.4 – 753.1	**.0**
Registration	-0.4	-0.5 – -0.3	**<.001**
Sex	484.2	-228.6 – 1197.0	.2
All logs	33.4	9.1 – 57.7	**.0**
All posts	-11.2	-37.7 – 15.2	.4
Registration:Sex	-0.1	-0.2 – -0.0	**.0**
Observations		241	
R^2 / adj. R^2		.262 / .243	
F-statistics		13.826***	

Significance codes:		
	0	'***'
	0.001	'**'
	0.01	'*'
	0.05	'.'
	0.1	' '

p-value < 0.05 in ***bold***

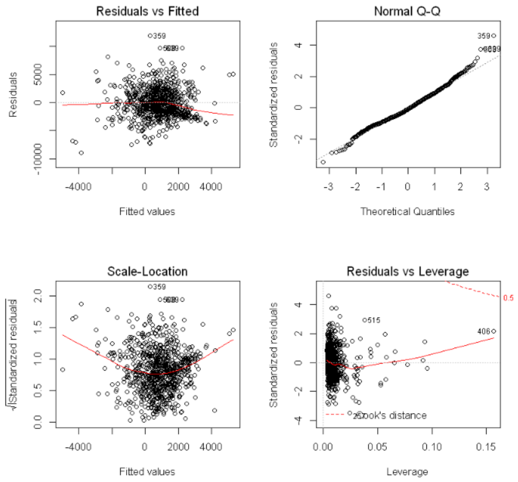
The four models are fitted using the standard ordinary least squares (OLS) method for N observations. The descriptive stats for the 'y_outcome' (*change in steps*) and the independent variables for the Full dataset are in Table 4.4 and for the four models compared in Table Appendix 2.1. The significance level is defined at 5%. The analysis was done on four models of different subsets (Table 4.3) to ensure consistency of the results.

Table 4.4 ***Change in steps, Full dataset Model: Descriptive stats & diagnostic plots***

Descriptive Statistics: Full dataset model

	Variable	Mean (SD)	Frequency
	y_outcome	788 (2849)	
	reg	6604 (3832)	
	all_logs	9 (11)	
	all_posts	3 (8)	
sex	Female_0	638 (2843)	455 (55.6%)
	Male_1	976 (2849)	363 (44.4%)
categ	Fitness_0	984 (2848)	409 (50%)
	Weightloss_1	591 (2839)	409 (50%)
team	Individual_0	719 (2789)	577 (70.5%)
	Team_1	954 (2987)	241 (29.5%)

Diagnostic Plots: Full dataset model



The validity of the models was assessed by inspecting the normal QQ-plots, Residuals vs. Fitted plots, scale-location plot and Cook's distance plot. See Table 4.4 for the Full dataset's diagnostic plots and the comparison of the models in Figure Appendix 2.1.

<u>Analysis using the four models on steps change</u> (see Table 4.5):

- Although the R^2 is low there is significance to explain between 14% and 24% of the variance in the steps change for the different datasets.

- The models provide evidence to support the argument that there is positive impact of being explicit about 'fitness' to increase physical activity (measure as daily steps count).

- Logging in to the platform makes a difference, because the platform as an intervention context (digital environment) seems to accentuate the proclivity to increase physical activity.

- There is a difference in how males and females respond to the intervention with regards to change in steps (outcome measure), although this difference is not present in the balanced dataset and the teams dataset. It still open for further research the analysis of the impact of a team as a factor that dampens the female – male difference.

Table 4.5 ***Change in steps, 4 models: Summary table***

Model	**Full dataset**	**Balanced dataset**	**Individuals dataset**	**Teams dataset**
Sample size	818	316	577	241
R^2	0.171	0.217	0.144	0.243
Significant terms (*) (*In grey not relevant*)	• ***Category*** • ***Registration*** • ***Sex*** • ***all_logs***	• ***Category*** • ***Registration*** • • ***all_logs***	• ***Category*** • ***Registration*** • ***Sex*** • ***all_logs***	• ***Category*** • ***Registration*** • • ***all_logs***
Category * , comparison	• Fitness +691 more than Weight loss	• Fitness +972 more than Weight loss	• Fitness +598 more than Weight loss	• Fitness +788 more than Weight loss
Sex * , comparison; *Registration = 0*	• Females +884 more than Males		• Females +914 more than Males	
All_logs *, for every 1 log-in(s) (…)	• Additional +28	• Additional +30	• Additional +21	• Additional +33

4.5.2 Being explicit about 'weight loss' and losing weight

The analysis is aimed at determining if it makes sense to be explicit about 'Weight Loss' to lose weight. As mentioned before, 'being explicit' in the context of this intervention is defined as the decision of a participant to be part of the 'Weight Loss' category. The outcome variable is the '*change in weight (%)*' (aggregated as a weekly average weight). The change in weight ('*change in weight*' or '*weight change'* indistinctly) was selected as the dependent variable to measure losing weight for the following reasons. Change in weight is a self-explanatory metric. Given the dataset, it is the best metric for a good sample size of 4,397 participants with weight data. Weight is a common metric captured manually or with e-connected weight devices. The change in weight allows a separate analysis for females and males. A follow-up intervention on change of weight can be assembled with low complexity. The sample can be balanced for statistical analysis. When performing a stratified analysis the stratum have good sub-sample sizes. Almost every person on an intervention can measure their weight on their own.

During the EDA, the BMI was discarded as a dependent variable due to the following reasons. Very few participants who logged their weight also provided their height and without the height BMI cannot be calculated. The sacrifice on the total size of the dataset would be too big, making it not viable.

The analysis goes as well through the revision of four explanatory models (Table 4.4) to ensure consistency of the results: '*Full dataset model*', '*Balanced dataset model'*, '*Females dataset model'* and a '*Males dataset model'*. Each one of these models corresponds to a data subset of the 4,397 participants who collected self-tracking weight data. The subsets were created using the following criteria.

- The '*Full dataset model*', taking a random sample of the Weight Loss' category to get a balanced sample of 310, split 50:50 (155, 155) for both categories ('Fitness' and 'Weight Loss').
- The '*Balanced dataset model*' is a subset of the '*Full dataset*' balanced sample for modality: team or individual.
- The '*Individuals dataset model*' is a subset of the '*Full dataset model*' filtered for 'Individuals'.
- The '*Teams dataset model*' is a subset of the '*Full dataset model*' filtered for 'Teams' only.

The *Individuals dataset model* and the *Teams dataset model* are similar to the *Full dataset model* and the *Balanced dataset model* with the exception of the 'sex', because sex is used for filtering process.

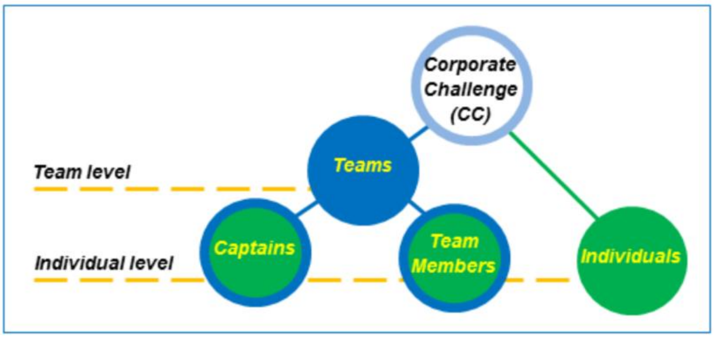


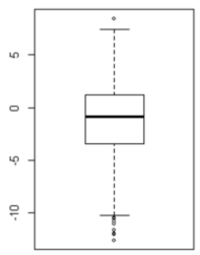
Figure 4.4 ***Individuals, Teams, Captains & Team members***

The Full dataset model has as potential predictors: (1) 'Category', *Fitness* or *Weight Loss*, (2) 'Sex', *Female* or *Male*, (3) 'Modality', *Team* or *Individual*, (4) 'Age', self-explanatory, (5) 'Completion', the stage of completion on the Corporate Challenge (Check-in 1 to Check-in 4), (6) 'All posts', total number of posts on the platform boards and (7) '*Captain'* is a nested variable under '*Team*', implying that only teams had a captain and not all team members were captains (see Figure 4.4). The nested variable '*Team/Captain*' provides insights about the impact of roles in a team (captain –vs- others), during an intervention.

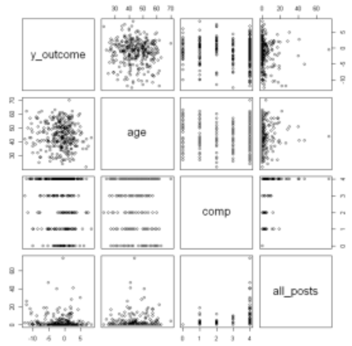
We assume the explanatory variables are not correlated as further confirmed by the matrix plot for the Full dataset model, see Table 4.6 below (for all the four models, see Table Appendix 2.4). The dependent variable *change in weight* is normally distributed for the Full dataset model (Table 4.6) and across the 4 models, (see Table Appendix 2.4). The normal distribution for the y_outcome (*change in weight*) remains within each category. The descriptive stats for the Full dataset model are in Table 4.8, below, and for all the models in Table Appendix 2.3.

Table 4.6 *Change in weight (%), Full dataset Model: Matrix plot*

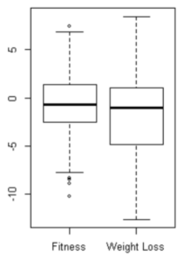
Y_outcome



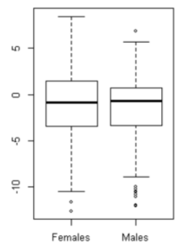
Continuous variables



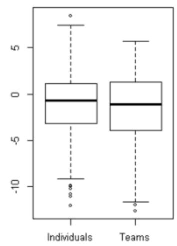
Category



Sex



Modality



Captain (Team only)

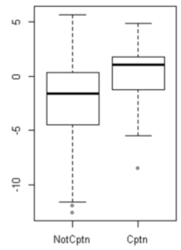


Table 4.7 *Change in weight (%), 4 models: Results table*

Full dataset model

Predictors	*Dependent Variables* y-outcome		
	B	*CI*	*p*
(Intercept)	0.93	-1.25 - 3.12	0.4
Category	0.71	0.28 - 1.15	< **0.001**
Sex	0.22	-0.2 - 0.65	0.3
Modality	0.10	-0.49 - 0.68	0.7
Age	-0.02	-0.07 - 0.02	0.3
Completion	-0.39	-0.68 - -0.09	< **0.01**
All_posts	-0.01	-0.07 - 0.05	0.7
Indvl:Cptn	*NA*	*NA*	*NA*
Team:Cptn	-1.22	-2.12 - -0.32	< **0.01**
Observations	310		
R^2 / adj. R^2	0.086 / 0.065		
F-statistic	4.054***		

Balanced dataset model

Predictors	*Dependent Variables* y-outcome		
	B	*CI*	*p*
(Intercept)	4.25	-0.11 - 8.62	0.1
Category	1.19	0.41 - 1.98	< **0.01**
Sex	0.66	-0.15 - 1.47	0.1
Modality	0.11	-0.83 - 1.05	0.8
Age	-0.08	-0.18 - 0.01	0.1
Completion	-0.59	-1.17 - -0.01	**0.05**
All_posts	-0.05	-0.17 - 0.06	0.3
Indvl:Cptn	*NA*	*NA*	*NA*
Team:Cptn	-1.50	-2.78 - -0.21	**0.02**
Observations	120		
R^2 / adj. R^2	0.222 / 0.173		
F-statistic	4.552***		

Table 4.7 ***Change in weight (%), 4 models: Results table (continued)***

Females dataset model

Predictors	*Dependent Variables* y-outcome		
	B	*CI*	*p*
(Intercept)	1.67	'-1.21 - 4.55'	0.3
Category	0.68	'0.11 - 1.26'	**0.02**
Modality	0.28	'-0.47 - 1.02'	0.5
Age	-0.04	'-0.1 - 0.02'	0.2
Completion	-0.41	'-0.82 - 0'	**0.05**
All_posts	0.03	'-0.07 - 0.13'	0.5
Indvl:Cptn	*NA*	*NA*	*NA*
Team:Cptn	-1.48	'-2.61 - -0.35'	**0.01**
Observations	176		
R^2 / adj. R^2	0.1 / 0.068		
F-statistic	3.126**		

Males dataset model

Predictors	*Dependent Variables* y-outcome		
	B	*CI*	*p*
(Intercept)	-0.05	'-3.52 - 3.42	1.0
Category	0.77	'0.09 - 1.44	**0.03**
Modality	-0.07	'-1.07 - 0.93	0.9
Age	-0.01	'-0.08 - 0.07	0.9
Completion	-0.40	'-0.83 - 0.04	0.07
All_posts	-0.04	'-0.13 - 0.04	0.3
Indvl:Cptn	*NA*	*NA*	*NA*
Team:Cptn	-0.77	'-2.36 - 0.81	0.3
Observations	134		
R^2 / adj. R^2	0.082 / 0.038		
F-statistic	1.879 .		

Significance codes: *0* '***' *0.001* '**' *0.01* '*' *0.05* '.' *0.1* ' '

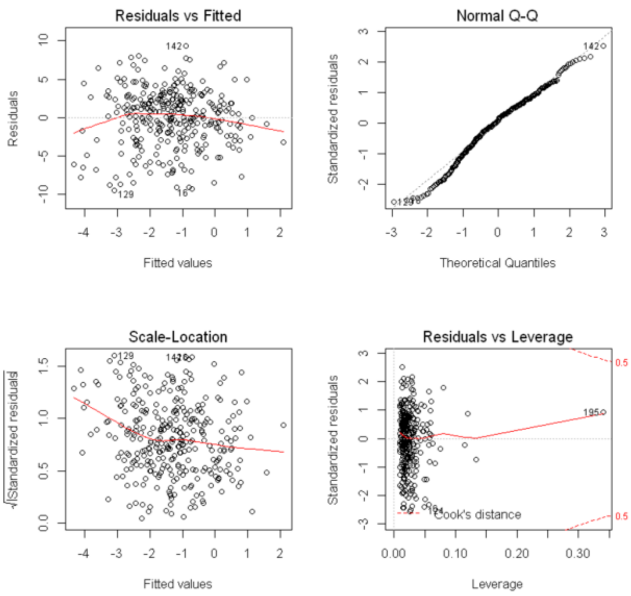
p-value < 0.05 in ***bold***

Table 4.8 ***Change in weight (%), Full dataset Model: Descriptive stats & diagnostic plots***

Descriptive Statistics: Full dataset model

	Variable	Mean (SD)	Frequency
	y_outcome	-1.35 (3.87)	
	age	44.83 (9.29)	
	all_posts	3.07 (7.57)	
	comp	2.73 (1.48)	
sex	Female_0	-1.19 (3.92)	176 (56.8%)
	Male_1	-1.56 (3.8)	134 (43.2%)
categ	Fitness_0	-0.76 (3.19)	155 (50%)
	Weightloss_1	-1.94 (4.37)	155 (50%)
team	Individual_0	-1.18 (3.74)	223 (71.9%)
	Team_1	-1.79 (4.18)	87 (28.1%)
Team_1:Cptn			
	Cptn_0	-2.44 (4.31)	287 (92.6%)
	Cptn_1	0.02 (3.22)	23 (7.4%)

Diagnostic Plots: Full dataset model



The four models are fitted using the standard ordinary least squares (OLS) method for N observations with nested variables. For one of the factors (factor A = Team), there is a nested factor (factor B = Captain), in which B only occurs as one level of A. Significance level is defined at 5%.

The validity of the models is assessed by inspecting the normal QQ-plots, Residuals vs. Fitted plots, scale-location plot and Cook's distance plot. See Table 4.8 for the Full dataset and the comparison of the models in Figure Appendix 2.2.

Analysis using the four models on weight change (see Table 4.9):

- Although the R^2 is low there is significance to explain between 6.5% and 17.3% of the variance in weight change for the different datasets.

- There is evidence to support the argument that there is positive impact of being explicit about 'weight loss' to increase lose weight (*measured as change % in weight*).

- Completing the intervention stages makes a difference to lose weight during the intervention

- It was possible to provide an explanatory model for females' responsiveness to the intervention with an outcome measure of weight loss (more than for males).

- Team members did better (lost more weight) than the team captains, which was a counter-intuitive result.

Table 4.9 ***Change in weight (%), 4 models: Summary table***

Model	Full dataset	Balanced dataset	Females dataset	Males dataset
Sample size	310	120	176	134
R^2	0.065	0.173	0.068	Not significant
Significant terms (*)	• ***Category*** • ***Completion*** • ***Team / Captain***	• ***Category*** • ***Completion*** • ***Team / Captain***	• ***Category*** • ***Completion*** • ***Team / Captain***	NA
Category * , comparison	• Weight L.: Loss more than Fitness	• Weight L.: Loss more than Fitness	• Weight L.: Loss more than Fitness	NA
Completion *, comparison	• Stages' Completion: Loss more	• Stages' Completion: Loss more	• Stages' Completion: Weight Loss	NA
Team /Captain *, comparison	• Team Members: Loss more than Captain:	• Team Members: Loss more than Captain:	• Team Members: Loss more than Captain:	NA

4.6 Discussion

The results so far indicate there is evidence of positive outcomes related to being explicit about a behaviour change goal. These results were evaluated for physical activity measured in steps count and weight loss, correspondingly being explicit about ‘fitness’ was positive for physical activity and being explicit about ‘weight loss’ was positive to lose weight. In order to assess if these results are due to the nature of the large sample size of the corporate wellness intervention, the results are evaluated to a control group. For this analysis the Corporate Challenge is defined as a ‘structured intervention’ and compared to a control group. Other factors are assessed as well: teams, females and males and the impact of adherence.

4.6.1 The ‘challenge effect’, a ‘structured intervention’ –vs- a control group

For the assessment of the results of Experiment 1, the ‘challenge effect’ was evaluated. The challenge effect is product of the comparison of the Corporate Challenge as a ‘*structured intervention*’ versus a control group, (completely unrelated to the Corporate Challenge), for the *change in steps* and the *change in weight*. The dataset for the models in this section was described as the second dataset of Section 4.4.2.

The Corporate Challenge is considered as a ‘*structured intervention’* because it was defined by a framework of intervention: time boundary of 4.5 months, an overarching goal to improve corporate health and wellbeing as a challenge, operational rules for participation, digital environment of intervention, a social context for interaction, intervention design and intervention evaluation design.

By experimental design the assessment of results is done by comparing to a control group. The control group is unstructured because there is no time boundary, there are: no explicit or clear goals, no explicit rules, no explicit or defined environment of intervention, no social interaction framework, no intervention design. The control group has the advantage and limitation that it is not known what they are doing with their apps/wearables or whether they have a specific goal in mind.

The models used to evaluate the challenge effect of the Corporate Challenge (for change in steps and for change in weight (%)) are fitted using a standard ordinary least squares (OLS) regression with an interaction term, and a nested variable. The interaction term is present on three types of models: ‘balanced’, ‘challenge’ and control. The nested variable is present on the ‘balanced’, ‘females’ and ‘males’ models only. For some of the models one of the factors (factor A: ‘label’, that compare the ‘challenge’ sample –vs- the control sample), there is a nested factor (factor B: ‘category’ which is present only on the ‘challenge’).

As part of the EDA a random sample of 500 participants in the Corporate Challenge was evaluated to assess qualitative insights capture in the surveys on the open questions. The highlights of this analysis follow:

- Reporting positive partial progress related to the selected goal will provide a higher likelihood of success.
- Reporting positive partial progress unrelated to the goal also provides a context for success.
- Reporting negative partial progress related to the goal contributes to the possible success.
- The three different strata of success are distinct (0--25%, 50-75%, 100-100+%).
- Discrepancy in results indicate that it is possible that people tend to report more optimistically when not using a tracker, hence the objective judgement was biased to give higher success rate to people without tracker.
- Leveraging on the above point, then people who had trackers and were reporting less success (based on objective success) do not necessary define themselves as less successful than people who were reporting more success but did not have a tracker.

4.6.1.1 The 'challenge effect', for increasing physical activity

This section evaluates if there is a '*challenge effect*' related to physical activity (steps) that is unique to the Corporate Challenge as a 'structured intervention', when compared to a control. If there is a challenge effect it should have an impact on change is steps. Figure 4.5 illustrates the 'challenge effect' for 6 strata comparing those participants who completed the challenge with those participants who did not complete the challenge and the control group.

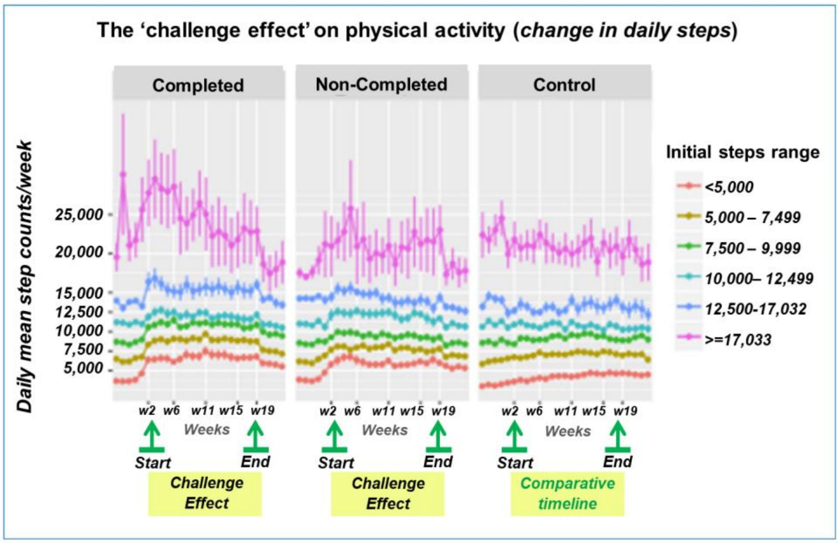


Figure 4.5 ***Challenge effect, 'Structured Intervention' –vs- control group: Daily mean step counts per week*** *(average)*

There is numerical evidence that there are differences between different strata (see Figure 4.5). The improvement in physical activity was proportionally bigger for those who were less active at the beginning of the intervention, the lower 4 strata. The activity level for those in the Corporate Challenge (regardless of the completion) seems to have improved more than for those in the control group; with the exception of those that were more active at the beginning (in pink, Figure 4.5 above). The strata in pink showed an initial increment and then reverted to their original (though fairly high) physical activity level.

As an illustration, please see Figure 4.6, which shows that change in steps by strata and age range. As it can be seen the 'challenge effect' is seen among those who completed and those who did not complete the challenge (when compared to a control group), highlighting in blue the value of a digital environment for an intervention of this kind.

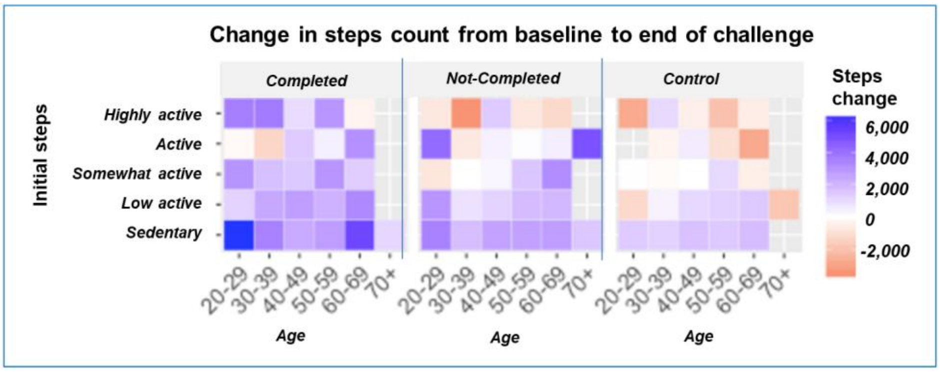


Figure 4.6 *Corporate Challenge: Challenge effect by age and strata*

To complement Figure 4.6, please see Table 4.14 which provides a numerical indication of the stratified change in steps for those in the structured intervention context (the challenge: complete & not-complete) versus the control group.

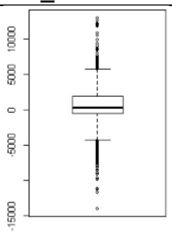
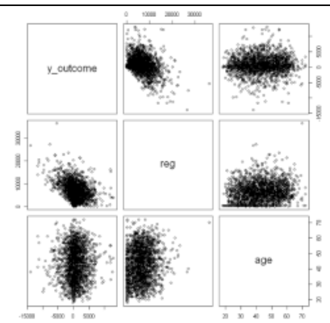
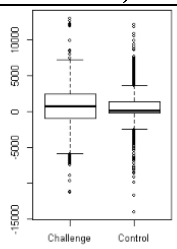
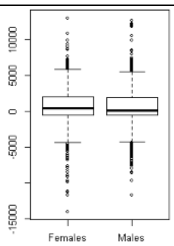
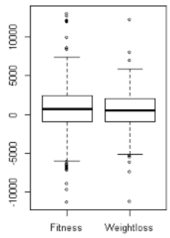
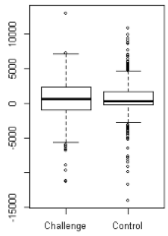
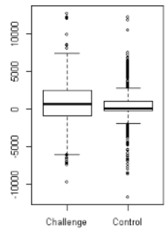
Table 4.10 *Challenge effect steps, strata: Corporate Challenge*

	Challenge Complete(SD), *n*	Challenge NOT complete(SD), *n*	Control(SD), *n*
<5,000	1,643 (2,469), 105	766 (2,314), 114	441 (1,657), 604
5,000-7,499	1,188 (2,637), 173	759 (2,639), 173	1,015 (2,878), 196
7,500-9,999	722 (3,095), 118	315 (2,993), 106	599 (3,111), 146
10,000-12,500	-209 (3,235), 105	787 (3,164), 73	-101 (3,413), 73
>12,500	353 (3,700), 49	-911 (3,084), 46	-418 (5,347), 43

The analysis comprises the revision of five explanatory models to ensure consistency of the results (Table 4.11) for the dependent variable *change in steps* (normally distributed across the 5 models). The 5 datasets required for 5 models, are summarised briefly in the list below:

- The balanced dataset prepared for the '*balanced model*' has the daily steps count data balanced for challenge and control data ('label'), and for females and males ('sex'). Sample size 2,124.
- The datasets for the '*challenge*' and control models were produced by filtering the balanced dataset by the 'label' ('category' and control, respectively). Sample size 1,240 participants each.
- The datasets for the '*females*' and '*males*' models were produced by filtering the balanced dataset by 'sex'. Sample size 1,062 participants each.

Table 4.11 ***Challenge effect steps, Balanced model: Matrix plot***

Y_outcome	**Continuous variables**			
				
Label (Challenge, Control)	**Sex**	**Category**	**Females**	**Males**
				

The normal distribution for the y_outcome (*change in steps*) remains within each category. We assume the explanatory variables are not correlated as further confirmed by the matrix plot in Table 4.10 for the Balanced model and for all the models compared in Table Appendix 2.6. The 5 models are described as a comparison on Table Appendix 2.5. The significance level is defined at 5%.

The validity of the models are assessed by inspecting the normal QQ-plots, Residuals vs. Fitted plots, scale-location plot and Cook's distance plot. For the Balanced model see Table 4.12, for all the models compared see Figure Appendix 2.3 *Challenge effect steps models: Balanced, Challenge, Control, Females, Males*.

Table 4.12 *Challenge effect steps, 5 models: Results table*

Balanced model

Predictors	*Dependent Variables* y-outcome		
	B	*CI*	*p*
(Intercept)	1209.9	'708.7 - 1711'	**0**
Age	17.30	'6.2 - 28.5'	**< 0.01**
Registration	-0.20	'-0.3 - -0.2'	**0**
Sex	331.80	'128.6 - 535'	**< 0.001**
Label	260.10	'125.8 - 394.3'	**0**
Sex:Registration	-0.10	'-0.1 - 0'	**0**
Challenge:Category	272.70	'87.8 - 457.5'	**0.01**
Control:Category	*NA*	*NA*	*NA*
Sex:Label	-88.50	'-205 - 28'	0.1
Observations	2124		
R^2 / adj. R^2	0.117 / 0.114		
F-statistic	40.1***		

Significance codes:
0 '***'
0.001 '**'
0.01 '*'
0.05 '.'
0.1 ' '
1

p-value < 0.05 in ***bold***

Challenge model

Predictors	*Dependent Variables* y_outcome		
	B	*CI*	*p*
(Intercept)	2410.1	1600.8 – 3219.3	**<.001**
Age	17.6	2.2 – 33.0	**.0**
Registration	-0.3	-0.4 – -0.3	**<.001**
Sex	128.5	-228.2 – 485.1	.5
Sex:Registration	-0.0	-0.1 – -0.0	**.0**
Observations	1240		
R^2 / adj. R^2	.178 / .176		
F-statistics	66.957***		

Control model

Predictors	*Dependent Variables* y_outcome		
	B	*CI*	*p*
(Intercept)	409.1	-90.4 – 908.5	.1
Age	12.3	-0.1 – 24.8	.1
Registration	-0.1	-0.1 – -0.1	**<.001**
Sex	139.8	-71.5 – 351.1	.2
Sex:Registration	-0.0	-0.1 – 0.0	.1
Observations	1240		
R^2 / adj. R^2	.039 / .036		
F-statistics	12.505***		

Females model

Predictors	*Dependent Variables* y-outcome		
	B	*CI*	*p*
(Intercept)	1783.7	'1107 - 2460.3'	**0**
Age	11.30	'-3.6 - 26.3'	0.1
Registration	-0.30	'-0.3 - -0.2'	**0**
Label	191.70	'10.7 - 372.8'	**0.04**
Challenge:Category	306.40	'55.9 - 556.8'	**0.02**
Control:Category	NA	NA	NA
Observations	1062		
R^2 / adj. R^2	0.155 / 0.151		
F-statistic	48.28***		

Males model

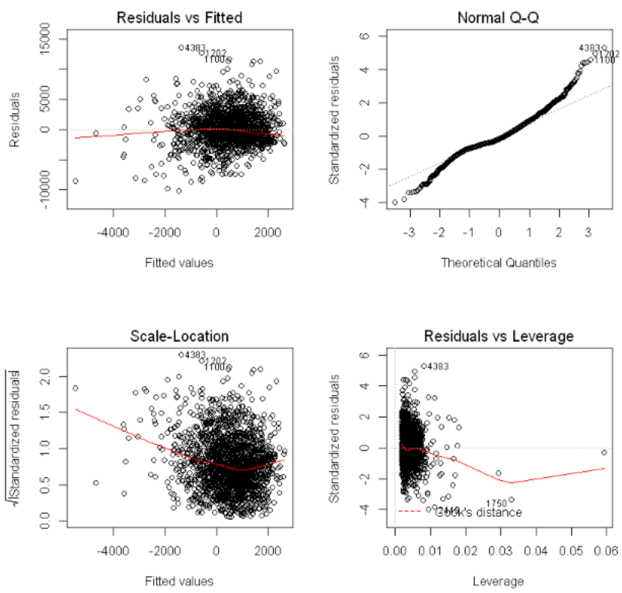
Predictors	*Dependent Variables* y-outcome		
	B	*CI*	*p*
(Intercept)	617.2	'-127.1 - 1361.5'	0.1
Age	23.80	'7.2 - 40.4'	**< 0.01**
Registration	-0.20	'-0.2 - -0.1'	**0**
Label	329.30	'130.1 - 528.4'	**0.001**
Challenge:Category	243.40	'-29.8 - 516.5'	0.08
Control:Category	NA	NA	NA
Observations	1062		
R^2 / adj. R^2	0.082 / 0.079		
F-statistic	23.64***		

Table 4.13 ***Challenge effect steps, Balanced model: Descriptive stats & diagnostic plots***

Descriptive Statistics: Balanced model

	Variable	Mean (SD)	Frequency
	y_outcome	590 (2728)	
	Age	42 (11)	
	Registration	6236 (4267)	
Sex	Female	605 (2704)	1062 (50%)
	Male	576 (2754)	1062 (50%)
Label	Challenge	684 (2905)	1062 (50%)
	Control	497 (2537)	1062 (50%)
Challenge	Category		
	Fitness	751 (2949)	819 (38.6%)
	Weightloss	459 (2746)	243 (11.4%)
Female	Label		
	Challenge	597 (2788)	531 (25%)
	Control	613 (2619)	531 (25%)
Male	Label		
	Challenge	771 (3018)	531 (25%)
	Control	380 (2449)	531 (25%)

Diagnostic Plots: Balanced model



<u>**Analysis using the five models on steps change**</u> (see Table 4.13):

- There is significance to explain between 3.6% and 17.6% of the variance in the steps change for the different datasets and respective models.

Challenge model ('<u>Structured intervention</u>')

- There was a significant change in steps (positive improvement) just for being in the challenge, the 'challenge effect' for the change in steps. In contrast to the control group, with no significant change.
- Age matters in the challenge, the older the participant the greater the change in steps.

Control model (control group), which clearly is different from the challenge:

- Overall there was no significant improvement in the control.
- Age does not impact steps improvement under the unstructured environment.
- There is no difference between gender on the improvement rate by initial steps.

Female and male models:

- The Category matters for females, but not for males:

- Females in fitness category have higher average improvement in steps (than those in the weight loss category).
- In contrast to the above, the step performance in males is about the same for both categories: fitness and weight loss.

- Age plays a part in steps improvement for males but not for females.
- Females and males in the challenge did better than the control group. The 'challenge effect' stands for positive change in steps across gender.

Balanced model ('<u>Structured intervention</u>' –vs- <u>Control group</u>)(without repetition):

- There is an even bigger 'challenge effect' for participants on the fitness category, compared to those in the weight loss category. Both categories of the challenge, did better than the control.

Table 4.14 ***Challenge effect steps, 5 models: Summary table***

Model	Balanced	Challenge	Control	Females	Males
Sample size	2,124	1,240	1,240	1,062	1,062
R^2	0.114	0.176	0.036	0.151	0.079
Significant & relevant terms (*) (*In grey not relevant*)	• ***Age*** • *Registration* • ***Sex*** • *Sex:Registration* • ***Label*** • ***Label/Category***	• ***Age*** • *Registration* • • *Sex:Registration* • •	• • *Registration* • • • •	• • *Registration* • • • ***Label*** • ***Label/Category***	• ***Age*** • *Registration* • • • ***Label*** •
Age * , for every 10 additional yrs (…)	• Additional year implies +173	• Additional year implies +176			• Additional year implies +238
Sex * , comparison females to males at Registration = 0	• Females +664				
Label *, comparison	• Challenge +520 more than Control			• Challenge +384 more than Control	• Challenge +657 more than Control
Label/Category * , comparison	Challenge label: • Fitness +793 more than Control • Weight.Loss +248 more than Control			Challenge label: • Fitness +690 more than Control • Weight.Loss +78 more than Control	

4.6.1.2 The ‘challenge effect’, for weight loss

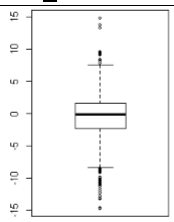
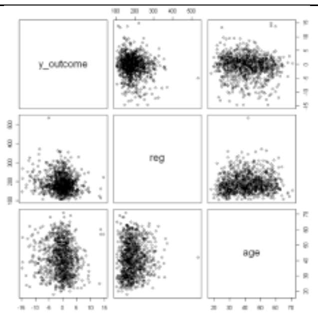
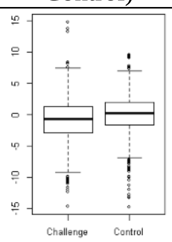
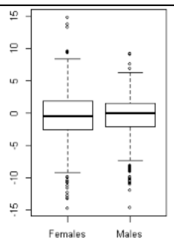
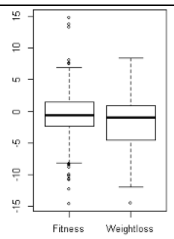
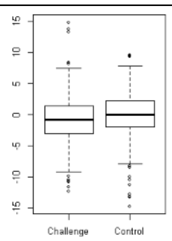
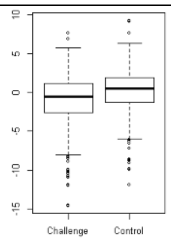
This section evaluates if there is a ‘challenge effect’ on weight change that is characteristic to the Corporate Challenge intervention. The challenge is considered a ‘structured intervention’ to be compared to a control group, just as it was done for steps on the previous sub-section. This section will use change in weight as a measure for weight loss.

The analysis takes into account the difference between females and males given the fact of the biological difference of weight change between the two. The analysis was done on the balanced model and the other dataset subsets to ensure consistency of the results, reflected in Table 4.16. The significance level is defined at 5%.

A summary of the datasets for the 5 models of this section follows:

- The ‘balanced’ dataset prepared for the ‘*balanced model*’ of this analysis has weight measurements data (‘weight’). It is balanced for challenge and control group data (‘label’), at the same as for females and males (‘sex’), with a total sample size of 956 participants.
- Each one of the datasets for the ‘*challenge*’ and control models have 551 participants. They were produced by filtering the balanced dataset by the ‘label’ (‘category’ and control group, respectively).
- The datasets for the ‘*females*’ and ‘*males*’ models have the data of 478 participants each. They were produced by filtering the balanced dataset by ‘sex’.

Table 4.15 ***Challenge effect weight (%), Balanced model: Matrix plot***

Y_outcome	**Continuous variables**			
				
Label (Challenge, Control)	**Sex**	**Category**	**Females**	**Males**
				

The matrix plot for the Balanced model for the Challenge effect on weight in on Table 4.15 below. The descriptive statistics for the 5 datasets for *change in weight* are in the Table Appendix 2.7, followed by the matrix plot on Table Appendix 2.8. The dependent variable *change in weight* is normally distributed across the 5 models. The normal distribution for the y_outcome (*change in weight*) remains within each category for all the models.

Table 4.16 ***Challenge effect weight (%), 5 models: Results table***

Balanced model

Predictors	*Dependent Variables*		
	y-outcome		
	B	*CI*	*p*
(Intercept)	1.54	'0.07 - 3.02'	**0.04**
Age	-0.01	'-0.04 - 0.01'	0.3
Registration	-0.01	'-0.01 - 0'	**0.001**
Sex	-0.42	'-1.46 - 0.63'	0.4
Label	-0.45	'-0.72 - -0.17'	**0.001**
Sex:Registration	0.00	'0 - 0.01'	0.5
Challenge:Category	0.58	'0.21 - 0.95'	**0.002**
Control:Category	*NA*	*NA*	NA
Sex:Label	0.15	'-0.1 - 0.39'	0.2
Observations	956		
R^2 / adj. R^2	0.042 / 0.035		
F-statistic	5.895***		

Challenge model

Predictors	*Dependent Variables*		
	y_outcome		
	B	*CI*	*p*
(Intercept)	2.13	-0.17 – 4.44	.1
age	-0.01	-0.04 – 0.03	.6
reg	-0.01	-0.02 – -0.01	<**.001**
sex1	0.03	-1.51 – 1.57	1.
reg:sex1	-0.00	-0.01 – 0.01	.9
Observations	551		
R^2 / adj. R^2	.028 / .021		
F-statistics	3.931**		

Control model

Predictors	*Dependent Variables*		
	y_outcome		
	B	*CI*	*p*
(Intercept)	1.61	-0.03 – 3.24	.1
age	-0.01	-0.04 – 0.02	.5
reg	-0.01	-0.01 – 0.00	.1
sex1	0.62	-0.64 – 1.87	.3
reg:sex1	-0.00	-0.01 – 0.00	.3
Observations	551		
R^2 / adj. R^2	.007 / .000		
F-statistics	1.010		

Females model

Predictors	*Dependent Variables*		
	y-outcome		
	B	*CI*	*p*
(Intercept)	1.5	'-0.61 - 3.64'	0.2
Age	-0.02	'-0.06 - 0.01'	0.2
Registration	-0.01	'-0.02 - 0'	0.09
Label	-0.25	'-0.66 - 0.16'	0.2
Challenge:Category	0.51	'-0.05 - 1.07'	0.08
Control:Category	NA	NA	NA
Observations	478		
R^2 / adj. R^2	0.022 / 0.013		
F-statistic	2.616*		

Males model

Predictors	*Dependent Variables*		
	y-outcome		
	B	*CI*	*p*
(Intercept)	1.4	'-0.57 - 3.45'	0.2
Age	0.00	'-0.04 - 0.03'	0.9
Registration	-0.01	'-0.02 - 0'	< **0.01**
Label	-0.66	'-1.02 - -0.3'	**0**
Challenge:Category	0.67	'0.18 - 1.16'	< **0.01**
Control:Category	NA	NA	NA
Observations	478		
R^2 / adj. R^2	0.072 / 0.064		
F-statistic	9.175***		

Significance codes: *0* *'***'* *p-value < 0.05 in* ***bold***
0.001 *'**'*
0.01 *'*'*
0.05 *'.'*
0.1 *' '*

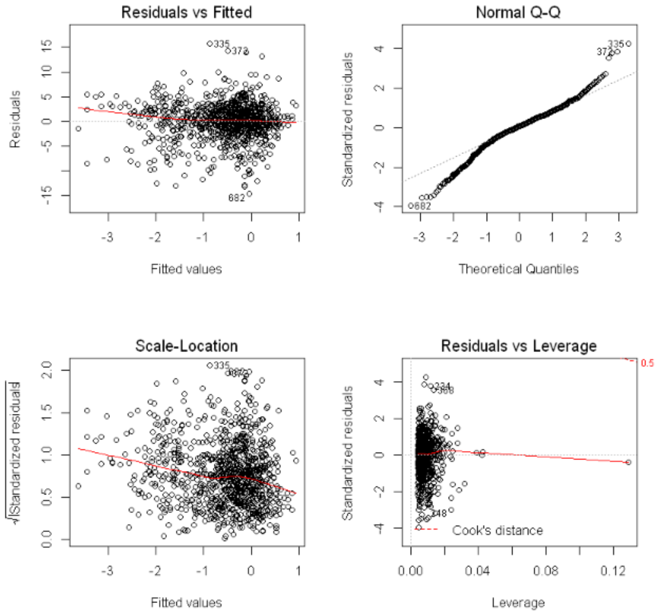
The validity of the models is assessed by inspecting the normal QQ-plots, Residuals vs. Fitted plots, scale-location plot and Cook's distance plot. For the Balanced model see Table 4.17, for all the models compared see Figure Appendix 2.4 *Challenge effect weight models: Balanced, Challenge, Control, Females, Males*). We assume the explanatory variables are not correlated as further confirmed by the matrix plot in Table Appendix 2.8.

Table 4.17 ***Challenge effect weight (%), Balanced model: Descriptive stats & diagnostic plots***

Descriptive Statistics: Balanced model

	Variable	Mean (SD)	Frequency
	y_outcome	-0.57 (3.78)	
	Age	41.24 (10.46)	
	Registration	190.41 (47.47)	
Sex	Female	-0.53 (4.1)	478 (50%)
	Male	-0.6 (3.44)	478 (50%)
Label	Challenge	-1.03 (3.92)	478 (50%)
	Control	-0.1 (3.58)	478 (50%)
Challenge	Category		
	Fitness	-0.64 (3.64)	140 (14.6%)
	Weightloss	-1.95 (4.4)	478 (50%)
Female	Label		
	Challenge	-0.83 (4.17)	239 (25%)
	Control	-0.24 (4.01)	239 (25%)
Male	Label		
	Challenge	-1.22 (3.65)	239 (25%)
	Control	0.03 (3.1)	239 (25%)

Diagnostic Plots: Balanced model



<u>Analysis using the five models on weight change</u> (see Table 4.18):

- There is significance to explain up to 6.4% of the variance in weight change for the different datasets and respective models.

Challenge model ('<u>Structured intervention</u>')

- There was a significant weight loss (positive improvement) just for being part of the challenge; this is the 'challenge effect' for weight change.
- For every 10 lbs. heavier at initial state (registration), a participant might lose -0.1% more weight. However, this change is negligible when compared to the impact of other factors.

Control model (control group), which clearly is different from the challenge:

- In general they performed worse than the challenge. This result validates the intervention as a digital environment because the control group is unstructured, with no explicit or clear goals, no explicit rules, no explicit or defined environment of intervention, no social interaction framework and no intervention design.

Female and male models:

- The Category matters for males, but not for females:
  - Males in fitness category lost less weight than those in the weight loss category.
  - In contrast to the above, weight change in females is about the same for both categories: fitness and weight loss.
- There is a different weight change by gender (determined by the initial weight level at registration). Although, the difference is negligible.
  - For females the initial weight is not a predictor of weight change
  - For males the initial weight can explain to some extent the change in weight
- Males in the challenge did better than the control group. The 'challenge effect' stands for weight loss in males.
- No significant factors were found in the female model, meaning that further research is required to understand the mechanics of weight loss in females.

Balanced model ('<u>Structured intervention</u>' –vs- <u>Control group</u>) (without repetition):

- There is an even bigger 'challenge effect' for participants on the weight loss category. They did better losing weight than the population of the challenge, which is already better than the control.

Table 4.18 ***Challenge effect weight (%), 5 models: Summary table***

Model	Balanced	Challenge	Control	Females	Males
Sample size	956	551	551	478	478
R^2	0.035	0.021	0.000	0.013	0.064
Significant & relevant terms (*) (*In grey not relevant*)	• • *Registration* • • • ***Label*** • ***Label/Category***	• • *Registration* • • • •	• • • • • •	• • • • • •	• • *Registration* • • • ***Label*** • ***Label/Category***
Label *, comparison to population	• Challenge: Loss more than Control.				• Challenge.: Loss more than Control
Label/Category * , comparison to population	Challenge label: • Fitness: Loss, -0.32% more than Control • Weight.L.: Loss, -1.48% more than Control				Challenge label: • Fitness : Loss, -0.65% more than Control • Weight.L. : Loss, -1.99% more than Control

4.6.2 The 'team effect'

As part of the discussion of the results the 'team effect' was reviewed in Experiment 1 for weight change (%) and steps change. There is a difference in the distributions of individual and team participants (only those in the categories 'Fitness' and 'Weight Loss' were included). The teams' distributions of outcome results (either *weight change* (%) or *change in steps*) are more concentrated around the mean. The individuals' distributions of outcome results have fatter tails. For illustration please see Figure 4.7 and Figure 4.8 below.

In general it can be said that *individuals* on the platform displayed a broader range of results (with fatter tails on both directions). This means that individuals in the context of challenges produce more extreme results either:

- Losing a significant amount of weight or gaining extra kilos / pounds
- Walking much more or much less

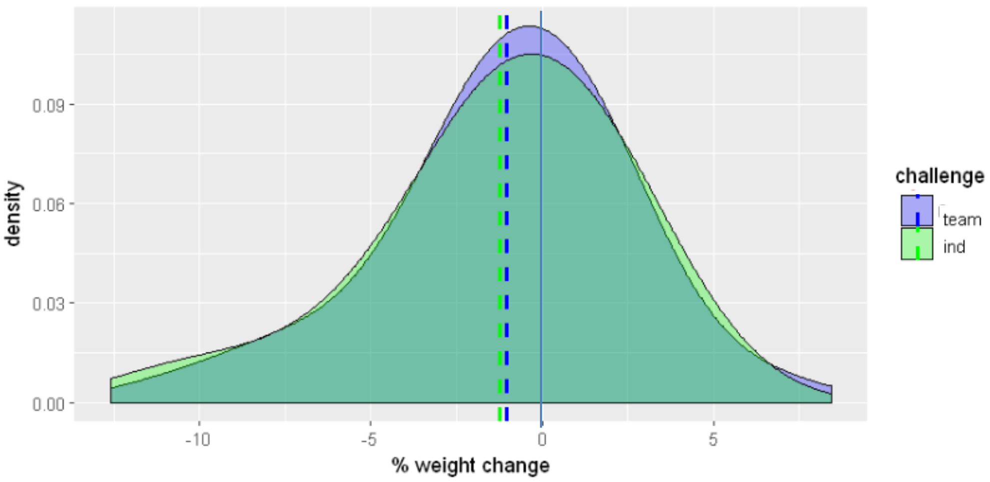


Figure 4.7 ***Corporate Challenge: Team effect for weight change (%), distributions***

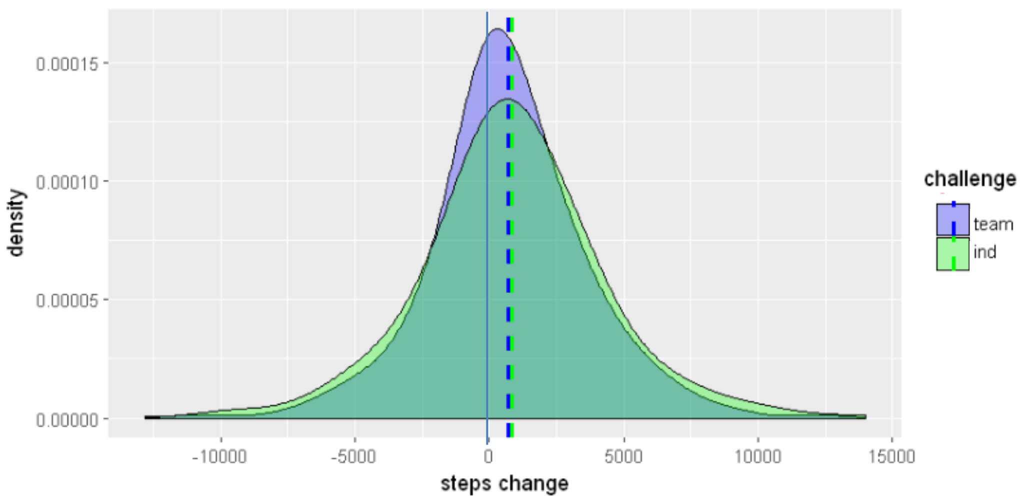


Figure 4.8 ***Corporate Challenge: Team effect for steps change, distributions***

The *teams* display a more compact / average range of results, meaning that teams encourage a more average change. This could mean that teams dampen extreme performers and support and average change of the target outcome result. (*The results represented for teams in Figures 4.7 and 4.8, are for each participant who is part of a team*).

4.6.3 The impact of adherence

The Experiment 1 can be analysed on the impact on *weight change (%)* using an *input-output analysis* in which the objective is to determine if completing more check-in stages (*input*) produces a higher weight loss (*output*). For the analysis, the '*input*' level (*x-axis*) is defined as the participants' adherence to the intervention, measured by the number of completed stages. The '*output*' is the weight change (%) (*y-axis*) on the subpopulation that completed each check-in stage (*x-axis*) only (Figure 4.9, below).

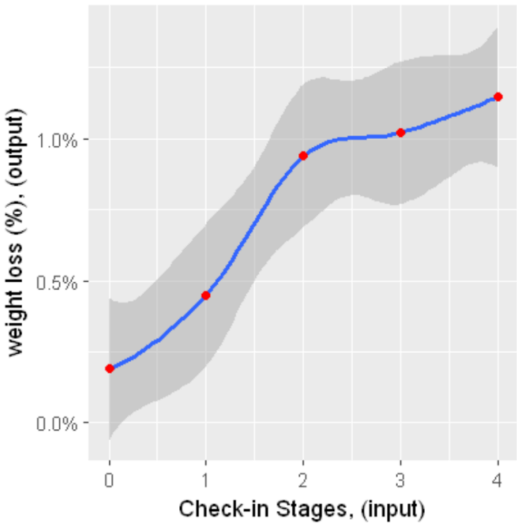


Figure 4.9 ***Corporate Challenge: Input-Output analysis for weight change (%)***

4.7 Conclusion and further work

In Experiment 1 it was possible to capture the behaviours of 24,797 participants, of which 7,092 of them where generating self-tracking data of multiple behaviours during 4.5 months, providing enough data to support the findings summarized in this section.

PHYSICAL ACTIVITY

The 'challenge effect'

- There was a significant change in steps (positive improvement) just for being in the challenge, the 'challenge effect' for the change in steps. In contrast to the control group, with no significant change or improvement.
- There is an even bigger 'challenge effect' for participants on the fitness category, compared to those in the weight loss category. Both categories of the challenge, did better than the control group.

Age matters

- Age matters in the challenge, the older the participant the greater the change in steps.
- Age does not impact steps improvement for the control, under the unstructured environment.
- Age plays a part in steps improvement for males but not for females.

Female and males

- Females and males in the challenge did better than the control group. The 'challenge effect' stands for positive change in steps across gender.
- There is no difference between gender on the improvement rate by initial steps.
- The Category matters for females, but not for males:
  - Females in fitness category have higher average improvement in steps (than those in the weight loss category).
  - In contrast to the above, the step performance in males is about the same for both categories: fitness and weight loss.

Being explicit about 'fitness' to improve the physical activity

- The models provide evidence to support the argument that there is positive impact of being explicit about 'fitness' to increase physical activity (measure as daily steps count). This result is supported by the 'challenge effect'.

Using the platform

- Logging in to the platform makes a difference, because the platform as an intervention context (digital environment) seems to accentuate the proclivity to increase physical activity, this is confirmed by the 'challenge effect'.

WEIGHT LOSS

The 'challenge effect'

- There was a significant weight loss (positive improvement) just for being part of the challenge; this is the 'challenge effect' for weight change.
- The control model, control group, (which clearly is different from the challenge, '<u>structured intervention</u>): in general they performed worse than the challenge.

Female and males

- Males in the challenge did better than the control group. The 'challenge effect' stands for weight loss in males.
- The Category matters for males, but not for females:

  - Males in fitness category lost less weight than those in the weight loss category.
  - In contrast to the above, weight change in females is about the same for both categories: fitness and weight loss.

Being explicit about 'weight' to lose weight

- There is evidence to support the argument that there is positive impact of being explicit about 'weight loss' to increase lose weight (measured as change in weight).
- There is an even bigger 'challenge effect' for participants on the weight loss category. They did better losing weight than the population of the challenge, which is already better than the control.

Completing the intervention

- Completing the intervention stages makes a difference to lose weight during the intervention

Team members –vs team captain

- Team members did better (lost more weight) than the team captains

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<u>Further Work</u>.

Further work is recommended to understand better the intervention drivers for physical activity and weight loss. A factorial design approach would be useful in order to make multiple simultaneous experiments while recycling the control groups to assess with more detail the interactions between intervention components.

Further work PHYSICAL ACTIVITY

- There is a difference in how males and females respond to the intervention as a change in steps (outcome measure), although this difference is not present in the balanced dataset and the teams dataset. The analysis of the impact of a team as a factor that dampens the female – male difference, this difference is still open for further research.
- The team effect for physical activity should be revisited.

Further work WEIGHT LOSS

- No significant factors were found in the female model, meaning that further research is required to understand the mechanics of weight loss in females.

- There is a different weight change by gender (determined by the initial weight level at registration). Although, the difference found was negligible, further research is recommended. It is worth to review:
    - For females the initial weight is not a predictor of weight change
    - For males the initial weight can explain to some extent the change in weight
- The team effect for weight loss should be revisited.

Further work OTHER METRICS

- For a future experiment other analytics should be captured: demographics, self-evaluation, personality traits, among others.

- This metrics should be captured at the on-boarding of the intervention and as the intervention is running.

The analysis of Experiment 1 continues in the following Chapter 5: "*The Network Effect, the Impact of Social Interaction (Experiment 1. PART TWO)*".

Chapter

5. The Network Effect, the Impact of Social Interaction, *(Experiment 1. PART TWO)*

This chapter covers the analysis of social interaction on Experiment 1, as a 'network effect' and its impact to increase physical activity and weight loss. The chapter covers: research motivation and objectives, methodologies, dataset description, results, discussion, conclusion and further work. This chapter continues the analysis done in Chapter 4 for the Corporate Challenge.

5.1 The impact of social interaction, is there a network effect?

There is evidence in literature about the spread of behaviour in social interaction: Centola highlights the importance of tight networks for behaviour change [137]; Christakis et al. mapped the epidemic spread of obesity [139]; Poncela-Casasnovas et al. analysed social structure and weight loss [147] and Rusinowska et al. have explored the relationships between centrality and influence [133]. As a continuation of Chapter 4, this Chapter 5 investigates if there was a 'network effect' on the Corporate Challenge affecting the increase of physical activity and weight loss. Network analysis was used to obtain the underlying complex structure of social dynamics during the Corporate Challenge. By mapping the postings to digital walls a bipartite network was created, then projected and filtered to obtain the affiliation network (Figure 5.1 and Section "*2.7.3 Applied network analysis*").

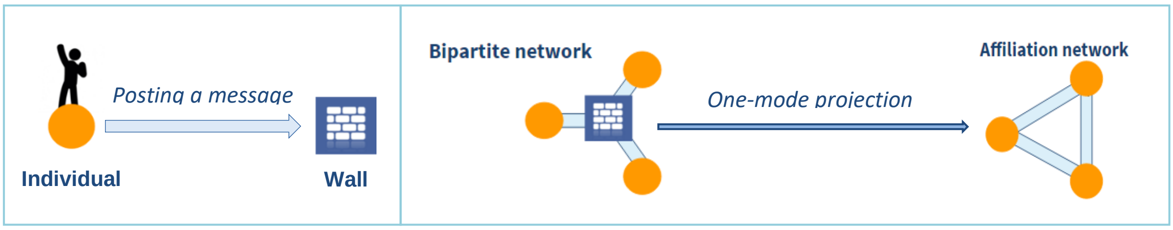


Figure 5.1 ***Social Interaction on the platform: from the bipartite network to social structure***

5.2 Research motivation & objectives

The research motivation for the network effect of the Corporate Challenge was to investigate the impact of social interaction on behaviour change related to physical activity and weight loss. There are two research objectives for this analysis:

- Assessment of the impact of social interaction as network effects and social structure
- Assessment of the impact of base characteristics on the social structure

5.3 Chapter structure

The following sections of the chapter cover experimental design, datasets and findings in the form of relevant results of the analysis of social interaction on the Corporate Challenge:

- There is a network effect increasing physical activity when an individual has a high degree of connection and a high level of communication.
- There was no significant network effect of social interaction for weight loss.

Followed by the discussion comprising:

- Base characteristics and some components of the Corporate Challenge are analysed to provide an explanation about the nature of social structure underlying participants' interaction.

The chapter finishes with conclusion and further work.

5.4 Research Methodology

The Corporate Challenge was designed with digital walls for postings. As observational research, it was expected that the use of digital walls would reveal the underlying social dynamics and social structures related to goals and base characteristics.

5.4.1 Experimental design

The walls were assigned based on the modality: a team would have only one collective digital wall for all the members of a team; individual participants would have an individualized digital wall. The mechanics of interaction as network topology are represented on Figure 2.8 and Figure 4.5. Network analysis was used to infer the inherent social structure by mapping the postings' as social interactions. A bipartite network was the result of the communication process. The bipartite network was transformed by one-mode decomposition, to obtain the resulting disjoint graph of the association/affiliation network representing the social structure of interaction analysed on this section. The structure indicates that the user interaction on the platform did not create a social network, instead the social interaction resulted in the formation of association networks.

5.4.2 Dataset

The key figures of social interaction on the platform describe the underlying nature of the social interaction: (i) participants that posted on a wall 4,385, (ii) walls used 3,097 and (iii) postings 9,860. The analysis is restricted to those participants who used the platform for social interaction. Not all the participants used the posting mechanism on-platform and there is no data for other means of social interaction of-platform.

The exploratory data analysis of this data subset revealed that: (1) the self-tracking data was important in order to do analysis on measurable outcomes, (2) a large number of participants posted only once on one wall and (3) in many cases the posting was only on their own wall. (4) The self-posting-only individual participants (did not post on someone else's wall) and to whom nobody else posted on their wall, could not be mapped to the social interaction structure. After the EDA the datasets were defined as those in which participants had in addition to social interaction data: (a) daily steps self-tracking data, 783 participants and (b) weight data, 721 participants.

5.5 Analysis and Results

The results generated by the Corporate Challenge for the analysis of social interaction as a 'network effect' with impact on physical activity and weight loss are now described in this section. The initial network analysis indicated that the factor that captures the network effect for this specific network is the interaction component '*Degree:All_posts*'. This interaction term *Degree:All_posts* captures how connected is an individual and the use that she/he makes of those connections (her/his network) by making postings. This term reflects the interaction between: '*All_posts*': the total number of postings made by a node (participant) and '*Degree*': the total number of direct connections a $node\_p_i$ has within the network.

The degree was transformed from its initial integer variable form into two categories: '*low*' (degree $\leq$ 2) and '*high*' (degree $\geq$ 3). Further subgroup analysis by Degree (Low, High) was also done by fitting the model to the each subgroup. The two models used to evaluate the network effect of the Corporate Challenge (one for change in steps and one for change in weight) are fitted using a standard ordinary least squares (OLS) regression with an interaction term.

5.5.1 The network effect of social interaction in physical activity

This section evaluates the impact of social interaction as a network effect influencing the increase (decrease) in physical activity. The dataset for this analysis has the daily steps count data ('steps') and the network metrics that reflect the implicit social interaction structure of 144 participants during the Corporate Challenge (the sample size was reduced to 144 participants after the process of data quality control to ensure enough data points are available for analysis).

The descriptive stats for the 'y_outcome' (*change in steps*) and the independent variables (*All_posts*, *Degree*) for the *Social interaction model* for *change in steps* are in Table 5.1.

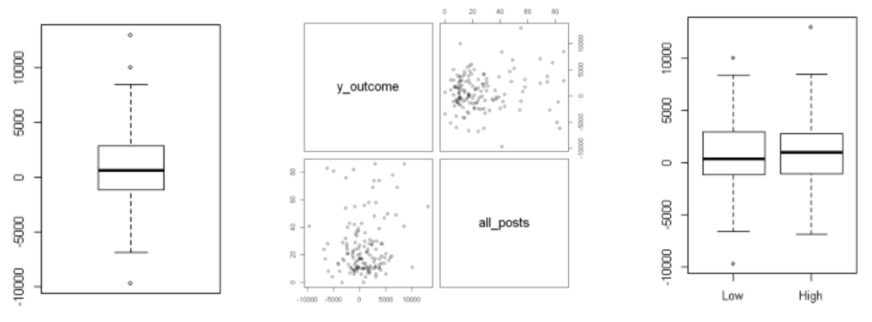
Table 5.1 ***Change in steps, Social interaction Model: Descriptive stats***

	Variable	Mean (SD)	Frequency
	y_outcome	765 (3381)	
	all_posts	25 (20)	
Degree	Low	450 (3330)	82 (57.3%)
	High	1187 (3431)	61 (42.7%)

The normal distribution for the y_outcome (*change in steps*) remains within each category. We assume the explanatory variables are not correlated as further confirmed by the matrix plot in Table 5.2 below.

Table 5.2 ***Change in steps, Social interaction Model: Matrix plot***

Y_outcome	Continuous variables	Degree



The dependent variable *change in steps* is normally distributed. The independent variable '*Degree*' has two levels (*low* and *high*) as described before. '*All_posts*' is the sum of all the postings made during the challenge. The normal distribution for the y_outcome (*change in steps*) remains within the degree. Significance level was defined at 5%. The analysis was done on the main model and the subgroup models to ensure consistency of the results, reflected in Table 5.3.

The validity of the *Social interaction model* and the subgroup models (*Social, low degree model* and *Social, high degree model*) are assessed by inspecting the normal QQ-plots, Residuals vs. Fitted plots, scale-location plot and Cook's distance plot (see Figure 5.2, the comparison between models is in Figure Appendix 2.5).

Table 5.3 ***Change in steps, Social interaction model and subgroups: Results table***

Social interaction model

Predictors	*Dependent Variables*		
	y_outcome		
	B	*CI*	*p*
(Intercept)	189.0	-788.3 – 1166.4	.7
Degree	976.3	-1.0 – 1953.7	.1
All Posts	7.9	-22.4 – 38.3	.6
Degree:All Posts	-47.9	-78.2 – -17.6	**.0**
Observations	143		
R^2 / adj. R^2	.083 / .063		
F-statistics	4.185**		

Significance codes:

0	'***'
0.001	'**'
0.01	'*'
0.05	'.'
0.1	' '
1	

p-value < 0.05 in ***bold***

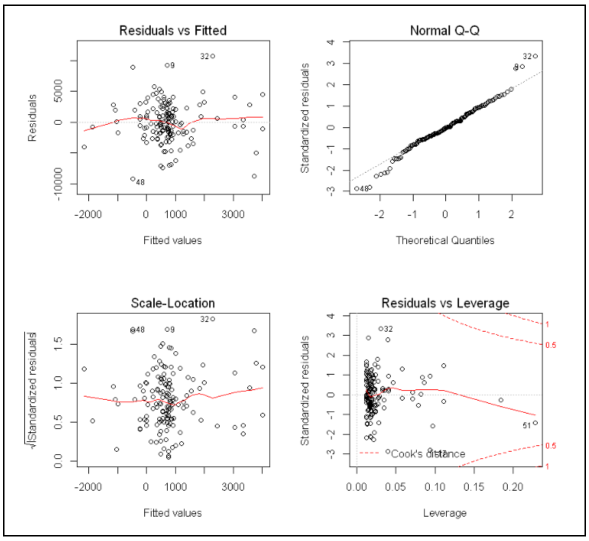
Social, low degree model

Predictors	*Dependent Variables*		
	y_outcome		
	B	*CI*	*p*
(Intercept)	1165.4	60.2 – 2270.5	**.0**
All Posts	-40.0	-86.7 – 6.7	.1
Observations	82		
R^2 / adj. R^2	.035 / .023		
F-statistics	2.901		

Social, high degree model

Predictors	*Dependent Variables*		
	y_outcome		
	B	*CI*	*p*
(Intercept)	-787.3	-2415.4 – 840.8	.3
All Posts	55.8	16.3 – 95.4	**.0**
Observations	61		
R^2 / adj. R^2	.119 / .104		
F-statistics	7.971**		

Figure 5.2 ***Change in steps, Social interaction Model: Diagnostic plot***



The comparative analysis of the *Low* or *High* degree of centrality interacting with the total number of postings and the impact that they have on the change in steps (*y_outcome*) is represented in the following Figure 5.3. The scatter plots have on the y-axis is the *y_outcome* (*change in steps*), the x-axis for both sub-plots is the total number of postings (*All_posts*).

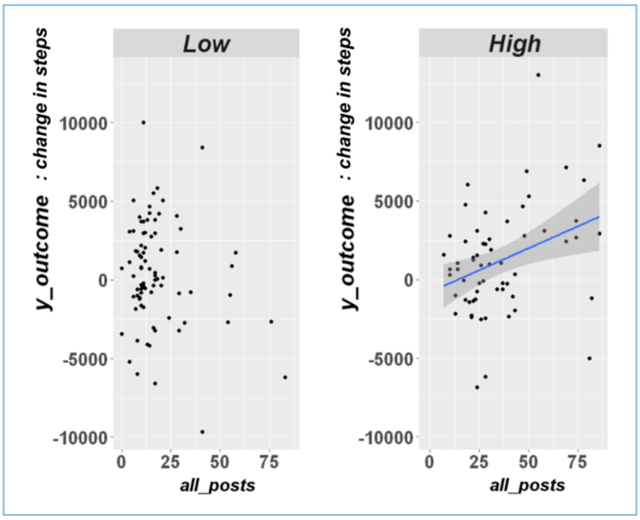


Figure 5.3 ***Comparison of change in steps for the interaction term, scatter plots: Low_degree:All_posts –vs- High_degree:All_posts***

As it can be seen on the '*Low*' (for Low degree) chart there is no clear trend. In contrast with the '*High*' chart that has a clear trend. This trend explains the nature of behaviour captured in the Social Interaction model, providing evidence to claim the presence of a 'network effect' for the improvement of physical activity on the Corporate Challenge.

<u>**Analysis using the Social interaction model & subgroups for change in steps**</u> (see Table 5.4):

- The impact of social interaction can result in a network effect for the individuals who have a direct social network of good size (measured as a high degree of centrality ≥ 3) if they communicate sufficiently with the members of this network. This network effect has the potential for positive influence to increase physical activity.

- There is significant evidence for a 'network effect' related to increasing physical activity measured as average daily count of steps. Although the R^2 is low there is significance to explain 6.3% of the variance in the steps.

- There is no evidence that the population of the intervention using the social interaction feature had a change in daily steps count.

Table 5.4 ***Change in steps, Social interaction model and subgroups: Summary table***

Model	Social interaction	Social, low degree	Social, high degree
Sample size	143	82	61
R^2	0.063	Not significant	0.104
Significant terms (*)	• ***Degree: All_posts***	NA	• ***All_posts***
Degree :All_posts* , For every 1 additional posting	• The change in HIGH degree + 96 , more than the change in LOW degree	NA	
***All_posts* *,** For every 1 additional posting		NA	• HIGH degree + 55.8

5.5.2 The network effect of social interaction for losing weight

This section evaluates if the impact of social interaction can result in a network effect with positive (or negative) influence for weight loss, measured as *change in weight*. After data quality control (to ensure enough data points are available for analysis) the sample size was reduced to 42 participants. The dataset has weight measurements data ('weight') and the network metrics that reflect the implicit social interaction structure of 42 participants during the Corporate Challenge.

The descriptive stats for the 'y_outcome' (*change in weight (%)*) and the independent variables (*All_posts*, *Degree*) for the model are in Table 5.5 (below). The dependent variable *change in weight* (%) is normally distributed. As described in the previous section the independent variable '*Degree*' has two levels (*low* and *high*) as described before. '*All_posts*' is the sum of all the postings he made during the challenge. The models analysed for the consistency of the results are in Table 5.7.

Table 5.5 ***Change in weight (%), Social interaction model: Descriptive stats***

Social interaction model

	Variable	Mean (SD)	Frequency
	y_outcome	-1.24 (4.4)	
	all_posts	23.07 (19.3)	
Degree	Low	-0.92 (4.22)	24 (57.1%)
	High	-1.67 (4.73)	18 (42.9%)

From the matrix plot in Table 5.6 below, some nonlinearity in the relationship between *Y_outcome* and *All_posts* can be seen. The sample size of 42 is small for the high variability observed, and this is an indication that the results might require further investigation (beyond the scope of this work).

Table 5.6 ***Change in weight (%), Social interaction Model: Matrix plot***

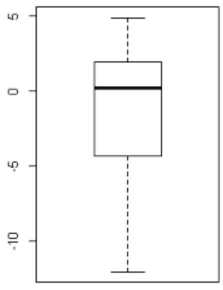
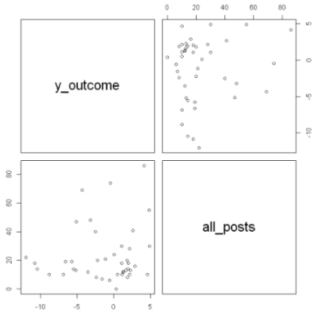
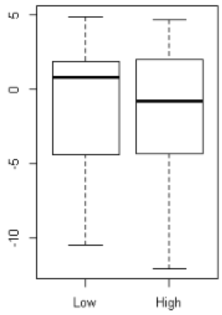
Y_outcome	Continuous variables	Degree
		

Table 5.7 ***Change in weight (%), Social interaction model and subgroups: Results table***

Social interaction model

Predictors	*Dependent Variables* y_outcome *B*	*CI*	*p*
(Intercept)	-2.6	-5.0 – -0.1	**.0**
Degree	-0.5	-2.9 – 2.0	.7
All Posts	0.1	-0.0 – 0.2	.1
Degree:All Posts	0.1	-0.0 – 0.2	.2
Observations	42		
R^2 / adj. R^2	.085 / .013		
F-statistics	1.174		

Significance codes:
*0 '***'*
*0.001 '**'*
0.01 ''*
0.05 '.'
0.1 ' '
1

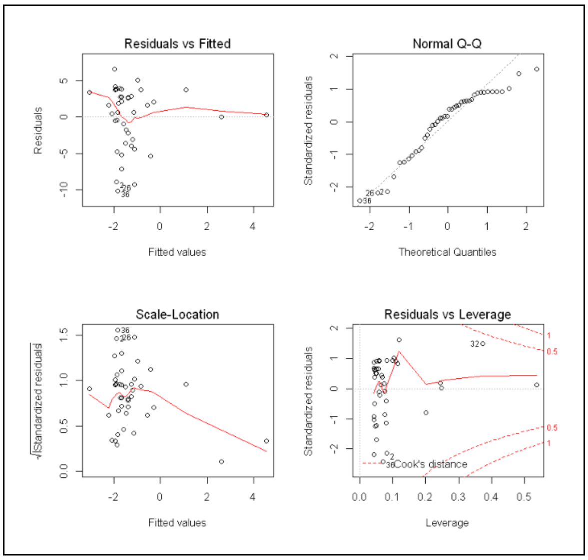
*p-value < 0.05 in **bold***

Social, low degree model

Predictors	*Dependent Variables* y_outcome *B*	*CI*	*p*
(Intercept)	-3.0	-5.8 – -0.2	**.0**
All Posts	0.1	-0.0 – 0.3	.1
Observations	24		
R^2 / adj. R^2	.147 / .108		
F-statistics	3.796		

Social, high degree model

Predictors	*Dependent Variables* y_outcome *B*	*CI*	*p*
(Intercept)	-2.1	-6.5 – 2.3	.3
All Posts	0.0	-0.1 – 0.1	.8
Observations	18		
R^2 / adj. R^2	.004 / -.058		
F-statistics	0.063		



The validity of the *Social interaction model* and the subgroup models (*Social, low degree model* and *Social, high degree model*) are assessed by inspecting the QQ-plots, Residuals vs. Fitted plots, scale-location plot and Cook's distance plot (see Figure 5.4 and the comparison between models in Figure Appendix 2.6).

Figure 5.4 ***Change in weight, Social interaction Model: Diagnostic plot***

There seems to be some violations of the assumptions of homoscedascity and linearity. *Hence, no significant conclusion can be and further work is suggested*.

<u>Analysis using the Social interaction model & subgroups for change in weight</u> (see Table 5.8):

- Further investigation is recommended to explore the 'network effect' related to weight loss.

Table 5.8 ***Change in weight (%), Social interaction model and subgroups: Summary table***

Model	**Social interaction**	**Social, low degree**	**Social, high degree**
Sample size	42	24	18
R^2	Not significant	Not significant	Not significant
Significant terms (*)	NA	NA	NA
***Degree / All_posts* *** **,** For every 1 additional posting	NA	NA	NA
***All_posts* *,** For every 1 additional posting	NA	NA	NA

5.6 Discussion

The results so far indicate there is evidence of positive outcomes related to a network effect for physical activity increase. The network effect cannot be assessed to a control group, because such control group does not exist. Further analysis is done to understand the nature of the network structure. Other factors are assessed as well: teams, females and males and the impact of adherence.

5.6.1 Social structure and social interaction

As part of the assessment of results, this subsection explores the drivers behind the structural formation of the social interaction that took place during the Corporate Challenge. The main question was the determination of which factors explain the formation of the association networks behind the results. The answer to this question has an expected high information gain for future interventions.

The initial approach was to determine if geographic location could explain the structure of the network. As it can be seen on Figure 5.5, it was not the case: the network layout (left) explains more compared to the same network on a map (right). In both cases the strength of the connection was determined by the 'weight' of the edge and represents a stronger link between participants.

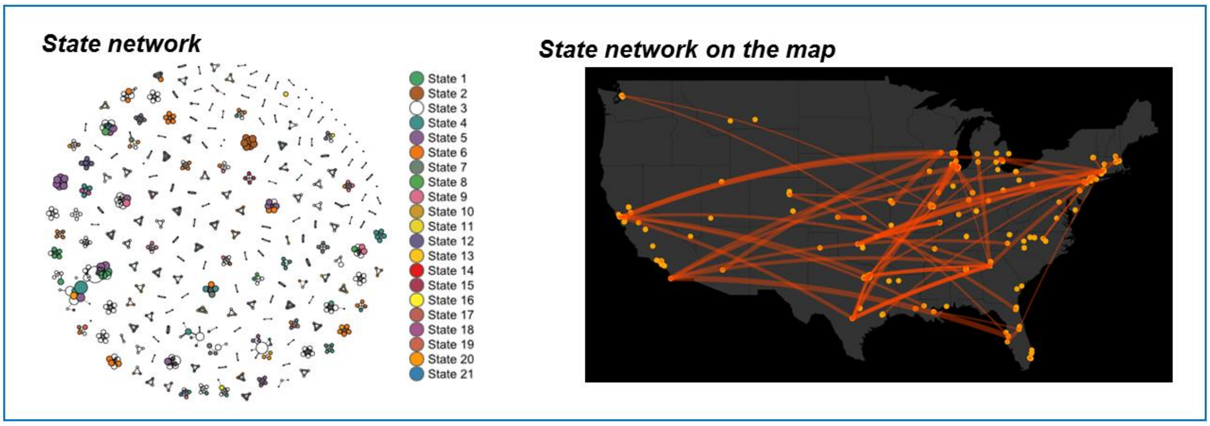


Figure 5.5 ***Comparison of the association networks related to state: 2 representations***

To assess the network structure, *Different segments* of the population (*x-axis* of the charts, Figure 5.6) where compared on the *node degree* (*y-axis*). The following statements summarize the assessment of these plots.

(1) Females are more connected than males.

(2) Team members are more connected than individuals.

(3) Management users are more connected than the other participants.

(4) Those in the fitness category are more connected than those on weight loss.

(5) As more stages are completed the degree in the system is higher.

(6) Participants of some business units are clearly more connected than others.

(7) Of those who have synced devices, those with 1 or 2 are more connected.

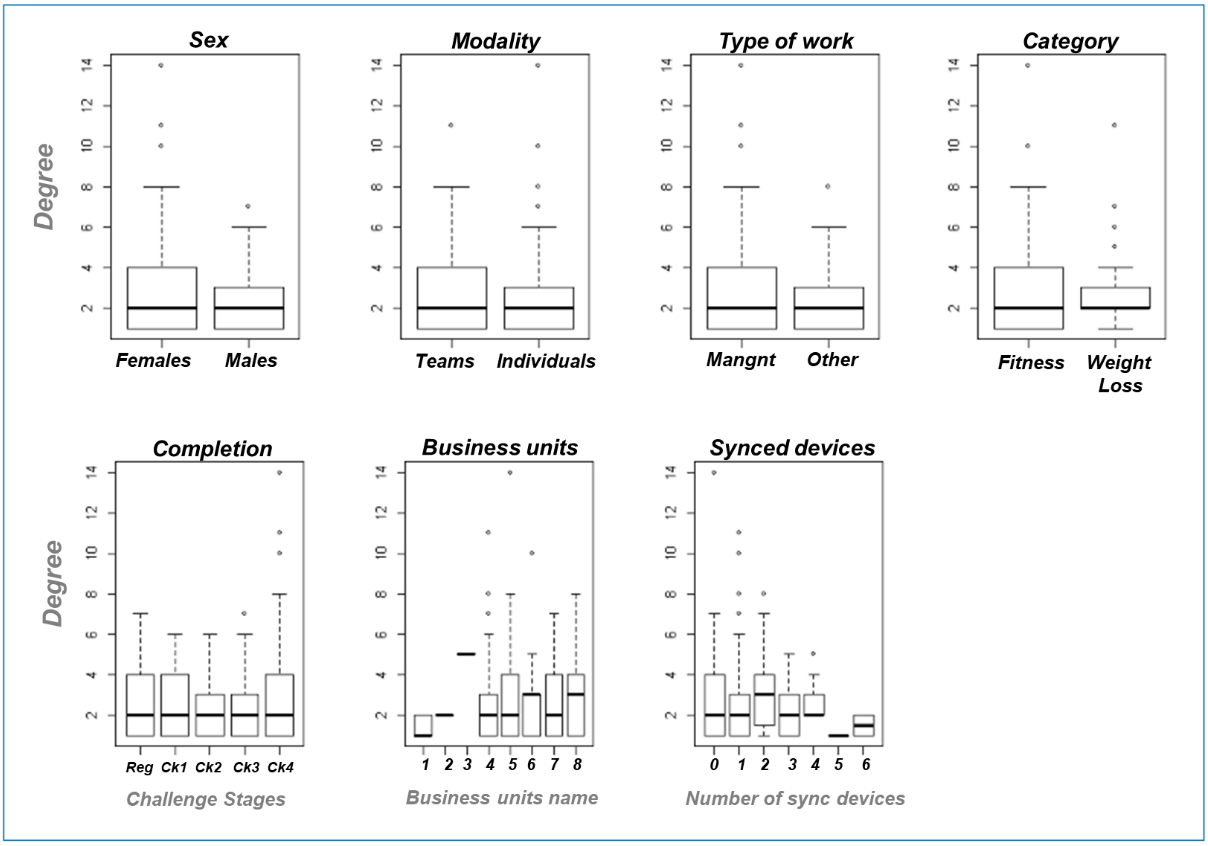


Figure 5.6 ***Comparison of nodes' degree, box plots: Sex, Modality, Type of work, Completion, Business units and Synced devices***

The association networks plotted in Figure 5.7 (below) display in network representation the same segments found on Figure 5.6 (with the exception of completion). The segments analysed are illustrated as colours in the nodes. The size of each node is the degree. The width of the edges is the number of postings, a proxy for connection strength.

The analysis indicates that the structure of the network seems to be determined by the *sex* and being part of *Business units 2 and 4*. Relevant to highlight as well, that the network of the Corporate Challenge was heavy loaded on teams, management and fitness.

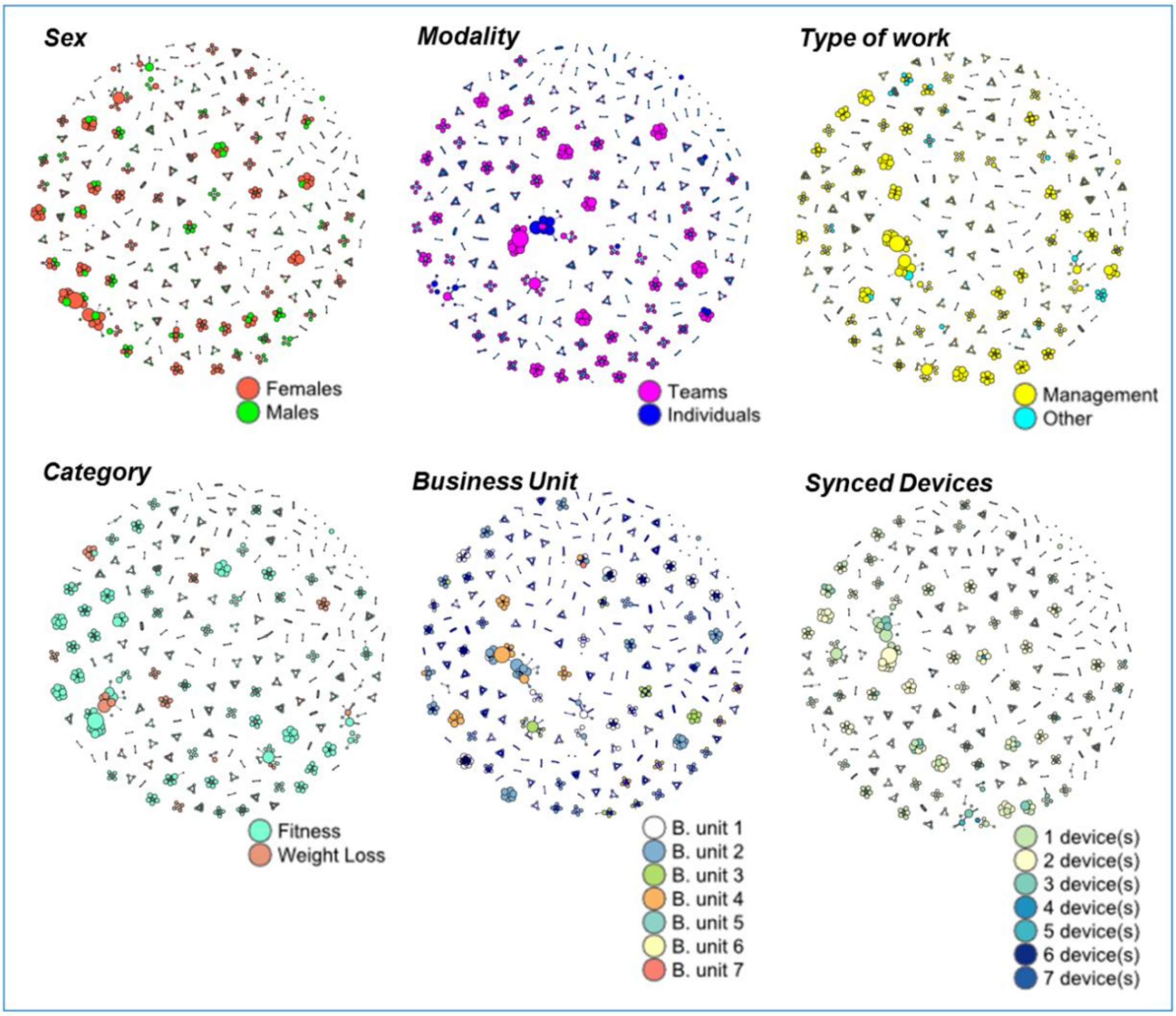


Figure 5.7 ***Comparison of the association networks represented by: Sex, Modality, Type of work, Category, Business units and Synced devices***

A similar analysis was done to determine if the affiliation/associative networks' structure was defined by the data collection concentration. The network diagram to the left of Figure 5.8 displays the amount of data (collected per user) as the size of the node. As it can be seen, the data collection was not a determinant of the network structure.

By colouring the same network by the business unit (Network diagram at the right of Figure 5.8), it was possible to determine that business unit 2 (technology and operations) comprises those participants with high levels of data collection.

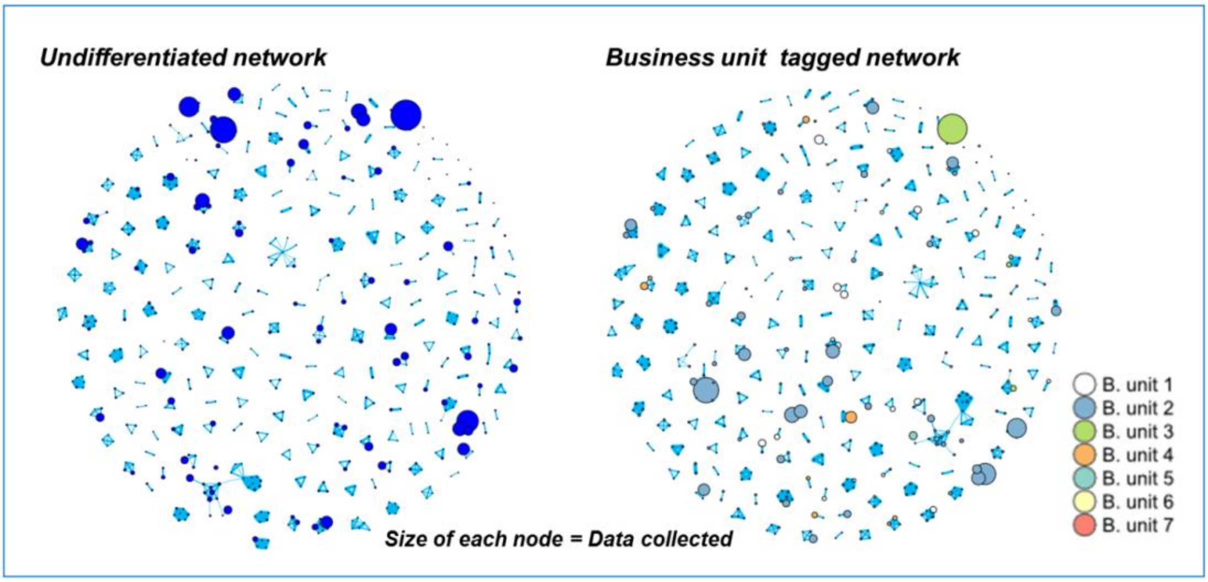


Figure 5.8 *Association networks and data collection*

5.7 Conclusion and further work

In Experiment 1 it was possible to capture the network effect effecting physical activity, but not for weight loss on this intervention. This network effect was product of social interaction and provides interesting insights for future interventions, the findings of the chapter are summarized in this section.

The NETWORK EFFECT for PHYSICAL ACTIVITY

- The impact of social interaction can result in a network effect for the individuals who have a direct social network of good size (measured as a high degree of centrality $\geq$ 3) if they communicate sufficiently with the members of this network. This network effect has the potential for positive influence to increase physical activity.

The STRUCTURE of the SOCIAL INTERACTION NETWORK

- The completion of the challenge is related to a higher degree for the nodes (participants)

- It seems that the structure of the network was influenced by:
  - the sex (females were more connected and communicative) and
  - two business units (bu. 2 & bu. 4)

- The network structure had predominant segments:
  - management predominant over other types of employees
  - team members predominant over individual participants

    - fitness category predominant over weight loss category
    - Participants with 1 or 2 synced devices predominant over those with 3 or more synced devices

- Geography was not a determinant on the structure of the network

- The data collection was not related to the structure of the network

---

<u>Further Work</u>.

Network effects have been found in weight loss for gaining weight as an epidemic process [139] and for losing weight related to social embeddedness (structure) [147], further work is suggested for multi-component technology-based behaviour change interventions. As well, further research is required to explore the factor interaction between physical activity and weight management as a function of social interaction.

Further work for PHYSICAL ACTIVITY

- It is worth to revisit the analysis of the 'network effect' related to physical activity measured as daily steps count. Although there is significance to explain 6.3% of the variance in the steps, the R^2 is low, a bigger sample might provide interesting results and contribute to literature [209].

Further work WEIGHT LOSS

- Further investigation is recommended to explore the 'network effect' related to weight loss since it has already been documented in literature [126, 139, 154]. Unfortunately the sample size was not big enough after the data quality control and filtering, there seems to be and underlying relationship which justifies further work.

Chapter

6. Identification of Critical Factors of an Intervention for Weight Loss and Physical Activity, *(Experiment 2.)*

Experiment 2, the 'Health & Nutrition' study (H&N), was an academic exercise on the identification of the effective components of a behavioural intervention on improving the target habits of nutrition and physical activity (steps count), measuring the change in weight as an outcome. The population of the study was balanced with the majority expressing interests on weight loss. The H&N required the recruitment of participants worldwide for a factorial design approach to analyse the effective components and the combinations of different interventions. The interventions that took place included: coaching, walking challenges, action plans and a discussion forum. The chapter covers: research motivation and objectives, methodologies, dataset description, results, discussion, conclusion and further work.

Experiment 2, was designed for the identification of the most critical factors of an intervention for weight loss and physical activity. The '*Health & Nutrition*' study (H&N) was a large, multi-component, technology-based behaviour change intervention, academic in nature, with simultaneous evidence-based components (see Figure 3.6) and the ethical approval of the UCL Research Ethics Committee (see, Table Appendix 3.1 *Ethical Approval 'Health & Nutrition' study*). For Experiment 2 the frameworks proposed in Chapter 7 (DSABI & ICPI) were used with the BCW, and applied HCI.

As a multi-disciplinary collaboration, Experiment 2's execution involved multiple parties. Tictrac, Industrial partner and financial sponsor: deployment of the platform and funding the intervention. UCL Centre for Behaviour Change: Dr. Carmen Lefevre, provided scientific guidance on behaviour change science. Intervention Design, Execution, Evaluation & Data Analysis: Rodrigo Mazorra Blanco as a UCL PhD researcher and responsible for R&D at Tictrac and Xiaoxi Yan as a Medical Statistician (currently PhD student at Duke-NUS Medical School). LJMU School of Sport and Exercise Science: David Dunne, performance nutrition coach and LJMU PhD researcher, provided the scientific approach for coaching with structured content (delivered by the accountability coaches); in addition to the content architecture for the 'Expert tips action plan' and the discussion forum. UCL, Computer Science Dept.: Professor Philip Treleaven, was the principal researcher as the PhD supervisor of the author of this thesis. UCL School of Management: Dr Soong Moon Kang, provided scientific guidance on computational social science. Accountability coaches, delivered 138 coaching sessions: David Dunne, Robert Seaborne, Mickael Legal, Xiaoxi Yan and Rodrigo Mazorra Blanco. Additional recruitment partners: Oleg Fomenko from SweatCoin; Henry Garcia as consultant for WSI-iStrategy; Healthware International, among many others.

6.1 Which are the critical factors for interventions targeting weight loss and physical activity?

The reference work for this study is the research by Spring and her collaborators [7-9] on multiple component interventions (MBC1 and MBC2) addressing behaviours of suboptimal diet and inactive lifestyle. Multi-component interventions have not been studied enough and have the potential to deliver bundled health behaviours and maximize the positive impact on public health [7]. For this reason (supported by literature) the H&N targeted multiple behaviours related to diet, activity [8] and weight loss [45, 46].

The most useful strategies for weight loss interventions identified by systematic review are [47]: self-monitoring, counsellor feedback and communication, social support, use of a structured program and use of an individually tailored program. The key features for physical activity [32] are: physical activity profiles, goal setting, real-time feedback, social support networking, and online expert consultation. The common ground of evidence-based interventions for weight loss, diet and physical activity that were selected for the H&N are: (1) <u>coaching</u>, (2) <u>walking challenge</u> (teams and individual), (3) <u>action plans</u> and (4) <u>social support / interaction</u> (in the form of a <u>discussion board</u>).

There is broad research on the effectiveness of each one of the four interventions selected, as single factor independent interventions for weight loss and physical activity. (1) <u>Coaching interventions</u> have been broadly studied [20, 151, 210-213], and there is evidence about its effectiveness for sustained behaviour change and on-intervention results. The challenge with coaching is to reduce costs (i.e. via abbreviated behavioural counselling), while providing long-term results. (2) <u>Interventions based on challenges or competitions</u> have positive impact on physical activity for competitive individuals [209, 214], but does not benefit individuals who are less or not motivated by competition. (3) <u>Action plans</u> are regarded as valuable [215-219] in the process of self-regulation, goal-setting as part of behaviour change related to health, physical activity and change in diet. Action plans seem to operate as sequential mediators between intentions and habit strength. It has been reported that the individual's responsiveness to action plans varies and further research is suggested. (4) <u>Social support and social interaction</u> are considered as effective for weight loss, diet and physical activity [147, 153, 154, 220-226]. There are various degrees of effectiveness depending on how social support and social interaction have been rolled out as interventions.

Experiment 2, the Health & Nutrition study was the context to evaluate the simultaneous four interventions selected for the technology-based intervention. An underlying factorial design approach (borrowed form engineering) was planned to recycle the control groups and to facilitate the determination of critical components and the impact of different combinations of interventions.

6.2 Experiment motivation & objectives

The research motivation of the Health & Nutrition study was the determination of critical intervention components for a technology-based, multi-component behaviour change intervention related to nutrition and physical activity with the measurable outcome of weight loss. The H&N study was designed as a pilot factorial randomised controlled trial of the feasibility and effect of a 6 weeks digital intervention consisting of 16 different combinations of four active components, on weight loss and the associated behaviour changes in diet and exercise.

As experimental research the H&N had a factorial design statistical framework and comprised a platform integrating four simultaneous interventions: (1) accountability *coach* (the booking system which may be present or absent); (2) walking *challenge* in which the participant may either be taken as a team (with randomly assigned team members) or as an individual; (3) *action plan* which may either be written by a nutrition expert or written by non-experts who assembled the content via online research; (4) discussion *forum* which may be present or absent.

The intervention components were selected based on previous literature suggesting that there are evidences about these components' effectiveness. The four digital components were delivered simultaneously on one digital platform, built for this specific purpose by Tictrac Ltd. The H&N's platform also had the capacity to connect self-tracking devices and apps re-contextualised as intervention components. The burden for participants was reduced by conducting the interventions within one digital environment and also effectively removing any platform-relevant confounders such as user-friendliness, popularity and preferences.

Experiment 2 has eight research objectives:

- Delivery of an independent intervention with Ethical Approval from the UCL Research Ethics Committee
- Determination of the most effective intervention components
- Determination of the best combinations of intervention components for changes in behaviours related to weight loss
- Determination of different sub-populations and their responsiveness
- Determination of the best outcome variables to evaluate the simultaneous interventions
- Determination of relevant base characteristics for behavioural interventions on nutrition, change in diet, weight loss and physical activity
- Comparative analysis of the actual use of different variations of product features (1 platform)
- Determination of metrics to gauge progress of an intervention as it is taking place ('live')

6.3 Chapter structure

The chapter covers experimental design, datasets, and relevant results of the analysis. The findings of the H&N provide the structure for the chapter:

- The critical factors that led to weight loss
- Non-linear relationships related to weight loss: BMI and change of diet habit
- What explains changes in diet habit and exercise habit

The assessment comprises:

- Scenario analysis is used to determine changes in diet habit and exercise habit
- Personality traits are analysed in the light of changes in diet habit and exercise habit
- Analysis of each one of the interventions

The chapter summarised the research with conclusions and suggests further work.

6.4 Research methodology

The H&N, Experiment 2 was designed as a multi-component intervention using the principles of behaviour change science for intervention design and intervention evaluation. With the objective of expanding on the findings of Experiment 1 and previous research, the H&N was inspired by factorial design. A platform was the substrate for simultaneous delivery of four evidence-based intervention components and the integration of wearables, re-contextualized for behavioural intervention. The components of the intervention as a whole are represented in Figure 6.1 below.

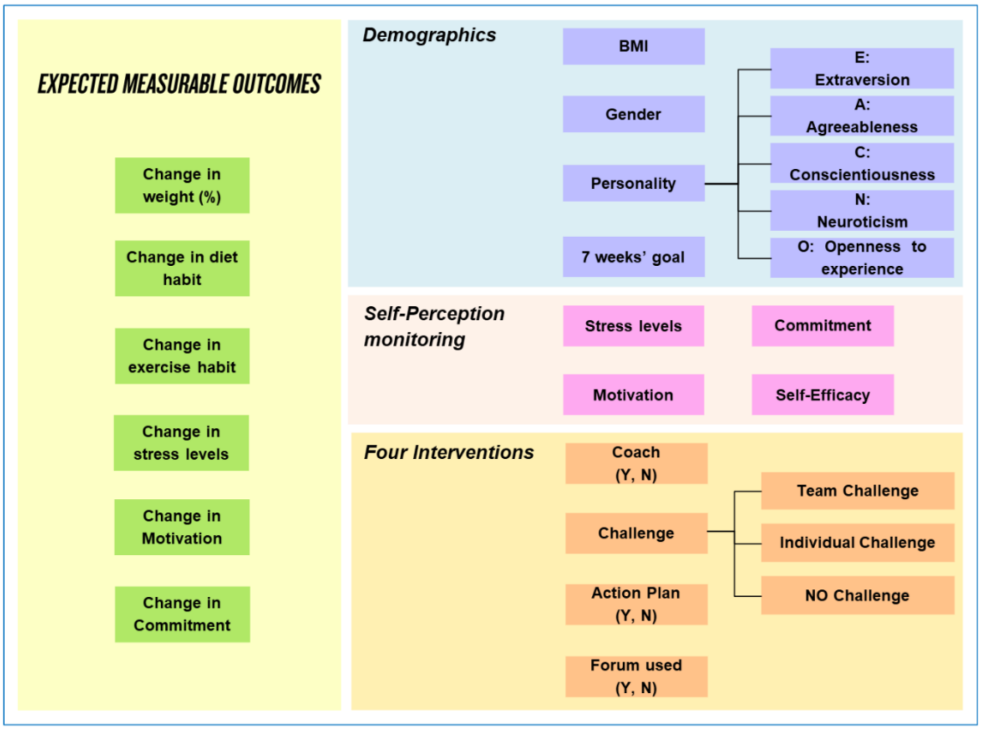


Figure 6.1 ***Health & Nutrition study: Expected outcomes & intervention components***

As part of the initial survey, the participants made explicit their goal interest with regards to weight change between three possible choices: (1) Lose weight, (2) maintain weight or (3) gain weight. The majority was interested in losing weight, followed by those who were interested in maintaining their weight level and with few who were interested in gaining weight (ie. to gain muscle). The analysis was done exclusively on those whose goal was to lose weight, since more than 80% of the participants were interested in losing weight. This predominant interest in losing weight might be related to the fact that more than half of the participants were overweight or obese.

6.4.1 Experimental design

The H&N lasted 10 weeks in total: 6 weeks of intervention, 2 weeks of follow-up and preliminary 2 weeks of recruitment (the exact dates are in Table Appendix 3.3 *'Health & Nutrition' study: Chronology*). The duration of the pilot study was determined by the available funding and resources available for the execution of Experiment 2. The participants on the H&N received an Amazon voucher of £10 GBP if they completed all the surveys required. The message put across to participants was carefully written to ensure that there was no misconception of incentivised performance on weight loss. The use of the experimental platform was not mandatory for the participants in order to receive the voucher.

The platform was encoded with behaviour change techniques as part of the UX/UI on some of the interaction journeys (See Table Appendix 3.2). Three of the four interventions were delivered via the H&N´s platform (walking challenges, action plans and forum). The coaching sessions were booked via the platform and conducted via skype by a team of 'accountability coaches'. Wearable devices and apps for self-tracking of the participants were connected (self-selection process) and used for the walking challenges. The data produced by the platform: via live analytics and aggregating self-tracking data was consolidated with surveys of the participants on a single database as an anonymised repository. The intervention participants were randomly allocated to one of 16 different combinations of the factorial design for the experiment, please see Table Appendix 3.4 *Health & Nutrition study: Factorial Design (PLANNED).* The different 16 combinations of the 4 interventions required different front-end UX/UI versions. A brief description of the interventions:

<u>Intervention 1, Coach</u>, a participant (*only on one of the following*):

- could have access to 3 coach sessions every two weeks (20-30 minutes each)
- or no access to the coaching calls and would not be informed about the coaching sessions

<u>Intervention 2, Walking Challenge</u>, a participant would participate for 5 weeks and have access to the leader boards of *only on one of the following*:

- a team challenge (teams of 4 to 5 members)
- an individual challenge

Intervention 3, Action Plans, a participant would have access to *only on one of the following*:

- 2 action plans designed by Tictrac ('Lose Weight', 'Healthy Eating')
- 1 action plan design by David Dunne, performance nutritionist coach ('Expert tips')

Intervention 4, Discussion Forum, a participant

- could have access to the discussion forum
- or not be aware at all about the forum

During the experimental design phase, resources were allocated to planning as well the intervention evaluation design. The intervention timeline (Figure 6.2) had an on-boarding period, surveys, three coaching sessions (for some participants) and a wrap-up period. The measurement of the intervention was done on the period of time between the 'start' and 'end'. For example, this is how the '*change in weight* (%)' and other outcomes were defined for analysis.

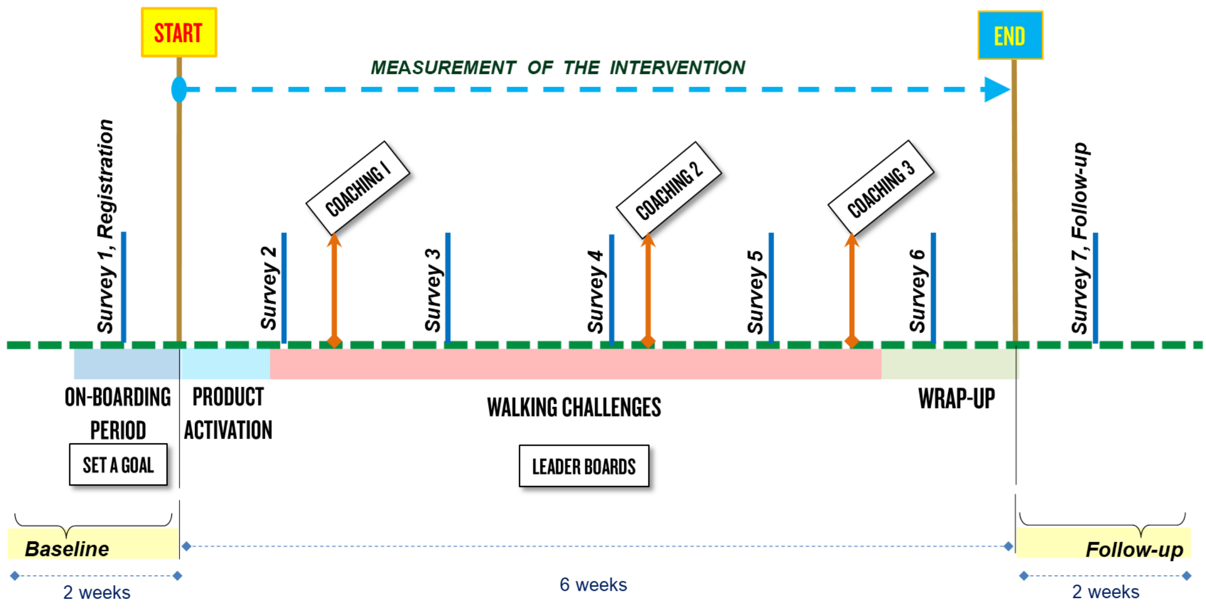


Figure 6.2 ***Health & Nutrition study: Measuring the intervention***

6.4.2 Participant recruitment and data collection

A sufficient number of participants were recruited for the study (see, Figure 6.3 and the recruitment funnel in Table Appendix 3.6). The dropout rate and non-compliance rates were difficult to determine *a priori* since the intervention components were new implementations on one experimental platform; hence no prior reference was available. However, it was expected a >50% attrition rate and for this reason as many participants as possible were recruited for the pilot study. The objective was to have at least 130 compliant participants at end of study to ensure a power of 80% for a moderate effect size (cohen's d0.5) of the main component at 95% confidence level (i.e. 65 participants in combinations with a coach –vs- 65 participants in combination without coach).

There were no complaints related to the physical exercise since each participant decided independently their own activity intensity. No participants were reported as sick or in need of medical attention. The data collection via survey questionnaires was less efficient than what was expected, since some participants dropped out half way into the study. The digital data trace of activity (walking, running, cycling) was collected via the use of the 'Moves' app, but not all the participants collected the self-tracking data. The platform interaction generated analytics to monitor behaviours on the app, and the level of engagement was higher than expected generating data for more than 30% of the users on the platform (30% being a high mark benchmark for apps usage). The data collected by the accountability coaches was rich although not all those that had access to a coach made use of this intervention service.

The data storage was done by Tictrac in encrypted form following the guidelines of PII the researchers had access only to anonymised data. The final database had no PII and personal information was stripped out. No data breaches and no instances of unauthorised access took place.

6.4.3 Datasets

The datasets of the Health & Nutrition study are product of a factorial design delimitated by the actual usage of the four interventions and the connection of self-tracking devices and apps (see Table Appendix 3.5).

The research population breakdown from '*recruitment*' to '*datasets for analysis*' is reflected in Figure 6.3. After filtering for sufficient data and outliers, the datasets for analysis were defined as: (A) '*Change of weight (%)*', (sample 132); (B) '*Change of Diet habit'*, (sample 124) and (C) '*Change of Exercise habit*', (sample 130).

Canonical correlation analysis was done to determine the outcome variables and the independent variables among all the H&N intervention components. This process reduced the set of 'expected measurable outcomes' (Figure 6.1) to only three outcome variables for analysis: *change of weight* (%), *change of diet habit* and *change of exercise habit*.

The filtering criteria to discern which participants would be part of the datasets A., B. and C. is now described: (1) the participant's goal had to be 'lose weight'; (2) the absolute total % change in weight had to be less than 10%, to cut outliers out; (3) they had to use an action plan at least 5 times during the intervention period; (4) they had to complete the 5 personality traits questions; (5) they have had to provide information about their dietary habits at 'start' and 'end'; (6) They have had to provide information about their exercise habits at 'start' and 'end.

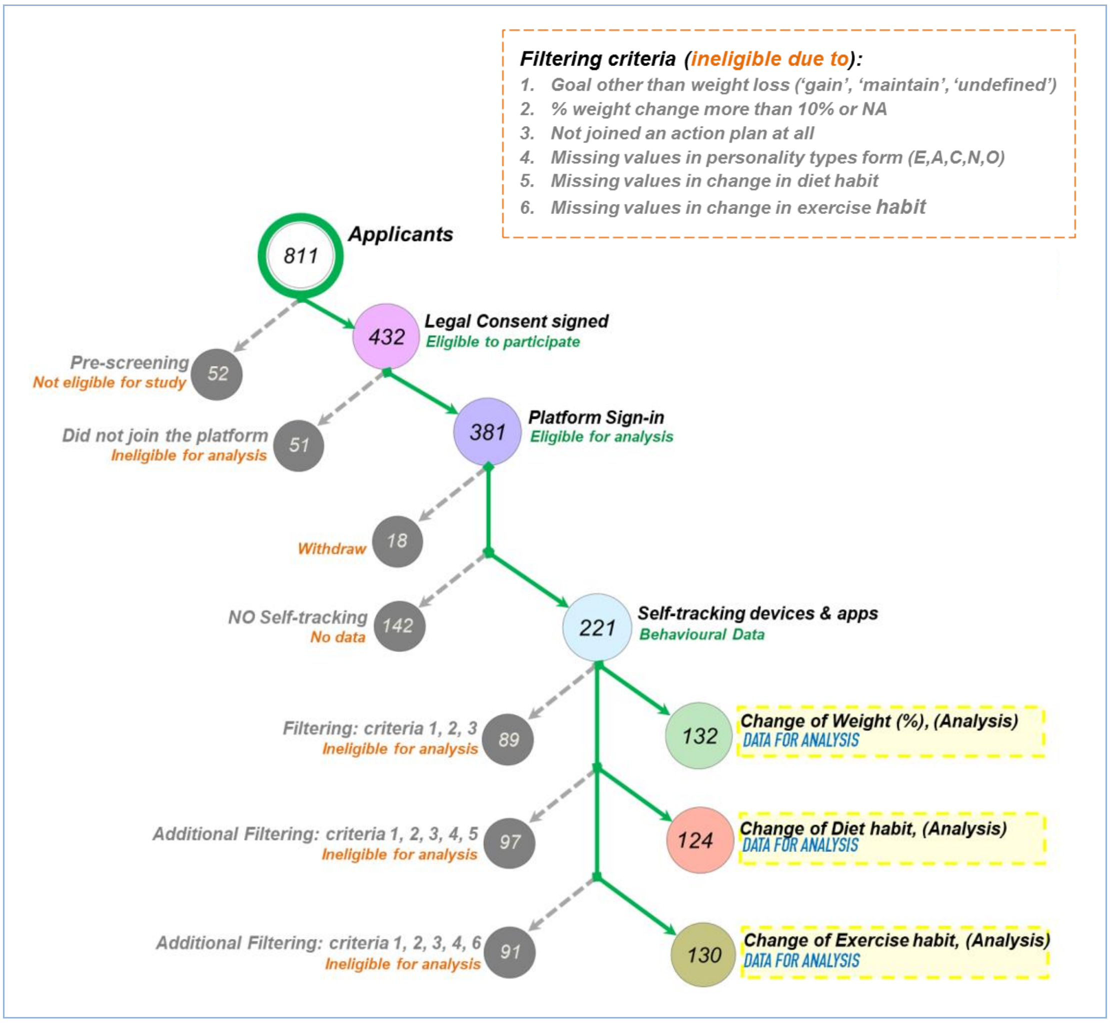


Figure 6.3 ***Health & Nutrition study: Data genealogy***

6.5 Analysis and results

There are many results generated by the Health & Nutrition study as a result of the factorial design approach. This section covers the analysis of the critical factors that led to weight loss, the non-linear relationships related to weight loss (BMI and change of diet habit) and an explanation about the changes in diet habit and exercise habit.

6.5.1 Critical factors that led to weight loss & non-linear relationships related to weight loss: BMI, change of diet habit

The *change in weight (%) model* for this analysis is fitted using a GAM, which is a flexible generalization of the standard OLS models (including those with interaction terms). The GAM *change in weight (%) model* was used for the determination of the effective combination of the four interventions and the components of the intervention. The GAM used splines to assess the possible non-linear effects of two terms: BMI and change of diet habit. The contrasts used for the models are treatment contrasts. The significance level is defined at 5%. The dataset for this analysis is a sample of 132 participants (dataset A, Section 6.4.3). The descriptive statistics for the dataset used in the *change in weight (%) model* are in the Table 6.1.

Table 6.1 ***Health & Nutrition study, Change in weight (%) model: Descriptive Stats***

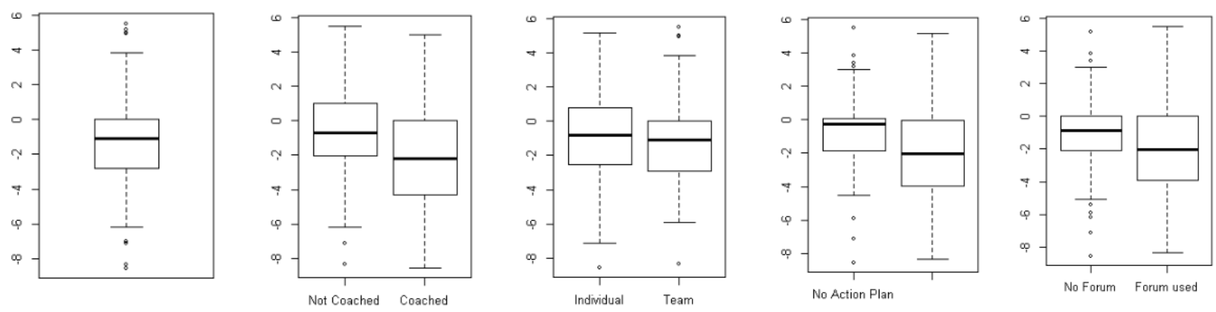
	Variable	Mean (SD)	Frequency
	y_outcome	-1.24 (2.67)	
	BMI	26.88 (5.51)	
	Delta Diet	-0.08 (0.33)	
	Delta Exercise	-0.18 (1.69)	
	Delta Stress	-0.11 (1.38)	
	Delta Commitment	-0.47 (1.04)	
Coach	Not Coached	-0.65 (2.61)	82 (62.1%)
	Coached	-2.2 (2.49)	50 (37.9%)
Forum	No Forum	-1 (2.41)	81 (61.4%)
	Forum used	-1.62 (3.01)	51 (38.6%)
Action Plan	No Action Plan	-0.71 (2.39)	69 (52.3%)
	Action Plan used	-1.82 (2.84)	63 (47.7%)
Challenge	Individual	-1.23 (2.85)	52 (39.4%)
	Team	-1.24 (2.55)	80 (60.6%)
Action Plan used	Forum		
	No Forum	-0.88 (2.39)	49 (37.1%)
	Forum used	-0.29 (2.4)	20 (15.2%)
No Action Plan	Forum		
	No Forum	-1.19 (2.46)	32 (24.2%)
	Forum used	-2.47 (3.1)	31 (23.5%)

The analysis was done on the weight change model represented in Table 6.3 and Figure 6.4. Two terms are ordinal scores: the change in stress (*delta stress*) and the change in commitment (*delta commitment*). These ordinal scores were provided by the participants' self-assessment on surveys and can be treated as continuous variables.

We assume the explanatory variables are not correlated as further confirmed by the matrix plot in Tables 6.2 (a.) & (b). The dependent variable *change in weight* is normally distributed. The normal distribution for the y_outcome (*change in weight*) remains within each category. Two of the terms are non-linear *initial BMI* and the *change in diet habit* and they are modelled as fitted splines (Figure 6.4). The dependent variable *change in weight* is normally distributed. The normal distribution for the y_outcome (*change in weight*) remains within each category. Two of the terms are non-linear *initial BMI* and the *change in diet habit* and they are modelled as fitted splines (Figure 6.4).

Table 6.2 ***Health & Nutrition study, Change in weight (%) model: Matrix plot***

Y_outcome	**Coach**	**Challenge**	**Action Plan**	**Forum**



Continuous variables

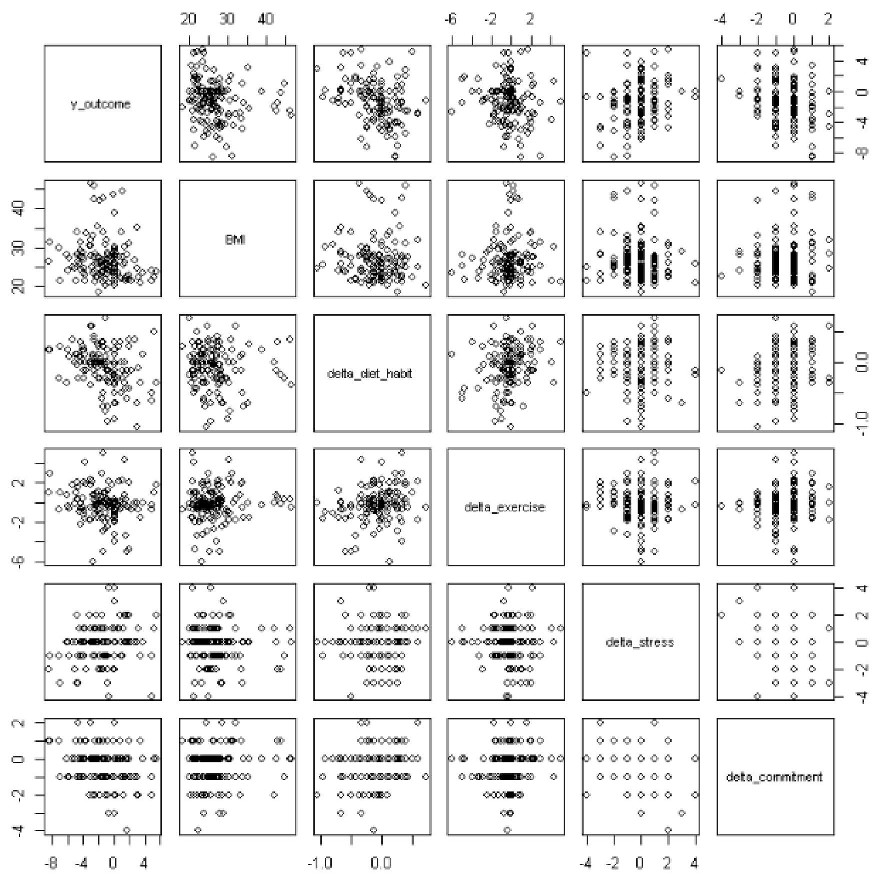


Table 6.3 ***Health & Nutrition study, Change in weight (%) model: Results table***

Weight Change (%)

Predictors	*Dependent Variables*			
	y-outcome			
	B	*CI*		*p*
(Intercept)	-1.2	'-2.06 - -0.3'		**0.01**
Coach	-0.97	'-1.88 - -0.07'		**0.04**
Challenge	0.04	'-0.79 - 0.88'		0.9
Action Plan	0.31	'-0.81 - 1.42'		0.6
Forum	1.59	'0.23 - 2.94'		**0.02**
Delta Exercise	-0.11	'-0.52 - 0.31'		0.6
Delta Stress	0.34	'-0.17 - 0.84'		0.2
Delta Commitment	-0.35	'-0.78 - 0.07'		0.1
Action Plan:Forum	-2.79	'-4.61 - -0.97'	<	**0.01**
Action Plan:Delta Exercise	0.11	'-0.57 - 0.79'		0.8
Forum:Delta Exercise	0.84	'0.05 - 1.64'		**0.04**
Challenge:Delta Exericse	-0.44	'-1.07 - 0.18'		0.2
Action Plan:Forum:Delta Exercise	-1.10	'-2.18 - -0.03'	<	**0.05**
Observations	132			
Deviance Explained / adj. R^2	0.413 / 0.318			

Significance codes
*0 '***'*
*0.001 '**'*
0.01 ''*
0.05 '.'
0.1 ' '
1

p-value < 0.05 in ***bold***

Weight Change (%), non-linear terms

	edf	*Ref.df*		*p*	*F*
s (BMI)	2.5	3.1		**0.001**	5.61
s (Delta diet habit)	3.01	3.79	<	**0.01**	4.23

The non-linear nature of the BMI and the change in diet habit ('delta habit') can be seen on Figure 6.4. For these two terms the estimated degrees of freedom (edf) and (Ref.df) indicate the presence of non-linearity (greater than 1) in the relationship of these terms to the change in weight (%).

The type of effect (linear or nonlinear) is determined by the optimal degree of smoothing which was estimated from the data using generalized cross validation. It was determined that *BMI* and *change in diet habit* have nonlinear effects. In the model they are denoted with '*s()*', a thin plate spline with automatic smoothing parameter selection based on generalized cross validation [173].

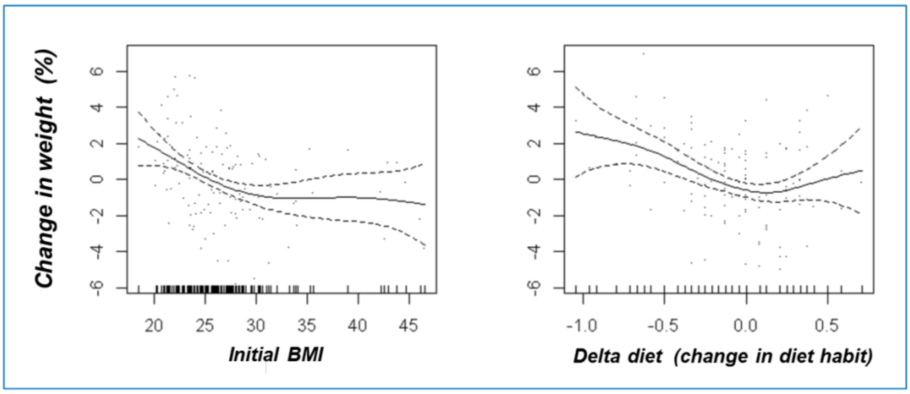


Figure 6.4 ***Health & Nutrition study, Change in weight (%) model: Non-linear terms***

The validity of the w*eight change (%) model* is assessed by inspecting the diagnostic plots (Figure Appendix 3.1 *Change in weight model: Experiment 2, Health & Nutrition study*). The Residuals vs. Fitted plots are randomly distributed. There is goodness of fit as can be seen on the Response vs Fitted Values, which is roughly scattered along the linear line (bottom right of Figure 6.5). The other two subplots to the left show there are normal distributions. Overall this indicates the model is valid to explain the *change in weight*. The Table 6.2 summarizes all the key findings.

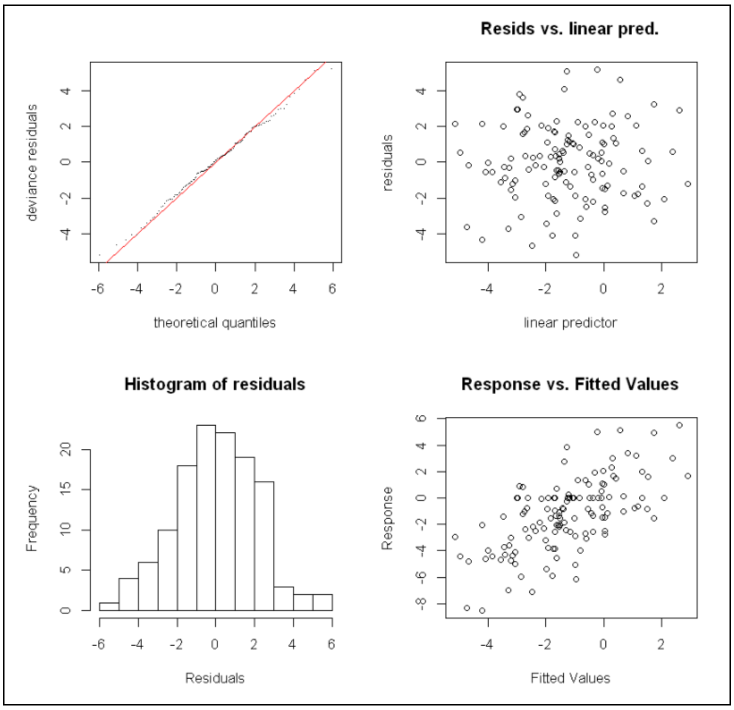


Figure 6.5 ***Health & Nutrition study, Change in weight (%) model: Diagnostic plot***

Analysis using the GAM Change in weight (%) model (see Table 6.4):

- There is significance to explain up to 31.8% of the variance in weight change.

Four interventions & their interactions:

- There was a significant weight loss (positive improvement) for those being coached.
- Using only the forum was not conducive to weight loss in the Health & Nutrition study, meanwhile those who did not use the forum lost more weight than those using it. This result may be related to the fact that as a product feature the *forum* operated as a repository of the coaches notes, instead of an engaging discussion forum.
- The combination (interaction) between action plans and forum was positive for weight loss.

Combinations of interventions and change in exercise habit(s):

- The use of the forum during the H&N opaqued the benefits of improvements on exercise habits.
- There was positive effect of the combination (interaction) between action plans & forum as an interaction with the improvements on exercise habits.

Non-linear relationships to change in weight, s(BMI) and s(change in diet habit):

- The initial BMI measure has three levels of response to weight change in a non-linear fashion. The healthy gained weight (maybe related to muscle gain? Further research is recommended). The overweight consistently lost weight, and have a potential positive response to interventions. The obese have a less effective response to lose weight and show wider range types of results, there is a potential for interventions. Further research is recommended to understand this responsiveness levels, although it is possible to suggest there is a higher caloric superavit among the overweight, than for the obese.
- The initial dietary habits measure has a non-linear relationship to weight change characterized by three different levels of response. The unhealthier are the initial dietary habits, the higher is the weight gain. With neutral diet habits (not characterized by unhealthy or healthy habits) the intervention produces weight loss. For healthy dietary habits the weight change results are neutral, some lose weight and others gain weight.
- A healthy dietary set of habits at the beginning of the intervention implies that to lose weight other lifestyle angles have to be targeted, because the capacity to change weight from diet habits' modification is limited. For example the combination with exercise habits improvement should be addressed, further investigation is suggested.
- The initial diet habits and BMI measure at the beginning of an intervention might be used to develop early signals of predicted change in weight for an intervention. These different initial states (of diet habit levels and BMI) have the potential to be determinants for prescribing different variations of intervention components. Further research is recommended.

Table 6.4 ***Health & Nutrition study, Change in weight (%) model: Summary table***

Model	**Weight Change (%)**
Sample size	126
R^2	0.318
Significant & relevant terms (*)	• ***Coach*** • ***Forum*** • ***Action Plan : Forum*** • ***Forum : Delta Exercise*** • ***Action Plan : Forum : Delta Exercise*** • ***s(BMI)*** • ***s(Delta Diet)***
Coach*, *comparison between sub-populations*	• Coach Weight Loss more than those Not coached.
Forum * , *comparison between sub-populations*	• No Forum.: Weight Loss more than those using the Forum
Action Plan : Forum * , *comparison between sub-populations*	• Action Plan : Forum : Weight Loss more than those with No Action Plan : No Forum
Forum : Delta Exercise * , *comparison between sub-populations with exercise increment 1 hr / week*	• Forum : Delta Exercise NO change : Weight Loss better than for Forum : Delta Exercise increase
Action Plan : Forum : Delta Exercise * , *comparison between sub-populations with exercise increment 1 hr / week*	• Action Plan : Forum : Delta Exercise increase: Weight Loss better than for Action Plan : Forum : Delta Exercise no change
s(BMI) * , *Non-linear relationship to weight change*	• 'Healthy' group (BMI < 25) : Weight Gain • 'Overweight' group (25 < BMI < 30): Weight Loss • 'Obese' (30 < BMI): Weight Loss
s(Delta Diet)* , *Non-linear relationship to weight change*	• 'Unhealthy' diet habits : Weight Gain • 'Neutral' diet habits: Weight Loss • 'Healthy' diet habits: Weight Neutral

6.5.2 What explains the change in the diet habit

The analysis of the effective tools that led the *weight change* (previous subsection) in the Health & Nutrition study showed that understanding the *change* in the *diet habit* and the *exercise habit* is relevant. Because of this reason this subsection and the following analyse the change in these two habits: diet habit and exercise habit.

The H&N collected in the initial and final surveys information about the dietary habits of the participants. These habits where classified as 'unhealthy' or 'healthy' and were counted at the 'start' and at 'end' of the study. Based on the total number of unhealthy and healthy habits reported they received a diet habit scoring. There are 2 scorings: the '*initial diet habit*' and the '*final diet habit*'. The difference between these two is the '*Delta diet*' used as a term on the previous weight change model. As described before, this term has a non-linear relationship to weight change and is significant. This section explores what is behind the change in dietary habits as it took place on the H&N study. From now on it will be referred as *delta diet*.

The investigation on *delta diet* (as the *y_outcome*) assumes that people are not accurate at reporting how much they change, but the direction of change is something that can rarely be wrong. By categorising delta diet it was possible to reduce the noise created by the uncertainty of accurate reporting, given the sample size of 124 participants (see Figure 6.3). The research interest on this case is to understand the direction of change that explains improvements for *delta diet* (or not), there is not much concern about the actual magnitude of change.

Because of the reasons expressed on the previous paragraph *delta diet* was explored using *a logistic regression model with treatment contrast* in which all the terms are adjusted by the other factors. A similar logistic model will be used as well on the next subsection to explain the change of exercise habits (‘*delta exercise*’). For a summary of the independent variables’ descriptive statistics please see Table 6.5. For this table ‘*No/ negative change*’ is the equivalent to ‘*no event*’ and a ‘*positive change*’ equivalent to an event.

Table 6.5 ***Health & Nutrition study, Diet habit change model: Descriptive stats. The values of OCEAN are a mean and standard deviation. All the other values are frequency counts and %.***

		No/negative change	Positive change	Total
Coach	Not Coached	50 (65.8%)	26 (34.2%)	76 (61.3%)
	Coached	31 (64.6%)	17 (35.4%)	48 (38.7%)
Action Plan	AP not used	45 (73.8%)	16 (26.2%)	61 (49.2%)
	AP used	36 (57.1%)	27 (42.9%)	63 (50.8%)
Forum	Forum not used	55 (74.3%)	19 (25.7%)	74 (59.7%)
	Forum used	26 (52%)	24 (48%)	50 (40.3%)
Challenge	Individual	32 (65.3%)	17 (34.7%)	49 (39.5%)
	Team	49 (65.3%)	26 (34.7%)	75 (60.5%)
Initial diet habit	Mean (SD)	0.23 (0.2)	0.09 (0.19)	
E		4 (1.5)	4 (1.4)	
A		5 (1.1)	5 (1)	
C		4.9 (1.2)	5.4 (1)	
N		3.5 (1.4)	3.1 (1.2)	
O		5.4 (1)	5.3 (1.1)	

There are 10 predictors (independent variables) of which 4 are dichotomous and 6 are continuous. The outcome (*delta diet*) is also dichotomous. The overall incidence rate is 43/124 (34.67%) and the number of events per variable (EPV) is 4.3 (43/10). The 4 dichotomous are the interventions reclassified for how they were used, or not, by the participants: *coach*, *challenge*, *action plans* and *forum*. The 6 continuous predictors include the *'initial diet habit*' and the five personality's traits: *openness to experience* (O), *conscientiousness* (C), *extraversion* (E), *agreeableness* (A) and *neuroticism* (N).

Table 6.6 ***Health & Nutrition study, Diet habit change model: Results table***

	Diet Habit Change		
	Odds Ratio	*CI*	*p*
(Intercept)	0.09	0.00 – 4.40	.232
Coach	0.77	0.28 – 1.99	.590
Action Plan	2.56	1.03 – 6.68	**.047**
Challenge	0.86	0.33 – 2.22	.748
Forum	3.59	1.43 – 9.64	**.008**
Negative Initial Diet Habit*10	1.64	1.28 – 2.19	**<.001**
Pers. type E	1.06	0.77 – 1.47	.703
Pers. type A	1.21	0.79 – 1.88	.389
Pers. type C	1.49	1.00 – 2.29	.057
Pers. type N	0.82	0.57 – 1.16	.266
Pers. type O	0.84	0.55 – 1.28	.420
Observations	124		
Deviance	125.490		
$X^2_{deviance}$	p=.000		
Hosmer-Lemeshow-X^2	1.339; p=.995		

Significance codes

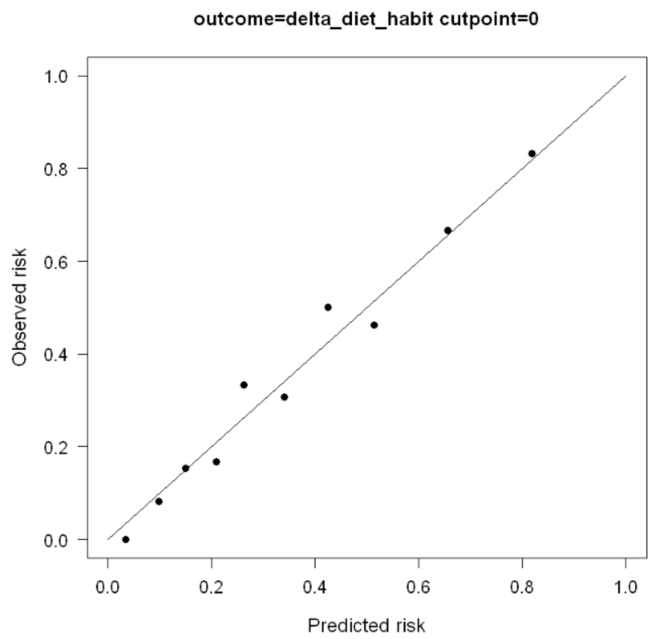
0	'***'
0.001	'**'
0.01	'*'
0.05	'.'
0.1	' '
1	

p-value < 0.05 in ***bold***

The assessment of the diet habit change model is reasonably good. Each factor of the model is adjusted by the other factors. There is a baseline population defined by: *not coached*, *no forum*, *no action plan*, *individual challenge* and with all the continuous variables = 0. Table 6.7 summarises all the key findings.

The LR model for delta diet is assessed by the Hosmer Lemeshow Goodness of fit plot and the Receiver Operating Characteristic (ROC) curve (Figure 6.6). The Hosmer Lemeshow Goodness of fit plot indicates that the predicted line is very close to the observed data. The p-value is 0.995 (from the results Table 6.6) is non-significant which translates as a measure of good fit. The AUC for the ROC curve is 0.8033 which means the model is not over fitted and predicts reasonably well. The results of the diet habit change model (Table 6.7) follow.

Hosmer Lemeshow Goodness of fit plot: Diet habit change model



Receiver Operating Characteristic (ROC) curve: Diet habit change model

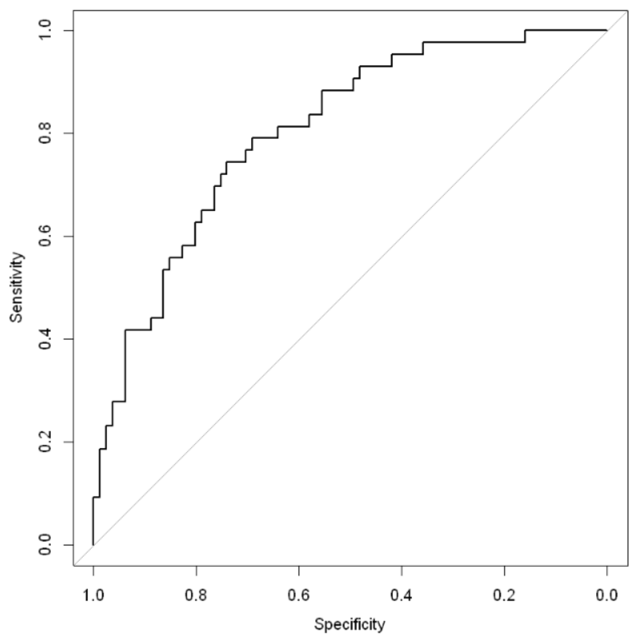


Figure 6.6 ***Health & Nutrition study, Diet habit change model: Assessing the model***

The LR model for delta diet is assessed by the Hosmer Lemeshow Goodness of fit plot and the Receiver Operating Characteristic (ROC) curve (Figure 6.6). The Hosmer Lemeshow Goodness of fit plot indicates that the predicted line is very close to the observed data. The p-value is 0.995 (from the results Table 6.6) is non-significant which translates as a measure of good fit. The AUC for the ROC curve is 0.8033 which means the model is not over fitted and predicts reasonably well. The results of the diet habit change model (Table 6.7) follow.

Analysis using the logistic regression diet habit change model (see Table 6.7):

- **Four interventions & their interactions**: The use of action plans increases the likelihood of positive change on diet habits change (delta diet). Using the forum increases potential for positive change on diet habits change (delta diet).

- **Initial Diet habit**: The unhealthier is the initial diet habits (the smaller the negative number), the more likely there will be positive change on diet habits change (delta diet).

Table 6.7 ***Health & Nutrition study, Diet habit change model: Summary table***

Model	**Diet habit change**
Sample size	124
Significant & relevant terms (*)	• ***Action Plan*** • ***Forum*** • ***Initial Diet Habit***
Action Plan*, *comparison between types of treatment*	• Action Plan: Odds increased (+) change in diet habit • No Action Plan.: Baseline
Forum * , *comparison between sub-populations*	• Forum: Odds increased (+) change in diet habit • No Forum.: Baseline
Initial Diet Habit * , *for every lower 0.1unit of initial diet habit score*	•Initial Diet Habit : Odds increased (+) change in diet habit

6.5.3 What explains the change in the exercise habit

As it was mentioned at the start of the analysis on delta diet (previous Section), the analysis of the weight change (%) model for the H&N incited the study of the change of habits (exercise and diet). This subsection of Chapter 6 will cover the analysis of the exercise habit and its change during the H&N. The H&N surveys covered the collection of information about the exercise habits of the participants.

For the change in the exercise habits (*delta exercise* from now on) a *logistic regression (LR) model* will be used to conduct the analysis: the '*exercise habit change model*'. The model is an LR model with treatment contrast and all the terms are adjusted by the other factors. With a sample size of 130 (see Figure 6.3), the model is aimed at capturing the direction of delta exercise's change to overcome the uncertainty (noise) around the reporting of exercise habits. From the functional point of view the *exercise habit change model* is a tool to understand what is behind the *delta exercise*. The exercise habit(s) is compared at two different moments of the H&N: 'start' and 'end' as described in Figure 6.2. *Delta exercise*, as the *y_outcome* of the *exercise habit change model*, is calculated as the difference between the exercise habits at the 'end' and those at the 'start' of the H&N.

As suggested by the World Health Organization [227] adults between the ages of 18 to 64, should do a minimum of 150 minutes per week of aerobic physical activity at a moderate intensity level throughout the week. As an alternative, throughout the week at least 75 minutes should be dedicated to vigorous intensity aerobic physical activity. The equivalent combination of moderate and vigorous intensity activity is also plausible. Aerobic activity should be performed as burst of 10 minutes or more. Additional benefits can be reached by adults who increase the moderate intensity aerobic activity to 300 minutes per week or dedicate 150 minutes to workouts of vigorous intensity (an equivalent combination of moderate and vigorous intensity activity is reasonable as well). The activities related to muscle strengthening should be done 2 or more days a week, ideally involving major muscle groups. (The changes in muscle were not captured during the study).

In alignment with the guidelines mentioned above [227], the exercise habits of the H&N's participants was measured at 'start' and 'end' via surveys. The calculation of the exercise habit was done by adding per week: total number of minutes of vigorous activity + ½ * the time spent on moderate intensity activity. The exercise of light intensity activity was omitted, in accordance to the WHO guidelines.

Similar to the *delta diet model*, there are 10 predictors (independent variables) of which 4 are dichotomous and 6 are continuous. The outcome (*delta exercise*) is also dichotomous. The overall incidence rate is 51/130 (39.23%) and the number of events per variable (EPV) is 5.1 (51/10).The 4 dichotomous are the interventions reclassified for how they were used, or not, by the participants (as explained in Section 7.3.): *coach, challenge, action plans* and *forum*. The 6 continuous predictors include the '*initial exercise habit*' and the five personality's traits: *openness to experience* (O), *conscientiousness* (C), *extraversion* (E), *agreeableness* (A) and *neuroticism* (N). Table 6.8 is a summary of the independent variables' descriptive statistics. For this table 'No/ negative change' is the equivalent to 'no event' and a 'positive change' equivalent to an event.

Table 6.8 ***Health & Nutrition study, Exercise habit change model: Descriptive stats. The values OCEAN are a mean and standard deviation. All the other values are frequency counts and %.***

		No/negative change	Positive change	Total
Coach	Not Coached	54 (66.7%)	27 (33.3%)	81
	Coached	25 (51%)	24 (49%)	49
Action Plan	AP not used	48 (71.6%)	19 (28.4%)	67
	AP used	31 (49.2%)	32 (50.8%)	63
Forum	Forum not used	52 (65%)	28 (35%)	80
	Forum used	27 (54%)	23 (46%)	50
Challenge	Individual	27 (52.9%)	24 (47.1%)	51
	Team	52 (65.8%)	27 (34.2%)	79
Initial exercise habit	Mean (SD)	2.06 (2.03)	1.26 (1.27)	
E		4 (1.5)	4.1 (1.4)	
A		4.9 (1.1)	5 (1.2)	
C		5.1 (1.2)	5.1 (1.1)	
N		3.4 (1.3)	3.2 (1.3)	
O		5.3 (1)	5.4 (1.1)	

Table 6.9 ***Health & Nutrition study, Exercise habit change model: Results table***

	Exercise Habit Change		
	Odds Ratio	*CI*	*p*
(Intercept)	0.54	0.02 – 17.22	.728
Coach	1.25	0.54 – 2.87	.594
Action Plan	2.94	1.32 – 6.78	**.009**
Challenge	0.49	0.21 – 1.10	.088
Forum	1.36	0.59 – 3.16	.467
Negative Initial Exercise Habit*10	1.35	1.06 – 1.78	**.022**
Pers. type E	1.00	0.76 – 1.33	.975
Pers. type A	1.15	0.80 – 1.67	.460
Pers. type C	1.01	0.71 – 1.45	.953
Pers. type N	0.91	0.66 – 1.24	.540
Pers. type O	0.98	0.66 – 1.44	.909
Observations	130		
Deviance	154.703		
$X^2_{deviance}$	p=.035		
Hosmer-Lemeshow-X^2	4.181; p=.840		

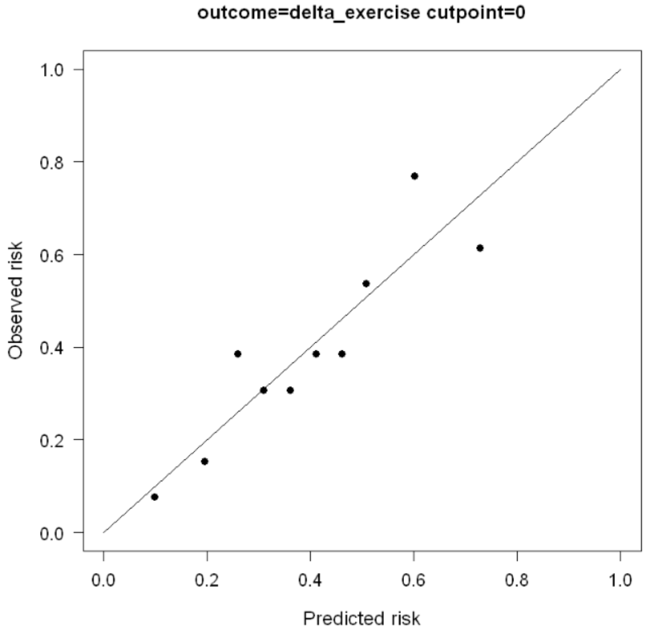
Significance codes

0	'***'
0.001	'**'
0.01	'*'
0.05	'.'
0.1	' '
1	

p-value < 0.05 in ***bold***

The assessment of the exercise habit change model is reasonably good. Each factor of the model is adjusted by the other factors. There is a baseline population defined by: not coached, no forum, no action plan, individual challenge and with all the continuous variables = 0.The LR model for delta diet is assessed by the Hosmer Lemeshow Goodness of fit plot and the Receiver Operating Characteristic (ROC) curve (see Figure 6.7).

Hosmer Lemeshow Goodness of fit plot: **Exercise habit change model**



Receiver Operating Characteristic (ROC) curve: **Exercise habit change model**

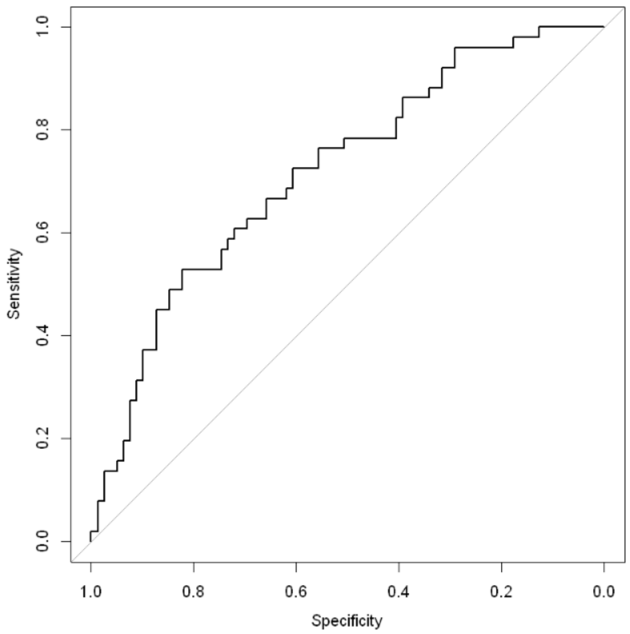


Figure 6.7 ***Health & Nutrition study, Exercise habit change model: Assessing the model***

The Hosmer Lemeshow Goodness of fit plot indicates that the predicted line is very close to the observed data. The p-value is 0.840 (from the results Table 6.9) is non-significant which translates as a measure of good fit.

The AUC for the ROC curve is 0.718 which means the model is not over fitted and predicts reasonably well. The results of the diet habit change model (Table 6.9). The key findings are in Table 6.10, below.

Analysis, logistic regression Exercise habit change model (see Table 6.10):

- **Four interventions & their interactions**: The use of action plans increases the likelihood of positive change on exercise habits change (delta exercise).

- **Initial Exercise habit**: The lower is the initial exercise level (related habits), the more likely there will be positive change on positive exercise habits change (delta exercise).

Table 6.10 ***Health & Nutrition study, Exercise habit change model: Summary table***

Model	**Exercise habit change**
Sample size	130
Significant & relevant terms (*)	• ***Action Plan*** • ***Initial Exercise Habit***
Action Plan*, *comparison between sub-populations*	• Action Plan: Odds increased (+) change in diet habit • No Action Plan.: Baseline
Initial Exercise Habit * , *for every 1 hr less of initial exercise level (habits)*	• Initial Exercise Habit : Increase the odds of (+) change in exercise habit

6.6 Discussion

The analysis of the results discussed so far indicate that change in weight is determined by change in diet habit, change in exercise habit. The intervention components behind this change are coaching, the interaction between action plans and forum, the initial BMI, the initial diet habit and the initial exercise habit as represented in Figure 6.8. The assessment of these results comprises: scenario analysis, considerations for the relevance of the personality traits via the five-factor model and the evaluation of the four interventions independently.

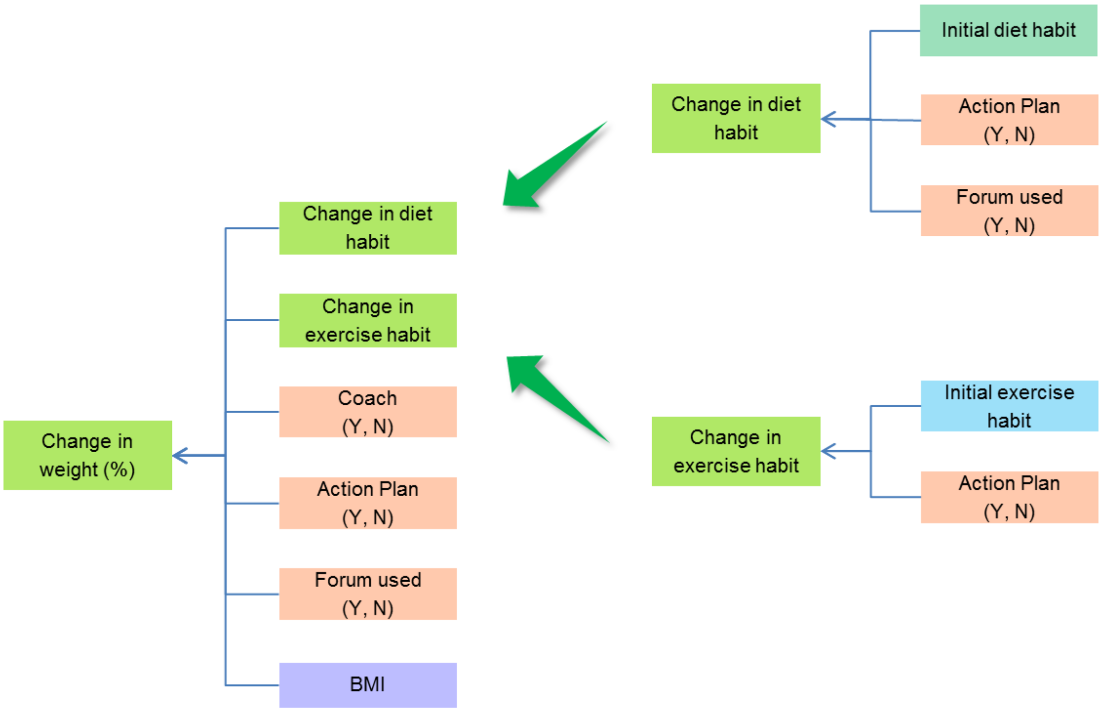


Figure 6.8 ***Health & Nutrition study: Summary graph change in weight, change in diet habit & change in exercise habit***

6.6.1 Scenario Analysis

As part of the assessment it is reasonable to evaluate and determine which combinations of interventions (coach, challenge, action plans and forum) provide the highest predicted probability of change of diet habit and change in exercise habit. The predicted combinations will then be contrasted to the results obtained before in Chapter 6.

6.6.1.1 Factors that explain the change in diet habit

This exercise can take place because the Hosmer Lemeshow Goodness of fit plot and the Receiver Operating Characteristic (ROC) curve show that the model is reasonably good it was possible to predict the probability of change for 16 different scenarios for the delta diet. These scenarios match the original factorial design combinations of the four interventions, (see Table Appendix 3.4 *Health & Nutrition study, Factorial Design (PLANNED)*).

This scenario analysis might be very useful for future intervention design, since it produces the probability of an effective intervention as defined by its key intervention components. For all the scenarios to be analysed now, the initial diet habit is on the x-axis (from 0 to 1, with increments of 0.1). All personalities are set to the median. As a result the model can be used to evaluate exclusively the predicted probability of change for the four main interventions: coach, challenge, action plans and forum.   The predicted probabilities for delta diet can be seen on Figure 6.9 below.

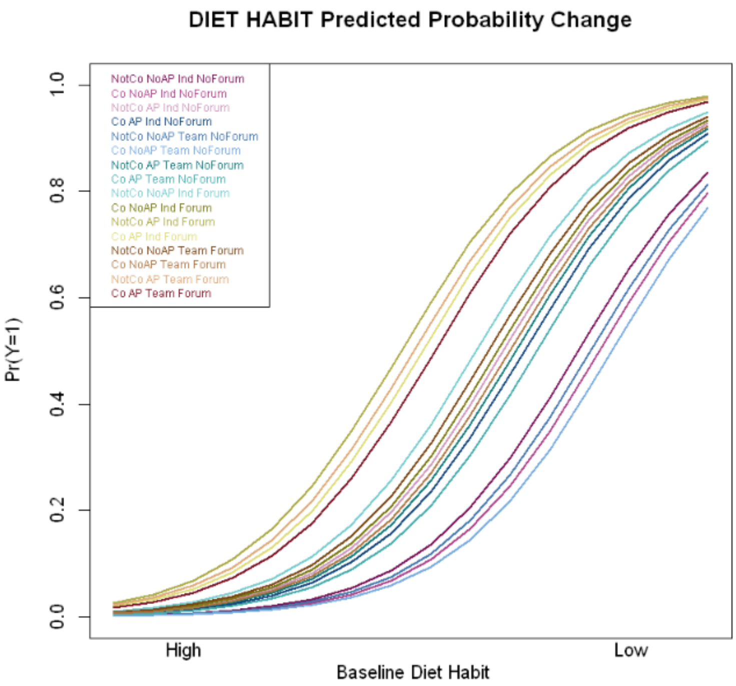


Figure 6.9 ***Health & Nutrition study: Predicted probabilities of diet habit change, scenario analysis***

<u>Analysis of this scenario analysis for change in diet habit</u> (see Table 6.11):

- The healthier is the initial level of diet habit, the harder it is to improve. The inverse is also valid, the unhealthier the initial diet habit, the bigger the potential for improvement
- Participating in a team challenge dampens the potential for change in diet habit
- The best combination product of the scenario analysis for delta diet is the interaction between action plans and forum
- The second best combination is the interaction between action plans, forum and team challenge
- The third best combination is the interaction of coach, action plans and forum
- The worst simulated combination is coach and team challenge.

Table 6.11 ***Health & Nutrition study, Diet habit change: Predicted probability table***

Simulations for Scenario Analysis: *Y_outcome (change in diet habit)*	
Predicted probability of Diet habit change: **Four interventions**	•The healthier is the initial level of diet habit, → harder to improve. •The unhealthier the initial diet habit, →more potential to improve •Team challenge → dampens the potential for change in diet habit •The 1st best interaction :action plans & forum •The 2nd best interaction: action plans & forum & team challenge •The 3rd best interaction: coach & action plans & forum

6.6.1.2 Factors that explain the change in exercise habit

Because the Hosmer Lemeshow Goodness of fit plot and the Receiver Operating Characteristic (ROC) curve show that the model is reasonably good it was possible to predict the probability of change for 16 different scenarios for the delta exercise. These scenarios match the original factorial design combinations of the four interventions, (see Table Appendix 3.4).

This scenario analysis might have valuable information for future intervention design, since it produces the probability of an effective intervention as defined by its key intervention components. For all the scenarios to be analysed now, the initial exercise habit is on the x-axis (from 0 to 1, with increments of 0.1). All personalities are set to the median. As a result the model can be used to evaluate exclusively the predicted probability of change for the four main interventions (coach, challenge, action plans and forum). The predicted probabilities of change in exercise habits can be seen on Figure 6.10, Table 6.12 summarises all the findings.

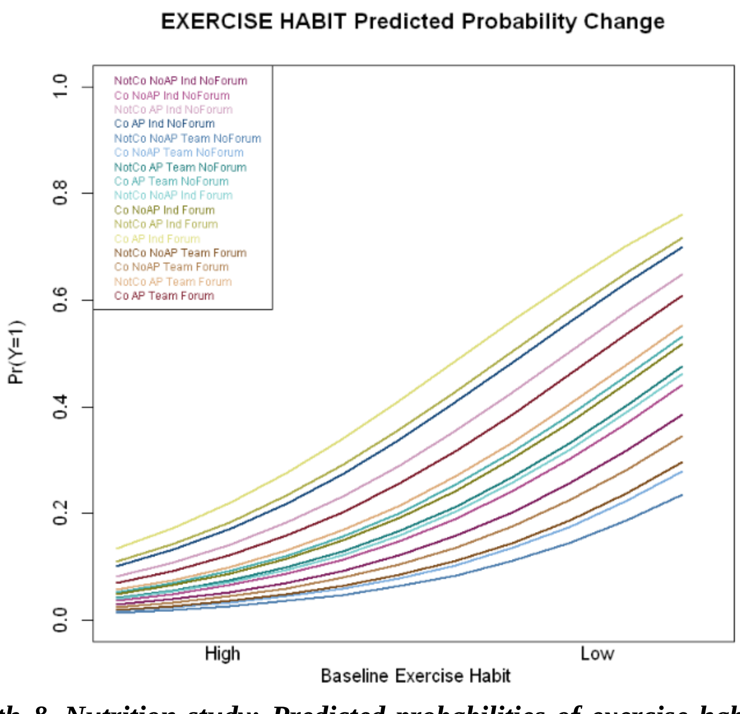


Figure 6.10 ***Health & Nutrition study: Predicted probabilities of exercise habit change, scenario analysis***

<u>**Analysis of this scenario analysis for change in exercise habit**</u> (see Table 6.12):

- The higher is the initial level of exercise habit, the harder it is to improve it. The inverse is also valid, the lower the initial exercise habit, the bigger the potential for improvement
- The best combination product of the scenario analysis for delta diet is the interaction between coach, action plans, individual challenge and forum

- The second best combination is the interaction between action plans and forum
- The third best combination is the interaction of coach and action plans
- The worst simulated combination is only being part of the team challenge.

Table 6.12 ***Health & Nutrition study, Exercise habit change: Predicted probability table***

Simulations for Scenario Analysis: *Y_outcome (change in exercise habit)*	
Predicted probability of Exercise habit change: **Four interventions**	• The higher is the initial level of exercise habit, → harder to improve it • The lower the initial exercise habit, →more potential to improve • The 1st best interaction :coach, individual challenge, action plans & forum • The 2nd best interaction: action plans & forum • The 3rd best interaction: coach & action plans

6.6.2 The relevance of personality traits

The same scenario analysis methodology explained on the previous subsections for the predicted probability of diet habit change and exercise habit change is now used to assess the relevance of the personality traits. They are evaluated via the five-factor model. The objective is to identify personal traits that might support or weaken the result of an intervention. These personality traits are:

- Openness to Experience (O),
- Conscientiousness (C),
- Extraversion (E),
- Agreeableness (A) and
- Neuroticism (N).

Although the personality traits (O.C.E.A.N.) on the *change in diet habit model* and the *change in exercise habit model* are not significant on the LR models, this scenario analysis introduces key concepts for this research and points at further investigation.

6.6.2.1 Change in diet habit and personality traits

The scenarios simulation shows that it seems there are two interesting relationships between the predicted probability of *diet change* and the five-factor model for personality traits in which:

- CONSCIENTIOUSNESS (C) a positive association and
- NEUROTICISM (N) a negative association.

The *predicted probability* for *change* in *diet habit*, for different combinations (see Figures Appendix 3.1 – 3.5) of interventions is:

- above the baseline when there is a strong personality trait for conscientiousness (C)
- under the baseline for a strong presence of the personality trait neuroticism (N)

This scenario analysis seems to be indicating that conscientiousness (C) might support positive predicted change in dietary habits. On the other side, neuroticism (N) might reduce the predicted potential for dietary improvement. The following Table 6.13 summarizes these findings about the five-factor scenario analysis of *delta diet*.

Table 6.13 ***Health & Nutrition study, Diet habit change: Personality traits***

Simulations for O.C.E.A.N. Scenario Analysis: *Y_outcome (change in diet habit)*	
Predicted probability of diet habit change: **Five personality traits OCEAN**	• It seems that conscientiousness (C) supports potential (+) change • It seems that neuroticism (N) might detriment change potential

6.6.2.2 Change in exercise habit and personality traits

The scenarios simulation show that it seems to be two interesting relationships between the predicted probability of *exercise habit change* and:

- AGREEABLENESS (A) a positive association
- NEUROTICISM (N) a negative association

The *predicted probability* for *change* in *exercise habit* for different combinations (see Figures Appendix 3.6 – 3.10) of interventions is:

- above the baseline when there is a strong personality trait for agreeableness (A)
- under the baseline for a strong presence of the personality trait neuroticism (N)

This scenario analysis seems to be indicating that agreeableness (A) might support positive predicted change in exercise habits. Neuroticism (N) in contrast, might reduce the predicted potential for exercise improvement. The following Table 6.14 summarizes the findings for the *delta exercise* five-factor scenario analysis.

Table 6.14 ***Health & Nutrition study, Exercise habit change: Personality traits***

Simulations for O.C.E.A.N. Scenario Analysis: *Y_outcome (change in exercise habit)*	
Predicted probability of diet habit change: **Five personality traits OCEAN**	• It seems that agreeableness (A) supports potential (+) change • It seems that neuroticism (N) might detriment change potential

6.6.3 Independent interventions

The last subsection of the assessment includes the revision of some interesting findings from the independent overview of the four interventions of Experiment 2 (coach, challenge, action plans & forum).

6.6.3.1 The coach intervention

During the H&N 75 unique participants were coached at least once in a total of 138 coaching sessions. Of the total population that had access to the coaching sessions only 32% made use of this 'premium' resource. Coaching had an impact on losing weight (Figure 6.11). After filtering for only the participants who had the 'lose weight' goal, there is clear difference between the participants that were 'coached' and those who were 'not coached' The 'Coached' distribution is skewed towards the left compared to those 'Not coached' meaning that the coaching sessions left a positive impact (more weight loss) on the users who made use of the coaching sessions. It also seems that people who were coached had a higher adherence to the intervention. It is worth to do further qualitative research to assess why the coach intervention is related to higher adherence.

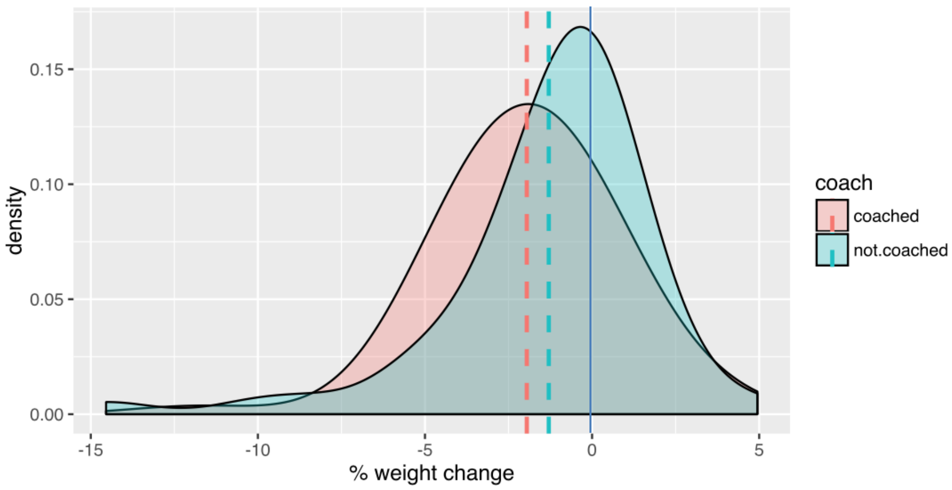


Figure 6.11 ***Health & Nutrition study: Coach, weight change (%), distributions***
(*range of weight change (x-axis) between -15% and +5%, without filtering high performers).*

6.6.3.2 The challenge intervention

During the 'Health & Nutrition' study it was possible to observe the difference between the individual and the team walking challenges, using as control those who did not connect a tracker (and did not participate on the challenges).

Challenge impact on losing weight:

The following Figure 6.12 shows that there is difference in the distributions of individuals, teams and control group (did not participate on the challenges). These distributions include only those in the 'lose weight' goal.

Highlights:

- The INDIVIDUAL CHALLENGE displays a broader range of results (fat tails on both directions), meaning that the individual challenge provides a context for extreme performers: some individuals lost a significant amount of weight, while other individuals gained a significant amount of weight.
- The TEAM CHALLENGE displays a more compact / average range of results, meaning that the teams encourage weight loss closer to average. This can mean that teams dampen the extreme performers, which is positive for losing weight but negative for gaining weight.

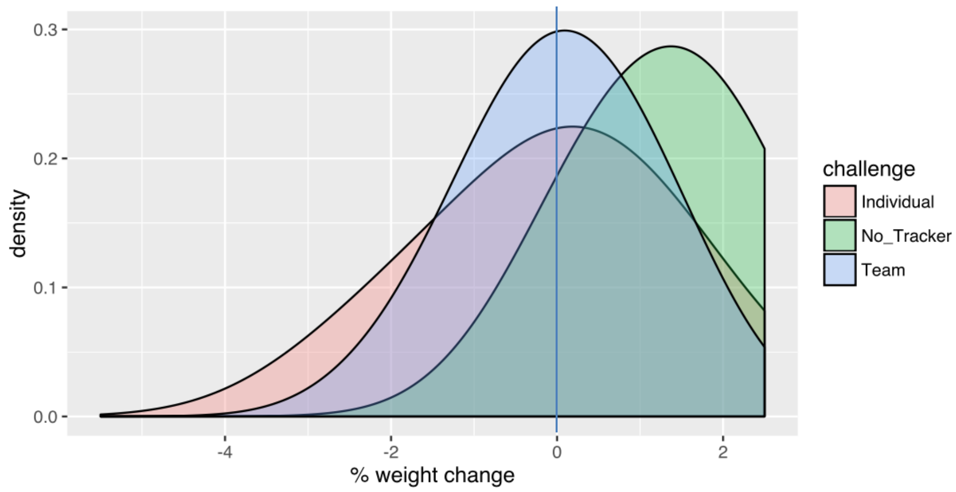


Figure 6.12 ***Health & Nutrition study: Challenges, weight change (%), distributions***
(*range of weight change (x-axis) between -5% and +2.5%, without filtering high performers*).

Challenge impact on daily steps count:

There is a clear difference in how the team dynamics affect the change on daily steps count when the individual challenge is compared to the team challenge (Figure 6.13). The participants of both challenges (improved on average), but the average improvement was much bigger for the teams:

- Participants of the Team challenge improved on average 340 daily steps
- Participants of the Individual challenge improved on average 16 daily steps

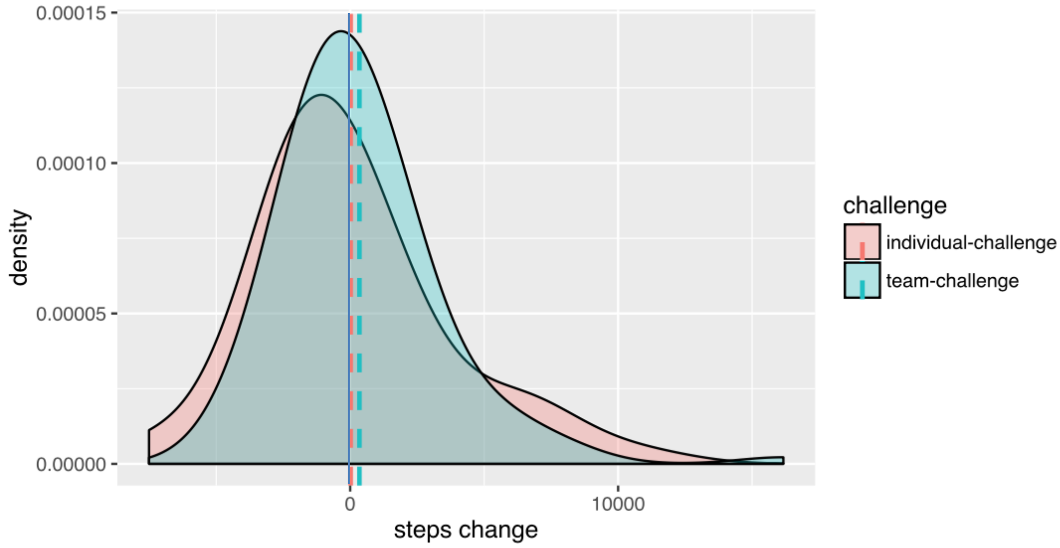


Figure 6.13 ***Health & Nutrition study: Challenges, steps change (%), distributions***
(range of steps change (x-axis) between -7,500 and +12,500, without filtering high performers).

Highlights:

- Some participants of the INDIVIDUAL CHALLENGE displayed an increase in daily number of steps that is 50% more than the top individuals of the Team challenge. The lower end of the ranking of the Individual challenge showed little progress and in many cases it is related to a reduction of the average daily number of steps.
- The TEAM CHALLENGE provided a context for improvement in the top teams. The team challenge also had the effect of averaging down many of the very active walkers (although each team member was accounted as an independent subject for the analysis).

6.6.3.3 Action plans as intervention

During the H&N only 78 (after filtering 73) participants used the 'Action Plans' (AP's). The Tictrac action plans were used by 46 participants and the Expert Tips action plan by 32. To 'use an action plan' is defined here as doing 5 times at least 1 habit included in an action plan (it required logging).

The comparison of the 2 Tictrac action plans ('Lose Weight', 'Healthy Eating') to the action plan designed by a professional nutritionist ('Expert's tips') had the purpose of determining if the use of 'professional content' would make a difference on an action plan.

On this initial analysis, there is no significant difference between the two types of action plans. In the context of this study, the comparative analysis of the two types of action plan indicates that there is no evidence that 'action plans' are effective on their own (see Figure 6.14).

For the H&N pilot study the action plans support other features but they should not be considered as main factors of behaviour change. However the literature suggests that action plans do indeed work, therefore some adjustments at the product level would have been required.

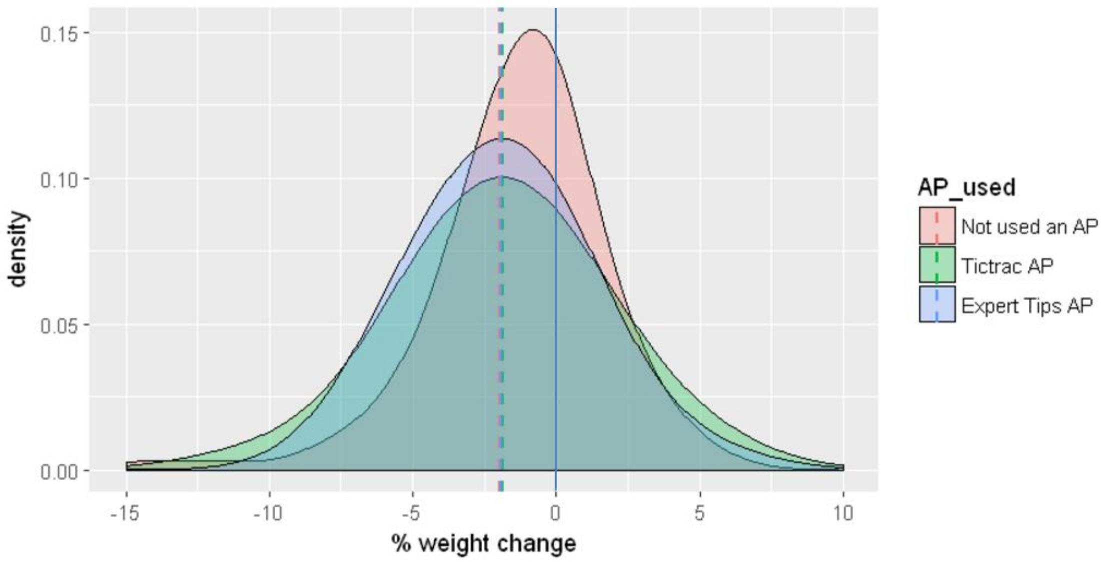


Figure 6.14 ***Health & Nutrition study: Action Plans, weight change (%), distributions*** *(range of weight change (x-axis) between -15% and 10%, without filtering outliers).*

6.6.3.4 Discussion forum intervention

The Forum was an additional feature added to the platform's product skeleton and was different in its UX / UI generating friction due to this difference. Although it was originally designed as part of the study to facilitate the observation of interaction between participants, it actually was used as a 'written repository' of David Dunne's (performance nutritionist) coaching tips. The Forum operated as a support feature to other main features (Challenge, Coaching).

Highlights:

- There is no significant difference on weight loss (p=0.2) between using the Forum and Not using it (Figure 6.15).
- An average of 9 topics was read by the participants during the study period. It seems that the more topics a user read the higher the percentage weight loss (this will require further research and is beyond this current investigation).

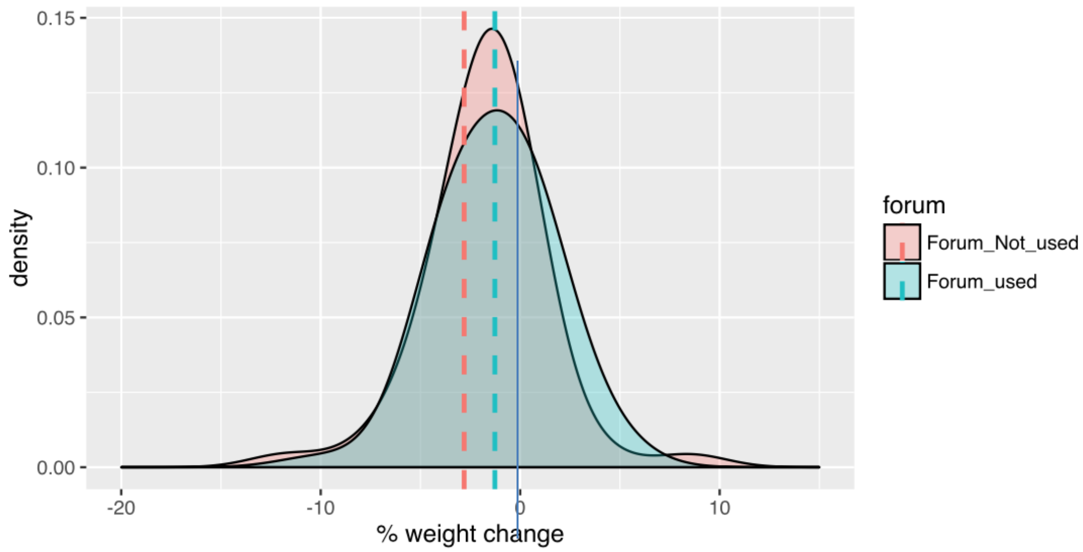


Figure 6.15 ***Health & Nutrition study: Forum, weight change (%), distributions***
(*range of weight change (x-axis) between -15% and +20%, without filtering outliers).*

6.7 Conclusion and further work

Experiment 2 was composed of 432 eligible participants of which 221 participants had self-tracking devices and apps generating behavioural data: 132 provided data for change of weight analysis, 124 for change of diet habit (delta diet) analysis and 130 for change of exercise habit (delta exercise). Although the number of participants was less than expected, these figures were large enough for explanatory analysis, here summarized as conclusions.

CHANGE of WEIGHT (%) ANALYSIS

Four interventions & their interactions:

- There was a 'coach effect', significant weight loss (positive improvement) for those being coached
- The combination (interaction) between action plans and forum was positive for weight loss.
- Using only the forum was not conducive to weight loss in the Health & Nutrition study, meanwhile those who did not use the forum lost more weight than those using it. This result may be related to the fact that as a product feature the *forum* operated as a repository of the coaches notes, instead of an engaging discussion forum.

Combinations of interventions & and change in exercise habit(s):

- The combination (interaction) between action plans and forum was boosted by improvements on exercise habits.
- The use of the forum during the H&N opaqued the benefits of improvements on exercise habits.

Non-linear relationships to weight change, s(BMI) and s(change in diet habit):

The measurement of the initial diet habits and BMI at the beginning of an intervention might be used to develop early signals of predicted change in weight for an intervention. It seems diet levels and BMI may impact on potential outcomes from the intervention particularly for overweight as opposed to healthy/obese. The early assessment of the potential for change is relevant for prescribing the best course of action for an individual, whilst increasing the probability of achieving a goal related to weight change.

- The initial BMI measure has three levels of response to weight change in a non-linear fashion.
    - The healthy gained weight (maybe related to muscle gain? Further research is recommended).
    - The overweight consistently lost weight, and have a potential positive response to interventions (further research is recommended).
    - The obese have a less effective response to lose weight and show a wider range types of results, there is a potential for interventions (further research is suggested).
- The initial dietary habits measure has a non-linear relationship to weight change characterized by three different levels of response.
    - The unhealthier are the initial dietary habits, the higher is the weight gain.
    - With neutral diet habits (not characterized by unhealthy or healthy habits) the intervention produces weight loss.
    - For healthy dietary habits the weight change results are neutral, some lose weight and others gain weight.
- A healthy dietary set of habits at the beginning of the intervention implies that to lose weight other lifestyle angles have to be targeted, because the capacity to change weight from diet habits' modification is limited.
- The initial diet habits and BMI measure at the beginning of an intervention might be used to develop early signals of predicted change in weight for an intervention.

CHANGE of DIET HABIT

Four interventions & their interactions

- Action plans and the use of the forum appear have positive potential for the change on diet habit.
- The scenario analysis provides as well the positive potential for delta habit by combining the interaction (action plans + forum) with the team challenge or the coach

Initial diet habit level

- The unhealthier is the initial diet habit, the bigger the potential for improvement (the inverse also applies)

Team effect

- It seems the Team challenge dampens the potential for change in diet habit, further research is suggested

Personality traits

- It seems that conscientiousness (C) supports positive (+) potential for change in diet habit, further research is suggested
- It seems that neuroticism (N) might detriment (-) change potential for change in diet habit, further research is suggested

CHANGE of EXERCISE HABIT

Four interventions & their interactions

- Action plans appear to have positive potential for the change on exercise habit.
- The scenario analysis provides as well the positive potential for delta exercise habit by combining action plans as an interaction with the forum or the coach
- The best combination is the product of the interaction (action plan + forum) with coach and individual challenge, further research is suggested

Initial exercise habit level

- The lower is the initial exercise habit, the bigger the potential for improvement (the inverse also applies)

Team effect

- It seems the Team challenge dampens the extreme individual potential for change in exercise habit, although it provides a context for average improvement, further research is suggested

Personality traits

- It seems that agreeableness (A) supports positive (+) potential for change in exercise habit, further research is suggested
- It seems that neuroticism (N) might detriment (-) change potential for change in exercise habit, further research is suggested

<u>Further Work</u>:

The results of the Health & Nutrition study so far are an invitation to further research on this direction; as such the H&N should be considered a pilot study that should conduct to a broader intervention research to confirm or debate the results found so far.

STUDY DESIGN & IMPLEMENTATION

Sample size

- As mentioned before it is worth to invest in further research on the direction of a new study similar to the Health & Nutrition study aiming at increasing the sample size and confirming or debating the results here presented.

Duration of the intervention, 6 weeks is not enough

- A future intervention would benefit of a longer period of implementation from baseline (before the intervention begins), through the active period of the intervention, up to the follow-up period. Ideally for a total period of 6 months with 3 months of intervention. The 6 weeks period for this study was restricted by budget, but sufficient for a pilot study.

Factorial Design

- The H&N unintentionally became a fractional factorial design due to lower numbers of usage of the intervention components (coach intervention, challenge intervention, action plans intervention and forum intervention). This implies that a future study should aim at increasing the initial recruitment around four times that of the H&N.

CHANGE of WEIGHT (%) ANALYSIS

Non-linearity of BMI

- The non-linear relationship between BMI and weight change is worth of further research
- Related to the above, there seems to be three levels of response to weight change in a non-linear fashion, further research is suggested
- The initial diet habits and BMI measure at the beginning of an intervention might be used to develop early signals of predicted change in weight for an intervention. These different initial states (of diet habit levels and BMI) have the potential to be determinants for prescribing different variations of intervention components. Further research is recommended.

Non-linear change of diet habit

- The non-linear relationship between the change in diet habit and weight change is worth of further research

- A healthy dietary set of habits at the beginning of the intervention implies that to lose weight other lifestyle angles have to be targeted, because the capacity to change weight from diet habits' modification might be already limited. For example the combination with exercise habits improvement should be addressed, further investigation is suggested.

Four interventions & their interactions

- It also seems that people who were coached had a higher adherence to the intervention. It is worth to do further qualitative research to assess why the coach intervention is related to higher adherence.
- An average of 9 topics was read by the participants during the study period. It seems that the more topics a user read on the discussion forum from the higher the percentage weight loss (this will require further research and is beyond this current investigation).

CHANGE of DIET HABIT

Team effect

- It seems the Team challenge dampens the potential for change in diet habit, further research is suggested

Personality traits

- It seems that <u>conscientiousness</u> (C) supports positive (+) potential for change in diet habits, further research is suggested
- It seems that <u>neuroticism</u> (N) might detriment (-) change potential for change in diet habits, further research is suggested

CHANGE of EXERCISE HABIT

Four interventions & their interactions

- The best combination is the product of the interaction (action plan + forum) with coach and individual challenge, further research is suggested

Team effect

- It seems the Team challenge dampens the extreme individual potential for change in exercise habit, although it provides a context for average improvement, further research is suggested

Personality traits

- It seems that <u>agreeableness</u> (A) supports positive (+) potential for change in exercise habit, further research is suggested
- It seems that <u>neuroticism</u> (N) might detriment (-) change potential for change in exercise habit, further research is suggested

Chapter

7. Proposed Frameworks for Future Large Scale Interventions for Behaviour Change

Chapter 7 presents two frameworks for the design and implementation of technology-based behaviour change interventions of large scale. Both are described: framework I, 'Data Science approach to behavioural interventions', followed by framework II, 'Implementation of computational platforms for intervention'.

The third objective of the thesis is fulfilled by proposing frameworks for future large scale interventions in behaviour change that use data science and computational platforms for delivery. Behaviour Change Science requires large-scale mechanisms for effective delivery and experimental investigation. This chapter is a contribution to all those who will carry on with the work required, by providing theoretical and practical frameworks as transferable knowledge to enable many other cost effective interventions that can scale to improve public health [6] and make use of the relevant findings of this investigation.

The major obstacle for the research was the absence of practical guideline frameworks that combined simultaneously: (a) applied principles of Behaviour Change Science for the design, development and deployment, (b) a Data Science workflow with an industrial standard and (c) principles of product management with the best practices for product design, UX / UI. To overcome this hurdle two frameworks were created and used for the experiments and research.

There is a broad literature on behaviour change interventions implementation [52, 144, 228] (and was used for the interventions of this thesis). The implementation of tech-based BCI's has motivated the research of a computational approach to support health behavior change [1] and the development of Behaviour Intervention Technologies (BIT) [229]. Many of these are oriented to operationalizing engagement [230]. There are yet limited references about Data Science as part of BCI's and make use of BIT's, whilst delivering a complete digital product. The two frameworks suggested in this chapter are an initial step towards overcoming this gap.

The first framework provides the '*Data Science approach to behavioural interventions*' (DSABI) as a practical guideline for the delivery and evaluation of interventions that require a Data Science approach. The main goal of the DSABI is to coordinate the whole data cycle (inclusive of data mining and pattern recognition) of an intervention from the ideation stage, going through execution intervention to the data analysis and sharing the results as part of the intervention evaluation. This framework ensures there are resources in place to enable a data science approach complementary to the classical analysis of behaviour change science (see Figure 1.2). The end-users of the DSABI are the BCI practitioners and the data scientists involved.

The second framework enables the '*Implementation of computational platforms for intervention*' (ICPI) and has as a main purpose facilitating: product design, product management, construction and deployment of these platforms for BCI's that require a Data Science approach, (see the blueprint for computational platforms for intervention, Chapter 3). The end-users of the ICPI are the professionals involved with product design, product management and technology development.

The use of the DSABI and the ICPI should facilitate the interaction between the main stakeholders and the robust delivery of future complex interventions. The implementation of these frameworks requires the preliminary mapping of the operations required for the intervention (Section 7.1) and comprises: stakeholders, roles and workflows.

7.1 Mapping the operation: stakeholders, roles and workflows in an intervention

There are different stakeholders in a technology-based, multi-component behaviour change intervention. Typically, the main stakeholders are: (i) researchers, (ii) funding 3rd party, (iii) product team, (iv) participants (and very likely many more). There are different roles that will be fulfilled by the stakeholders (see the circles in Figure 7.1) and they should not be conflicted (i.e. in principle a researcher should not be a participant, unless it is a 'friendly trial'). The end-users of the DSABI are the BCI practitioners and the data scientists involved.

A bipartite network diagram is used to represent the involvements (lines) of the roles (circles) in different workflows (rectangles), see Figure 7.1. In this diagram colours are used to differentiate the different types of roles, relationships and workflows: (1). *roles* and *relationships*: *circles* and *lines* in ***blue*** are related to the *intervention* and in ***purple*** to the *platform / product*; (2) *workflows*: *rectangles* in *dark blue* are related to the *intervention* and those in *light blue* to the *platform / product build*. Figure 7.1 can be used as well as a map of roles, relationships and workflows. This map will be relevant for future researchers and practitioners involved in the development of (hopefully) engaging new platforms and apps with multi-component behavioural interventions.

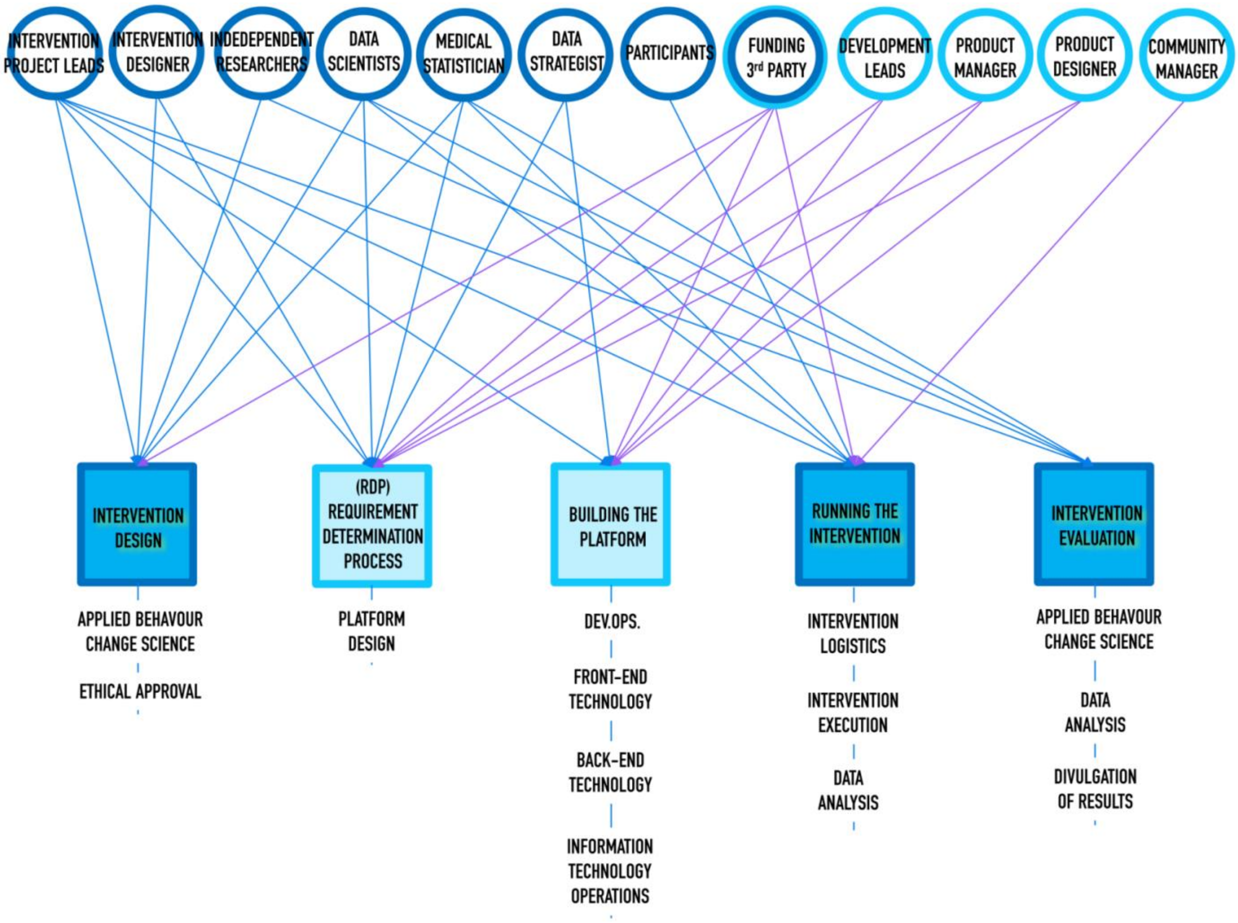


Figure 7.1 ***Roles and workflows for technology-based, multi-component behavioural interventions***

The map of stakeholders makes possible to determine *who* is involved, in *which* workflow, at *which* stage of the intervention's processes and *how* is the required intervention being delivered. The number of roles a stakeholder has will be determined by the size of the intervention and the available budget. For example, in Experiment 2 (H&N study) the author of this research had multiple roles: *intervention project lead*, *intervention designer*, *data strategist*, *data scientist* and *independent researcher*.

7.2 Framework 1: 'Data science approach to behavioural interventions', DSABI

The 'Data science approach to behavioural interventions' (DSABI) is a powerful analytical tool to *plan* and *consolidate* the *interventions*, the *data generation* and the *data analysis*, *data mining* and *pattern recognition* by *optimising* the *data cycle* of the *experimental platforms* of any study. The DSABI is suggested as an analytical framework that combines data science and behaviour change science for future behavioural experiments and interventions. The 'behaviour change science guidelines' for the DSABI have as a source the literature by Michie and her colleagues [49-51, 53, 54, 56] encompassing: COM-B model, behaviour change wheel, behaviour change techniques (BCT's), target behaviours, Intervention design, intervention evaluation, etc. (as described in Section 2.1).

The implementation of large scale interventions has additional complexity requiring: data capture, interface design, data management, data quality control, data aggregation, data transformation, data extraction, live analytics on platform's usage, consolidating multiple data streams and can include active *feedback loops* that could be the result of *machine learning* algorithms deployed as part of the product/platform features. The DSABI overcomes the limitations by combining an industrial *Data Science Workflow* (Figure 1.3) with the 'behaviour change science guidelines'. The DSABI comprehends 5 main components: (1) *capturing behaviours*, (2) *applied behaviour change science*, (3) *intervention design implementation*, (4) *data science for data analysis, algorithmic feedback loops during the intervention and intervention evaluation*, (5) *complex systems*.

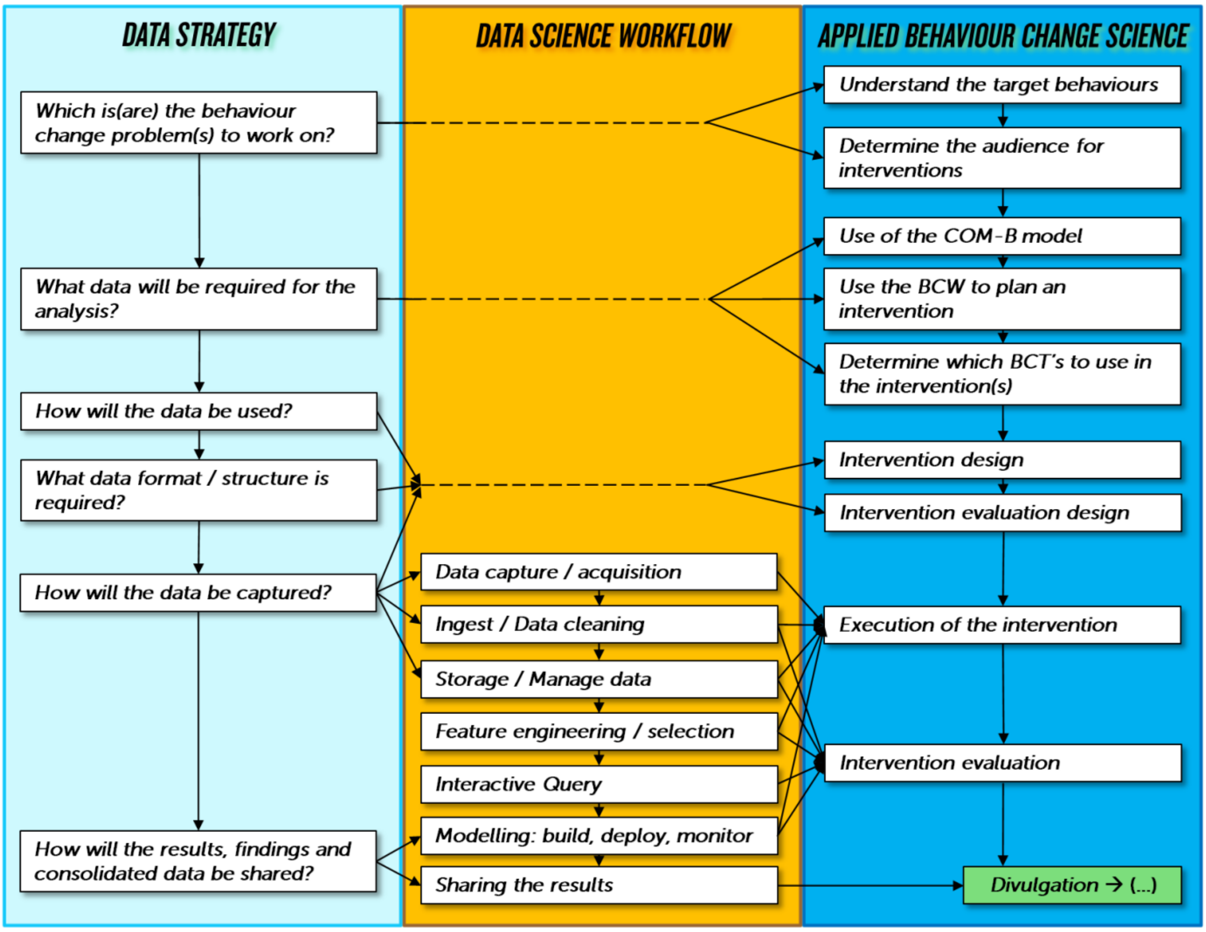


Figure 7.2 ***DSABI, 'Data science approach to behavioural interventions': <u>functional diagram</u>***

The DSABI encompasses the whole cycle of designing a data strategy suitable for purpose with a data science workflow that matches the application of behaviour change science for interventions. A functional description of the DSABI is in Figure 7.2, comparing side by side: (i) data strategy, (ii) data science workflow and (iii) applied behaviour change science. As Figure 7.2 shows. the *Data Strategy* discussions should start at the same time as the considerations about which *target behaviours* should be aimed at and by determining to 'whom', 'when', in 'which context' and 'how' (the recipient *audience*). The *Data Strategy* is represented here as questions, the answers to these questions will build the actual data strategy for the intervention. The *Data Science Workflow* (DSW) starts later, as the *Data Strategy* tasks are finalized. The *data capture* process (part of the DSW) is in line with the *execution of the intervention*. The *Intervention design* has to be completed for the implementation. Everything should be ready for *intervention execution* as the data starts flowing in.

The DSABI's guideline for implementation is proposed as 4 actionable stages with documental output, see Figure 7.3 below. These stages and documents are presented as four practical checklists, and will be later used during the application of the ICPI framework (see Figure 7.4).

- *DSABI Planning document*: Scopes the intervention project, provides an intervention plan and describes general considerations for the data science workflow.
- *DSABI Operation data document*: Describes the operationalisation of the data, and produces documental reference for the execution of the intervention and the intervention evaluation.
- *DSABI Execution & data analysis plan document*: Covers the behavioural execution and data analysis, suggesting the analytical action path.
- *DSABI Consolidates data analysis document*: Consolidates all the data analysis.

Figure 7.3 ***DSABI, 'Data science approach to behavioural interventions':implementation guideline***

Step 1: DSABI PLANNING DOCUMENT

Data Strategy: 'Scoping the problem', answer the following questions:
- Which is(are) the behaviour change problem(s) to work on?
- A control dataset is required? Describe it...
- What data will be required for the analysis?
- How will the data be used?
- What data format / structure is required?
- Anonymised? Or not?
- How will the data be captured?
- How will the results, findings and consolidated data be shared?

Applied Behaviour Change Science 'Plan the Intervention':
- Understand the target behaviours
- Determine the audience for interventions
- Use of the COM-B model
- Use the BCW to plan an intervention
- Determine the BCT's to use in the intervention(s)
- Intervention design
- Intervention evaluation design

Data Science Workflow: 'Plan the data analysis':
- Considerations about the output of the exploratory data analysis
- Considerations about the data analysis on partial results
- Considerations about the data analysis output for observational analysis
- Considerations about the data analysis results for hypotheses testing
- Plan the quantitative identification of the intervention components

Step 2: DSABI OPERATIONAL DATA DOCUMENT

Data Strategy: 'Operationalise the data', answer the questions:
- How will the data by shared?
- What are the interests of different stakeholders on the data?
    - o Participants
    - o Other researchers & collaborators
    - o Data commons
    - o etc.

Applied Behaviour Change Science: 'Execution of the Intervention':
- Ethical approval considerations, *describe*
- Trial design (ie. PoC, Action research, pragmatic/randomised controlled trials, etc.) , *describe*
- Qualitative data required, *describe*
- Unstructured data required, *describe*
- Considerations for system design?, *describe*
- Data protection including GDPR, *describe*
- Duty of care protocols, *describe*
- Data security, *describe*
- Conducting data impact assessments, *describe*
- Execution of the intervention, *describe*
- Intervention evaluation, *describe*

Data Science Workflow: 'Plan the data preparation':
- How will the data analysis be performed?
    - o Python, R, SQL, MatLab, BigML, Strata, SAS, etc.?
- Data preparation process required for analysis
- Data quality control
- Data aggregation required for analysis (hourly, daily, weekly, …)

Figure 7.3 ***DSABI, 'Data science approach to behavioural interventions':<u>implementation guideline</u> (continued)***

Step 3: DSABI EXECUTION & DATA ANALYSIS PLAN DOCUMENT

Applied Behaviour Change Science: 'Execution of the Intervention':
- Data compliance in action, enforcing data governance
- Execution of the intervention
- Closing the intervention
- Intervention evaluation
- Decommissioning the intervention

Data Science Workflow: 'Plan and execute the data analysis methods':
- Exploratory data analysis (general overview of the data)
- Statistical analysis (determine the main drivers / features & data structure)
  - o Linear models, Non-linear models, Logistic regression, …
  - o Other statistical models
- Machine Learning (ML) methods (as intervention feedback loop?)
  - o Classifiers: Random Forests / SVM / Naïve Bayes classifier,…
  - o Determine the dataset size required (training & testing data)
  - o Other ML methods…
- Modelling techniques (if required)
  - o Basket analysis
  - o Other modelling techniques…
- Complex network analysis (if required, for Social Interaction)
  - o Determine what outputs of the networks required
  - o Determine how big and complex might the networks be
  - o Determine the data structure input required
  - o Determine the possible network metrics you might use
  - o Plan which attributes to assign to the nodes and links
  - o Other Network analysis methods

Step 4: DSABI CONSOLIDATED DATA ANALYSIS DOCUMENT

Data Science Workflow: 'Finalize the data analysis':
- Consolidate the output of the exploratory data analysis
- Consolidate the data analysis output for observational analysis
- Consolidate the data analysis results for hypotheses testing
- Final quantitative identification of the intervention components

7.3 Framework 2: 'Implementation of computational platforms for intervention', ICPI

The purpose of the 'Implementation of computational platforms for intervention' framework (ICPI) is to facilitate all processes related to product design, product management, construction and deployment of platforms for BCI's that require a data science approach (DSABI) and building a product for intervention.

The end-users of the ICPI are the professionals involved with product design, product management and technology development. For this reason, the ICPI was created for the 'developer mind' and the 'product mind' typical of the professionals that are required for design, implementation and operation of platforms (apps), who are not practitioners of behavioural change science.

The use of the ICPI should result in the technical specifications required to build and operate the platform for intervention (Figure 7.4). As such it combines the technical requirements determination process, product viability analysis, product design, live analytics design, workflows for building and deploying the platform. It also integrates the sequence of intervention execution with the recruitment of participants, data science workflows, data analysis and decommissioning of the platform.

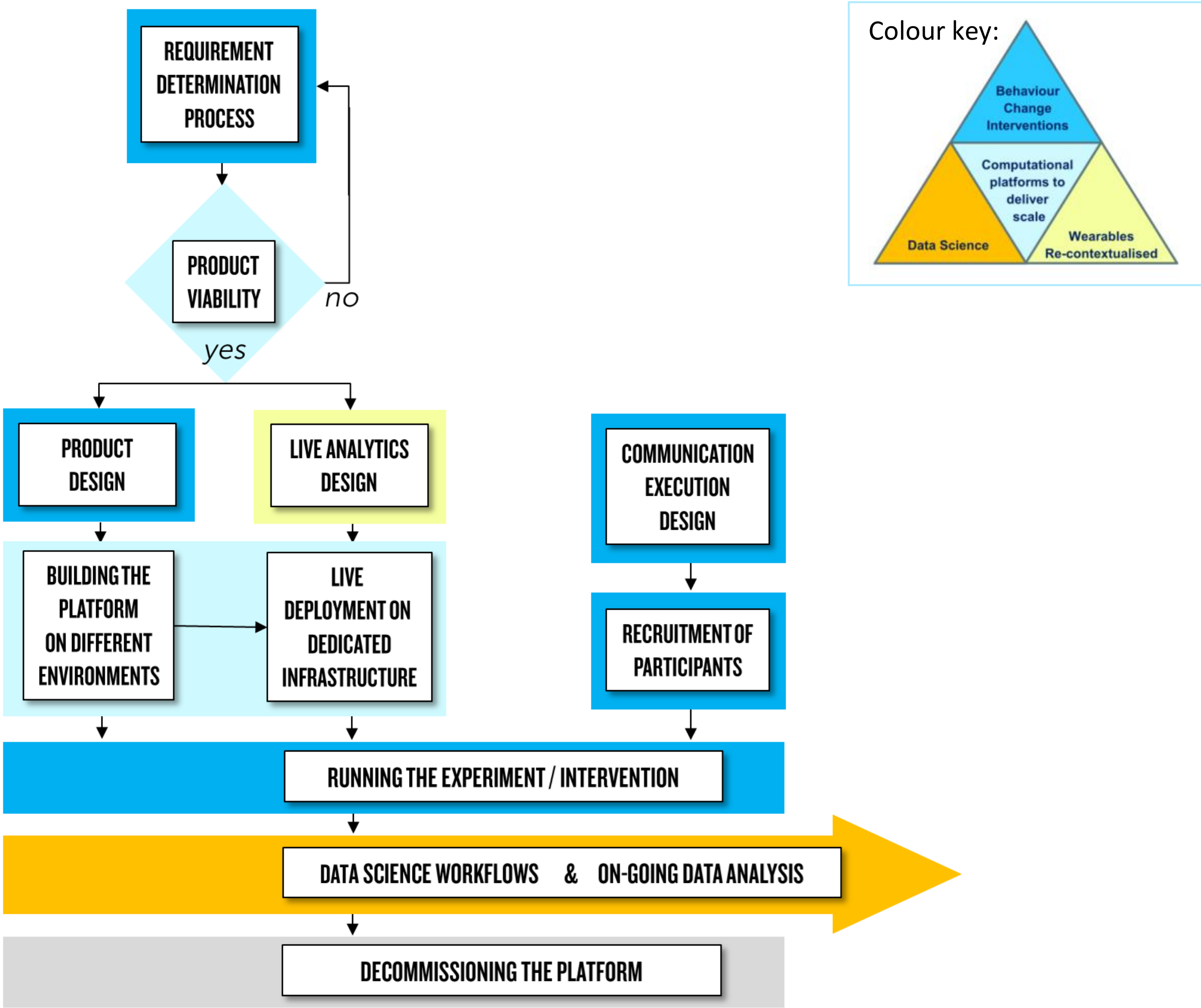


Figure 7.4 ***ICPI, 'Implementation of computational platforms for intervention': <u>core components</u>***

The ICPI core components (Figure 7.4) are now explained and described in detail.

PROJECT PLANNING

Requirement determination process (RDP): Assess the scope and define and describe the requirements for the experimental platform from the technical, product, and the intervention point of view. As a result produce a '*ICPI Platform's scope and requirement*' for validation with the relevant partners of the project. The process continues (as an iteration) until the requirement has been validated and signed-off by the key stakeholders of the project. The team in charge if the RDP should include representative roles of the tasks that will be required for the project, to name few: 'Data Strategist', 'Data Scientist' (can be the same Data Strategist), 'Product Manager', 'Front-End Technology', 'Back-End Technology', 'Information Technology Operations' / 'DevOps', 'Intervention Designer / Manager', 'Communications & Community Manager', 'Project Manager' / 'Scrum mentor'. There will be 1 or 2 'Project Leads' that will bear the responsibility of taking the project to fruition from ideation to delivery of results and leading the connection an alignment between the different teams involved (i.e. academic entities, funding institutions, among others).

PRODUCT

Product viability: Assessment and evaluation of the product's viability from the user experience, user interface (UX / UI) and describe the product features: interface, data generation, live analytics, environments (iOS, Android, Web), and timeline of events (i.e. day a challenge starts, duration and team modality / or not). If additional features are required, the external integration with third party solutions is considered and suggested. A'*ICPI Product viability document*' is created and shared with all the relevant parties (internal and external). The product viability takes place once the requirement determination process has begun, in parallel, or once the RDP has been completed.

Product design: The product design team uses the '*ICPI Product viability document*' and the '*ICPI Platform's scope and requirement*' (once it has been validated) as the starting point to produce 'mock screenshots', 'functional descriptions' and 'user journeys' (i.e. 'on-boarding', 'join a challenge'). As part of the product design stage, the best practice is to 'user test' the product design with 10-15 test users of the same demographic as the target participants of the behaviour change experiment. Once the product design is stable and delivers the functionalities as described on the '*DSABI planning document*' and the '*ICPI Platform's scope and requirement*', consolidate the work on a '*ICPI Product design guidelines document*'.

Product implementation: Use the '*ICPI Product design guidelines document*' and plan the implementation of the product with the technical development team (back-end, front-end, API, Analytics, Data output). Check for quality assurance procedures (Q&A) to make sure that the platform is operational at all levels and fit for purpose. Test the intervention from the functional point of view to make any corrections or adjustments wherever required.

ANALYTICS

'Live analytics' design & **'Live analytics' implementation**: Design the 'live analytics' using the '*DSABI planning document*', '*ICPI Platform's scope and requirement*' and the '*ICPI Product design guidelines document*'. Map the 'user journeys' and all the data capture processes for tested analytics as 'events' that take place in the system. Plan the data capture related to behaviours as described in the '*DSABI planning document*', map and match all the metrics required for intervention execution and the intervention evaluation, as a result produce the '*ICPI Platform's live analytics document*'. If additional data streams are being collected and aggregated into the platform, test for all the connections under different situations to detect any problems in the data collection that results from the product use.

COMMUNICATION AND RECRUITMENT

Communication plan and execution: Based on the '*DSABI planning document*', create a communication plan for: pre-registration (screening for those fit for the intervention, as described in the ethical approval as required), registration, electronic signature of the legal consent, and all the key communication dates required within the intervention. Create the programmatic sequence of communication as required (surveys, emails or internal communications within the platform) and verify language expression to avoid misinterpretations on the target participant population. Produce a '*ICPI Communication plan document*' with the results of this planning and make it available to the team members of the project. Assign an official communication person to make regular contact, (as required) with the participants and possibly as the 'community manager' if it is part of the intervention.

Recruitment of participants: Based on the '*DSABI planning document*', determine the target audience of participants. Create and plan a recruitment strategy: channels, frequency of campaigning, campaigning copy messages, segments / microsegments, recruitment partners, etc. Launch the digital campaign using all the channels within reach (Linkedin, Twitter, Facebook, Callforparticipants.com, specialized networks & groups, distribution lists, etc.). Measure the impact of different campaign versions and the responsiveness per micro-segment. Iterate to get a sample of participants as normal and random as possible.

BUILDING THE PLATFORM

Building the platform on different development environments: In connection with the 'Product Implementation' and as required build the required different environments (iOS, Android and Web).

Allocating infrastructure for the live platforms, the data collection and data analysis: With the documents: '*ICPI Platform's live analytics document*', '*DSABI planning document*', '*ICPI Platform's scope and requirement*', '*ICPI Product Design guidelines document*' and the '*DSABI Operational data document*' design with the DevOps lead the information technology and operations infrastructure scope the machines, databases, back-ups, and additional requirements in which the platform will run when deployed for production once the development in different environments has been completed. Provision resources for this purpose and document it in the '*ICPI Platform information technology and operations infrastructure document*'. In accordance to the overall development project make the platform fully operational on the production environment.

INTERVENTION EXECUTION

Running the intervention(s) / experiment(s): once the experimental platform is built, tested and operational it will be time to run the experiments (as behavioural change interventions). Set-up an 'experiment kick-off day' for a date after all authorizations and approvals have been granted. If you already obtained the required approvals to proceed, consider the recruitment as the initial activity of the experiment. Launch the recruitment campaign and provide enough time for recruitment, depending on the trial design (i.e. 1-2 months). Consider that the shortest is the period between recruitment, screening for health conditions, and the actual start date of the active participation on the experiment the less people will churn. Verify that the on-boarding of the participants on the platform is as planned and they complete the tasks assigned (in the case of Experiments 1 & 2, i.e. connecting a wearable activity tracking device or app). Check for the active participation in collective processes or competitions, since many participants might not consider the intervention has started until they experience interactions on the experimental platforms. Following the descriptions of the '*DSABI Execution & data analysis plan document*' produce the partial results to monitor behaviours (i.e. dashboards on the platform), data collection and the efficacy of the live analytics in place. Make adjustments in the data capturing process, if required by the monitoring of the experiments. Share with the key stakeholders partial results that may be relevant, making clear that they are 'partial'. Provide a 'help desk' to address problems in the UX / UI or running the intervention. If participants do not receive 'help desk answers' they might drop their participation, so monitor that they are receiving the right answers and attention.

Decommissioning the platform: Once the experiment has been completed and the follow-up (or cooling period) is over, the platform's access will be restricted after informing the participants the 'end of use' of the platform. After this period verify that the data captured and aggregated is accessible out of the platform context before providing the sign-off for decommissioning of the platform. Produce documental evidence of the platform UX / UI for future reference since once it had been shut off it might not be possible to access this interfaces in the future (back-ups might not be enough to capture functionality). Once there is certainty that the required data will be available post decommissioning shut down the platform in a planned fashion in collaboration with the technological lead and the person / team in charge of DevOps.

ANALYSIS OF RESULTS

On-going data analysis: As described in the '*DSABI Execution & data analysis plan document*' the data analysis should start during the intervention and will postdate the decommissioning of the platform. The large scale of the data wrangling might require data science industrial workflows with dedicated servers, databases and data processing pipelines. Execute the data analysis as planned and required to obtain and produce results on behavioural analytics and the impact of the intervention. The final results will then be contained in the '*DSABI Consolidated data analysis document*'.

7.4 Conclusion and further work

The proposed frameworks (i) '*Data Science approach to behavioural interventions*', (DSABI) and (ii) '*Implementation of computational platforms for intervention*', (ICPI) have the potential for facilitating future BCIs that require a data science approach and building a product/platform. For an illustration of the integration of both frameworks please see Figure Appendix 4.1.

The use of DSABI and ICPI for the two interventions of this study is an initial validation of the suggested approach using these frameworks. Future work is required to determine the viability of either framework.

Chapter

8. Conclusions, Assessment and Future Work

This chapter consolidates the findings, conclusions and assessment of the research on technology-based, multi-components, large-scale behaviour change interventions for physical activity and weight loss. The chapter aggregates the conclusions, assessment and suggested further work for the study done on Experiments 1 & 2. Both interventions are compared on weight loss and physical activity.

The experiments completed during this research support the fact that behavioural sciences' can effectively make use of computational platforms for multi-component interventions integrating self-monitoring devices for the improvement of physical activity and weight loss [1-5]. The complexity of the investigation was higher than expected due to the required multi-disciplinary approach to: design the technology-based interventions, integrate the evidence-based components and doing experimental behavioural research on the computational platforms that were built. This high complexity explains why there is an academic gap in this type of studies and a very limited number of similar evidence-based commercial applications.

Experiment 1, the Corporate Challenge study (Chapters 4 & 5) fulfilled the 2nd research objective and provided evidence about how a large behaviour change intervention can be delivered using a computational approach which involved building a dedicated platform and making use of wearables effectively for physical activity and weight loss in a corporate wellbeing setting. Experiment 2, the Health & Nutrition study (Chapter 6) fulfilled the 1st research objective and was conceived to identify critical intervention mechanisms (isolated or as interactions) for a computer delivered intervention for weight loss, change in diet and physical activity. From inception the H&N was an extension of Experiment 1 and had a similar intervention format. The suggested frameworks, DSABI & ICPI (Chapter 7) fulfilled the 3rd research objective as theoretical and practical principles to facilitate and enable researchers and practitioners in the journey of creating future cost effective interventions to improve and scale public health.

8.1 Comparative analysis between Experiment 1 & Experiment 2

Both experiments (Corporate Challenge and the Health & Nutrition study) are compared on the findings and results for: weight loss, physical activity, 'team effect' and the impact of adherence.

8.1.1 Comparative analysis on weight loss

The findings, analysis and results on weight loss from Experiment 1 and Experiment 2 are summarised and compared on Table 8.1. There is evidence about the benefits for weight loss about: being explicit 'weight loss' to lose weight, a structured intervention over a control group, completing an intervention, being coached, the interaction of action plans with discussion forums and team based challenges for people with low levels of physical activity, who are competitive. Individuals have more extreme outcomes than teams. Females lose weight regardless of being explicit about 'weight loss' or 'fitness', while males only if they are explicit about 'losing weight'. The non-linear relationship between the initial BMI and weight loss indicates that there are three distinct responsiveness levels related to the 'BMI classification': being healthy, unhealthy or obese at the beginning of an intervention. The change in the diet habit is non-linear as well and will determine the capacity to change as a potential.

Table 8.1 ***Comparison between Experiment 1 & Experiment 2: Weight loss (%)***

	Experiment 1: ***Corporate Challenge study***	Experiment 2: ***Health & Nutrition study***
Being explicit about a motivation: • Being explicit about 'weight loss' is good to lose weight	Yes	*Not available*
Challenge effect: • Comparison *structured intervention* –vs- *control group*	Yes	*Not available*
Team Effect: • Individuals, more extreme results with fatter tails • Team, results are more compact / average range	Yes	Yes
Females and Males: • <u>Category matters for males but not females</u>, *weight loss* (%) • Males did better than the control group	Yes	*Not available*
Completing the intervention • Completing the intervention makes a difference	Yes	Yes
Interventions' effectiveness and their interactions (excluding 'Challenge effect') • 'Coach effect' • Interaction between 'Action Plans' & 'Forum'	*Not available*	Yes
Non-linear relationship to *weight loss* (%): • BMI • Change in diet habit	*Not available*	Yes
Change in habits • Diet habit • Exercise habit	*Not available*	Yes

8.1.2 Comparative analysis on physical activity

The research on *physical activity* covered in Experiment 1 and Experiment 2 is compared on the following Table 8.2. There is evidence about the positive impact for increasing physical activity from: being explicit about ´fitness´ increase physical activity, the challenge effect (defined as a structured intervention), social interaction as network effect, logging to the platform, completing the intervention, being coached, the interaction between action plans and forum. Individuals displayed more extreme outcomes than teams, although teams on average increased more their physical activity. Being explicit about 'fitness' or 'weight loss' makes a difference for females to increase their physical activity, for males there is no difference. The older is a participant the greater the increase on physical activity, although age matters for males but not for females.

Table 8.2 ***Comparison between Experiment 1 & Experiment 2: Physical activity***

	Experiment 1: ***Corporate Challenge study***	Experiment 2: ***Health & Nutrition study***
Being explicit about a motivation: • Being explicit about 'fitness' is good to increase physical activity	Yes	*Not available*
Challenge effect: • Comparison *structured intervention* –vs- *control group*	Yes	*Not available*
Team Effect: • Individual results, more extreme fatter tails • Team results, more compact / average range	Yes	Yes
Network effect: • Social interaction has the potential to increase physical activity	Yes	*Not available*
Females and Males: • Category matters for females but not males, physical activity • There is no difference between sex on the improvement from the initial level	Yes	*Not available*
Using the platform: • Logging in to the platform makes a difference	Yes	*Not available*
Completing the intervention • Completing the intervention makes a difference	Yes	Yes
Age matters: • The older the participant the greater the change • Age matters for males but not for females	Yes	*Not available*
Interventions' effectiveness and their interactions (excluding 'Challenge effect') • 'Coach effect' • Interaction between 'Action Plans' & 'Forum'	*Not available*	Yes

8.1.3 Comparison of the 'team effect' on both interventions

In this subsection the 'team effect' is revisited for the Corporate Challenge and the Health & Nutrition study for *weight loss* (%) and *physical activity* (Figure 8.1). There is a difference in the distributions of teams and individuals. The teams' distributions for *weight loss* and *physical activity* are more concentrated around the mean. The individuals' distributions have fatter tails.

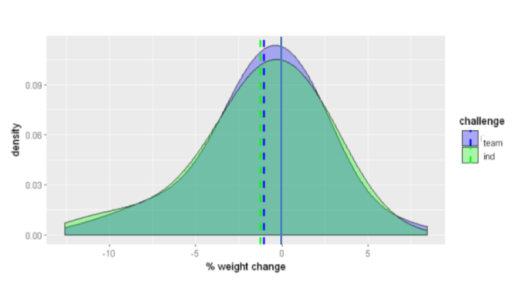
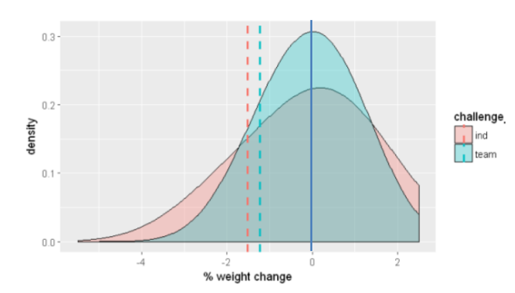
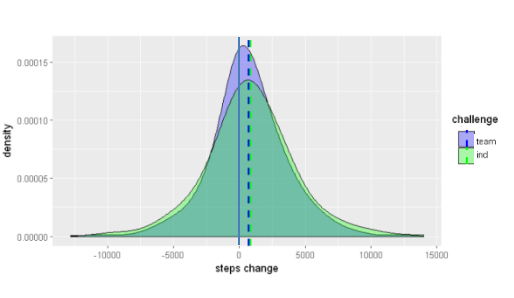
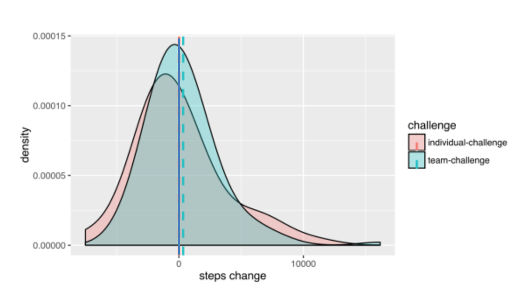
	Experiment 1: ***Corporate Challenge***	*Experiment 2:* ***Health & Nutrition study***
Weight loss (%)		
Physical Activity (*steps change*)		

Figure 8.1 *Comparison between Experiment 1 & Experiment 2: Team effect*

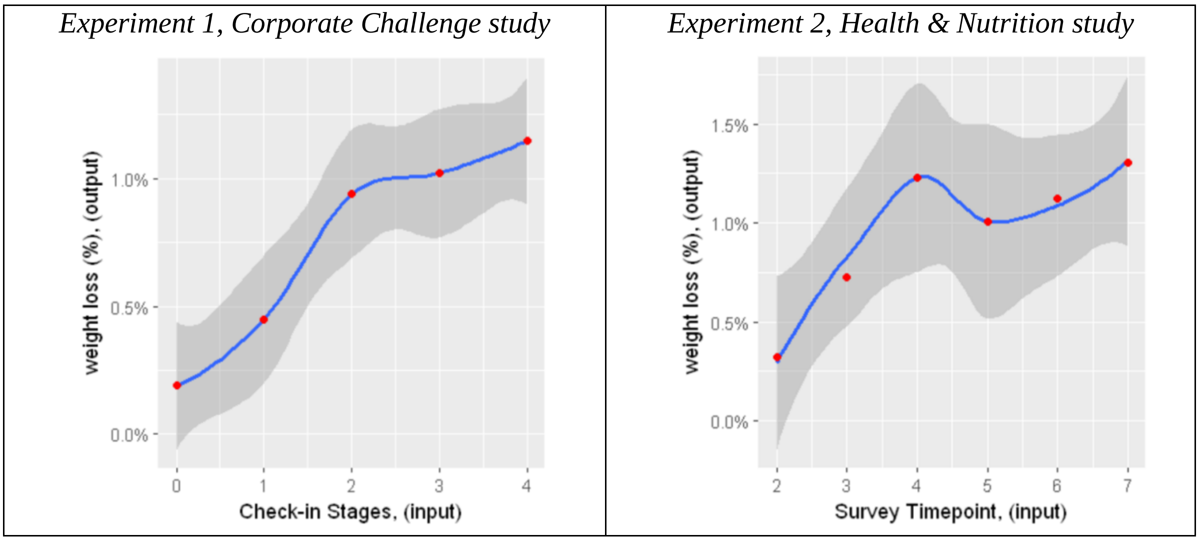
In general it can be said that The TEAMS display a more compact / average range of results, meaning that teams encourage a more average change. This could mean that teams dampen extreme performers and support an average change of the target outcome result. In contrast, INDIVIDUALS on both experiments displayed a broader range of results. Although the fat tail of gaining weight (right side of the distribution) in the Corporate Challenge is proportionally smaller than the equivalent tail on the Health & Nutrition study. This means that individuals in the context of challenges produce more extreme results either losing a significant amount of weight or gaining extra kilos / pounds or walking much more or much less.

8.1.4 Comparative analysis, the impact of adherence

When both experiments are analysed with an *input-output analysis* for *weight loss* (%) it is possible to confirm the importance of adherence (Figures 8.2). We observe that a bigger input (adherence in this case) produces a larger output.

Although the x-axis does not have the exact time scale for both experiments (the 'Corporate Challenge' lasted 4.5 months and the 'Health & Nutrition' 10 weeks), it is possible to conclude unsurprisingly that the benefits of the intervention are greater for those participants who adhere to the intervention for a longer period of time. This suggests that the participants benefit the most from staying on the intervention until the end. There seems to be a change of regime half way into the intervention, further research is suggested.

Comparative Input-Output analysis for weight loss (%):



Figures 8.2 (a) & (b) ***Experiment 1 & Experiment 2: Input-Output analysis for weight loss (%)***

8.2 Conclusions

Platforms integrating multi-component interventions are robust tools that enable a direct contact with a target population, and facilitate the improvement of product management / design. Factorial design optimizes the use of resources, recycles the control groups and delivers abundant results. The main findings are now described.

PHYSICAL ACTIVITY

The 'challenge effect': There was a significant change in steps (positive improvement) just for being in the challenge, the 'challenge effect' for the change in steps. This is in contrast to the results of the control group, which had no significant change or improvement. There is an even bigger 'challenge effect' for participants on the fitness category, compared to those in the weight loss category. Both categories of the challenge did better than the control group.

Age matters: Age matters in the challenge, the older the participant the greater the change in steps. Age does not impact steps improvement for the control group, under the unstructured environment. Age plays a part in steps improvement for males but not for females.

Female and males: Females and males in the challenge did better than the control group. The 'challenge effect' stands for positive change in steps across gender. There is no difference between genders on the improvement rate by initial steps. The Category matters for females, but not for males: females in fitness category have higher average improvement in steps (than those in the weight loss category). In contrast to the above, the step performance in males is about the same for both categories: fitness and weight loss.

Being explicit about 'fitness' to improve the physical activity: The models provide evidence to support the argument that there is positive impact of being explicit about 'fitness' to increase physical activity (measure as daily steps count). This result is supported by the 'challenge effect'.

Using the platform: Logging in to the platform makes a difference, because the platform as an intervention context (digital environment) seems to accentuate the proclivity to increase physical activity, this is confirmed by the 'challenge effect'.

The NETWORK EFFECT for PHYSICAL ACTIVITY

The impact of social interaction can result in a network effect for the individuals who have a direct social network of good size (measured as a high degree of centrality ≥ 3) if they communicate sufficiently with the members of this network. This network effect has the potential for positive influence to increase physical activity.

The STRUCTURE of the SOCIAL INTERACTION NETWORK

The completion of the challenge is related to a higher degree for the nodes (participants). It seems that the structure of the network was influenced by: the sex (females were more connected and communicative) and two business units (bu. 2 & bu. 4).

The network structure had predominant segments: management predominant over other types of employees, team members predominant over individual participant, fitness category predominant over weight loss category, and participants with 1 or 2 synced devices predominant over those with 3 or more synced devices. Geography was not a determinant on the structure of the network. The data collection was not related to the structure of the network.

WEIGHT LOSS

The 'challenge effect': There was a significant weight loss (positive improvement) just for being part of the challenge; this is the 'challenge effect' for weight change. Control model (control group), which clearly is different from the challenge ('*Structured intervention*'): In general they performed worse than the challenge.

Female and males: Males in the challenge did better than the control group. The '*challenge effect*' stands for weight loss in males. The category (fitness, weight loss) matters for males, but not for females: males in fitness category lost less weight than those in the weight loss category. In contrast to the above, weight change in females is about the same for both categories: fitness and weight loss.

Being explicit about 'weight' to lose weight: There is evidence to support the argument that there is positive impact of being explicit about 'weight loss' to increase lose weight (measured as change in weight). There is an even bigger 'challenge effect' for participants on the weight loss category. They did better losing weight than the population of the challenge, which is already better than the control.

Completing the intervention: Completing the intervention stages makes a difference to lose weight during the intervention

Team members –vs team captain: Team members did better (lost more weight) than the team captains

CHANGE of WEIGHT (%) ANALYSIS

Four interventions and their interactions: There was a '*coach effect'*, significant weight loss (positive improvement) for those being coached. The combination (interaction) between action plans and forum was positive for weight loss. Using only the forum was not conducive to weight loss in the Health & Nutrition study, meanwhile those who did not use the forum lost more weight than those using it. This result may be related to the fact that as a product feature the *forum* operated as a repository of the coaches notes, instead of an engaging discussion forum.

Combinations of interventions and change in exercise habit(s): The combination (interaction) between action plans and forum was boosted by improvements on exercise habits. The use of the forum during the H&N opaqued the benefits of improvements on exercise habits.

Non-linear relationships to weight change, s(BMI) and s(change in diet habit): The initial BMI measure has three levels of response to weight change in a non-linear fashion. The healthy gained weight (maybe related to muscle gain? Further research is recommended). The overweight consistently lost weight, and have a potential positive response to interventions (further research is recommended). The obese have a less effective response to lose weight and show a wider range types of results, there is a potential for interventions (further research is suggested). The initial dietary habits measure has a non-linear relationship to weight change characterized by three different levels of response. The unhealthier are the initial dietary habits, the higher is the weight gain. With neutral diet habits (not characterized by unhealthy or healthy habits) the intervention produces weight loss. For healthy dietary habits the weight change results are neutral, some lose weight and others gain weight. A healthy dietary set of habits at the beginning of the intervention implies that to lose weight other lifestyle angles have to be targeted, because the capacity to change weight from diet habits' modification is limited. The initial diet habits and BMI measure at the beginning of an intervention might be used to develop early signals of predicted change in weight for an intervention.

CHANGE of DIET HABIT

Four interventions & their interactions: Action plans and the use of the forum appear have positive potential for the change on diet habit. The scenario analysis provides as well the positive potential for change in diet habit by combining the interaction (action plans + forum) with the team challenge or the coach.

Initial diet habit level: The unhealthier is the initial diet habit, the bigger the potential for improvement (the inverse also applies).

Team effect: It seems the Team challenge dampens the potential for change in diet habit, further research is suggested.

Personality traits: It seems that *conscientiousness* (C) supports positive (+) potential for change in diet habit, further research is suggested. It seems that *neuroticism* (N) might detriment (-) change potential for change in diet habit, further research is suggested.

CHANGE of EXERCISE HABIT

Four interventions & their interactions: Action plans appear to have positive potential for the change on exercise habit. The scenario analysis provides as well the positive potential for change in a exercise habit by combining action plans as an interaction with the forum or the coach. The best combination is the product of the interaction (action plan + forum) with coach and individual challenge, further research is suggested.

Initial exercise habit level: The lower is the initial exercise habit, the bigger the potential for improvement (the inverse also applies).

Team effect: It seems the Team challenge dampens the extreme individual potential for change in exercise habit, although it provides a context for average improvement, further research is suggested.

Personality traits: It seems that *agreeableness* (A) supports positive (+) potential for change in exercise habit, further research is suggested. It seems that *neuroticism* (N) might detriment (-) change potential for change in exercise habit, further research is suggested.

8.3 Future work

The data science approach to behaviour change explored in this investigation is just the beginning of a field of scientific research that very likely will develop and evolve in many different ways. It is reasonable to consider the development of further work towards autonomous and semi-autonomous systems and mechanisms of intervention for behavioural interventions or for the use of behavioural interventions as parts of products or operational structures for providing services or managing information. The potential is grand and there is long way to go.

Further work PHYSICAL ACTIVITY: There is a difference in how males and females respond to the intervention as a change in steps (outcome measure), although this difference is not present in the balanced dataset and the teams dataset. It still open for further research the analysis of the impact of a team as a factor that dampens the female – male difference. The team effect for physical activity should be revisited.

Further work WEIGHT LOSS: No significant factors were found in the female model, meaning that further research is required to understand the mechanics of weight loss in females. There is a different weight change by gender (determined by the initial weight level at registration). Although, the difference found was negligible, further research is recommended. It is worth reviewing the following: (1) for females the initial weight is not a predictor of weight change; (2) for males the initial weight can explain to some extent the change in weight and (3) the team effect for weight loss.

Further work NETWORK EFFECTS: Network effects have been found in weight loss for gaining weight as an epidemic process [139] and for losing weight related to social embeddedness (structure) [147], further work is suggested for multi-component technology-based behaviour change interventions. As well, further research is required to explore the factor interaction between physical activity and weight management as a function of social interaction. It is worth to revisit the analysis of the 'network effect' related to physical activity measured as daily steps count. Although there is significance to explain 6.3% of the variance in the steps, the R^2 is low, a bigger sample might provide interesting results and contribute to literature [209]. Further investigation is recommended to explore the 'network effect' related to weight loss since it has already been documented in literature [126, 139, 154]. Unfortunately the sample size was not big enough after the data quality control and filtering, there seems to be and underlying relationship which justifies further work.

Further work CHANGE of WEIGHT (%) ANALYSIS

Further work Non-linearity of BMI: The non-linear relationship between BMI and weight change is worth of further research. Related to the above, there seems to be three levels of response to weight change in a non-linear fashion, further research is suggested. The initial diet habits and BMI measure at the beginning of an intervention might be used to develop early signals of predicted change in weight for an intervention. These different initial states (of diet habit levels and BMI) have the potential to be determinants for prescribing different variations of intervention components. Further research is recommended.

Further work non-linear change of diet habit: The non-linear relationship between the change in diet habit and weight change is worth further research. A healthy dietary set of habits at the beginning of the intervention implies that to lose weight other lifestyle angles have to be targeted, because the capacity to change weight from diet habits' modification might be already limited. For example the combination with exercise habits improvement should be addressed, further investigation is suggested.

Further work four interventions & their interactions: It seems that people who were coached had a higher adherence to the intervention; worth to do further research if this is maybe because of emotional commitment (out of the scope of this investigation). An average of 9 topics was read by the participants during the study period. It seems that the more topics a user read on the discussion forum from the higher the percentage weight loss (this will require further research and is beyond this current investigation).

Further work CHANGE of DIET HABIT

Further work team effect: It seems the Team challenge dampens the potential for change in diet habit, further research is suggested.

Further work personality traits: It seems that *conscientiousness* (C) supports positive (+) potential for change in diet habits, further research is suggested. It seems that *neuroticism* (N) might detriment (-) change potential for change in diet habits, further research is suggested.

Further work CHANGE of EXERCISE HABIT

Further work four interventions & their interactions: The best combination is the product of the interaction (action plan + forum) with coach and individual challenge, further research is suggested.

Further work team effect: It seems the Team challenge dampens the extreme individual potential for change in exercise habit, although it provides a context for average improvement, further research is suggested.

Further work personality traits: It seems that *agreeableness* (A) supports positive (+) potential for change in exercise habit, further research is suggested. It seems that *neuroticism* (N) might detriment (-) change potential for change in exercise habit, further research is suggested.

Further work STUDY DESIGN & IMPLEMENTATION

Further work sample size: As mentioned before it is worth to invest in further research on the direction of a new study similar to the Health & Nutrition study aiming at increasing the sample size and confirming or debating the results here presented.

Further work duration of the intervention, 6 weeks is not enough: A future intervention would benefit of a longer period of implementation from baseline (before the intervention begins), through the active period of the intervention, up to the follow-up period. Ideally the intervention should by for a total period of 6 months with 3 months of intervention.

Further work factorial design: The H&N unintentionally became a fractional factorial design due to lower numbers of usage of the intervention components (coach intervention, challenge intervention, action plans intervention and forum intervention). This implies that a future study should aim at increasing the initial recruitment around four times that of the H&N.

A broader list of further work would include:

- Implementation of adaptive behaviour interventions with computational engines informed by well-studied statistical processes that explain the characteristics of the current population, distribution of behaviours and the critical paths to the desired target behaviours. Such adaptive multicomponent behavioural interventions could be structured using factorial experimental design and build on the Multiphase Optimization Strategy (MOST).
- The study of network effects and the emergence or disappearance of behaviours combining the work done on complex networks by many computational social scientists with the research of behaviour change scientists.
- Implementation and study of multi-target interventions on large scale using an underlying computational media for delivery.
- A computational approach to behaviour change, via interventions and the evaluation of sustained effects to isolate the key characteristics of the individual, the system of context or the intervention for prolonged and long lasting results.
- Implementation of systemic risk analysis as mechanism to understand and provide feedback loops for intervention of behaviour.
- Determination of critical paths for choice architecture for products or services that involve or require behaviour change mechanisms or interventions.
- Understanding of human response to computer decision based processes for intervention optimisation.

8.4 Limitations

Like every research work, the study has several limitations that need to be addressed. The first limitation is related to data quality, there is always room to improve behavioural analytics data. While the experiments captured a significant amount of data during the interventions, there were data capture limitations on the baseline (before the interventions began) and follow-up (after the intervention was over). It was particularly hard to capture this 'out of intervention' data, due to the limited incentives for participants to provide it. The follow-up data is relevant to measure the sustained effects of the interventions. There was limited follow-up data, overcoming this limitation would provide more generalised results and enable the determination of intervention strategies for sustained effects [18]. Data aggregation should be considered as a limitation to some extent, since the granular behavioural events' had to be aggregated for analysis at the daily level and then averaged weekly. This aggregation was required for the current analysis, although future work on the interventions' dynamics might require more resolution and different granularity.

The second limitation of the research is intervention adherence, the improvement of engagement has positive consequences to health [231, 232]. Although both experiments did well in comparison to other technology-based interventions, the actual adherence to the experiments reduced the total number of participants analysed. Large scale interventions mitigate (to some extent) the impact of reduced data collection product of partial adherence, by providing large population samples for data analysis. This implies that it is recommendable to recruit far more participants than the target sample size.

The third limitation resides on the different duration of Experiment 1 and Experiment 2, affecting their comparability. Although it was possible to make comparisons across both interventions, there was not an exact match for the periods of intervention. This was known from the inception of Experiment 2, because it was designed to produce additional but related results to those found in Experiment 1. For future work and comparability of results the duration of intervention should be addressed at the intervention design (it has cost and logistics implications).

The fourth limitation is on the models used for the analysis done, although they are sufficient. The rationale for the OLS models used was to provide explanatory descriptions of the underlying intervention mechanisms and to explain the outcomes observed. There might be better models than the ones used and it is encouraged to explore them for the analysis of complex dynamics present in physical activity and weight loss.

The fifth limitation is on recruiting: (1) Experiment 1 was a corporate wellness intervention with recruitment within a large corporate institution and (2) Experiment 2 was purely academic and required a broad recruitment strategy (it was a harder recruitment process). The recruitment of both experiments has the signature of self-selection bias given the nature of the interventions, the use of wearable devices and the personal interests of each participant. The people that might benefit more from the outcomes of these types of analysis might have not been part of the studies (or might be underrepresented within the samples). Because conclusive results are required for all the target populations that might benefit of these interventions, future research should be inclusive of all the target populations.

The sixth limitation is on the use of wearable devices and the comparison of the behavioural analytics captured with them [6, 233-235]. The measurements captured with different wearables and apps vary widely, although the fact of capturing them and generating awareness is valuable in itself. The actual number of participants using wearable devices was a limitation, because only half of the participants decided to use wearables (and connected them to the platforms). The analysis had to take this into account. Future studies should be designed with this limitation in mind in addition to the re-contextualization of wearables for intervention.

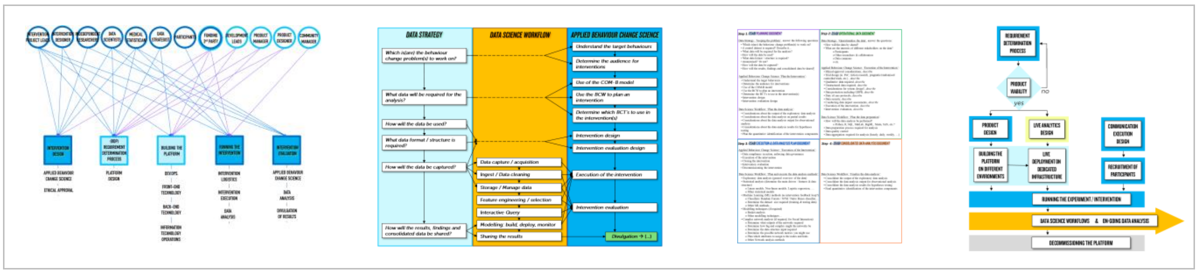
The seventh limitation of this study is related to the experimental design. Experiment 1 was in large scale format, Experiment 2 was inspired by factorial design. Factorial design produced a higher amount of results per number of participants. It would have been ideal to use factorial design for Experiment 1 as well, and its use is strongly recommended for future studies. It is suggested that future interventions should be defined as 'adaptive interventions', for relevant references see the MOST and SMART interventions [175].

Finally as future development, the frameworks explained in Chapter 7 (DSABI and ICPI) should be useful to overcome these limitations for the benefit of participants and researchers of tech-based, multi-component, large scale behavioural interventions.

8.5 Stakeholders, roles and workflows in an intervention

With respect to stakeholders, roles and workflows, the main lesson for the future is to address and manage the tension between the researcher(s) and the product team. This is expressed as the tension between the *experiment's features* and the *product / platform's features*. To illustrate this tension, in the H&N study the experiment features required 16 different interfaces (matching the factorial design combinations). To make this possible, the product required a hack to enable to 'switch on' or 'switch off' of different product features for different sub-populations randomly allocated. In this case, there was a negotiation that took place between the researchers, the product team and the development leads to determine the actual product features that carried the intervention components.

Behaviour Change interventions are hard and complex in many dimensions; they require design, implementation and analysis of large scale interventions. This complexity was translated in this research into the frameworks developed covering the intervention's states end-to-end: the DSABI and ICPI frameworks presented in Chapter 7 (summarised in Figures 8.3 below).



Figures 8.3 (a), (b), (c) & (d) ***Summary: DSABI & ICPI frameworks***

The DSABI and ICPI frameworks enabled the execution of Experiments' 1 & 2, by facilitating the design, implementation and analysis of the behavioural interventions. It is the hope of the author that these frameworks and this thesis (as reference research) will expedite and inspire future academic and commercial technology-based, multi-component behaviour change interventions.

8.6 Publications

Mazorra, R., Yan, X., Dunne, D., Seaborne, R. Legal, M. Zhou, S., Kang, S.M., Aste, T., Treleaven, P., Lefevre, C., (2018); Identification of critical factors of a multi-component, tech-enabled, intervention for behaviour change related to weight loss & physical activity: "The Health & Nutrition Study". *Held as Part of CBC Conference 2018th Annual Conference - Behaviour Change for Health: Digital & Beyond*, London, United Kingdom, February 21-22, 2018, Proceedings.
(*http://www.ucl.ac.uk/behaviour-change/events/conf-18/presentations/7.A.2.pdf*)

Publications in preparation:

Mazorra, R., Yan, X., Dunne, D., Kang, S.M., Lefevre, C. (2018);
Critical factors of a multi-component, tech-enabled, intervention for behaviour change related to weight loss & physical activity.

Mazorra, R., Yan, X., Dunne, D., Koshiyama, AS., Kang, S.M., Lefevre, C.(2018);
Early signals of behaviour change in a multi-component, tech-enabled intervention for weight loss & physical activity.

Mazorra, R., Yan, X., Kang, S.M., Aste, T. Lefevre, C.(2018);
Association networks in a corporate wellbeing intervention: the impact of social interaction on behaviour change related to weight loss & physical activity.

Mazorra, R., Yan, X., Dunne, D., Treleaven, P., Lefevre, C., (2018);
Frameworks for the design and implementation of technology-based, multi-component behaviour change interventions.

9. Appendix 1: Preliminary Work

Capturing long-term behaviours with wearables

The preliminary work, 'Capturing long-term behaviours with wearables' was foundational for this thesis as the scenario in which Data Science was used to capture and display the dynamics of behaviour change as analytics. It provided a real case to design, build and implement a Data Science workflow for behavioural analytics. As a by-product it proved the viability of the research. The analysis covered the behaviour of runners with wearables for 56 weeks in more than 20 countries.

Description

The preliminary work was done using a decentralized app ('dapp') commissioned by a third party (a client of Tictrac Ltd., the industrial partner) as a technological solution for UX / UI, data collection and aggregation. Tictrac was responsible for the integration of data streams from wearables tracking physical activity (the 'wearables platform' of the dapp). The fact that a third party controlled the release and technological integration of the dapp enabled the observation of behaviours as recorded digital traces. The behaviours displayed were unique on their own, regardless of how the app was designed, deployed and received by the target audience.

The platform enabled under one sign-off the connection of multiple wearables (as devices and apps), with the data records generated (see Figure Appendix.1.1). At the substrate of the data streams aggregation, there were users interested in self-tracking for example using apps like 'Fitbit', 'Moves' or 'Google Fit' (among many others).

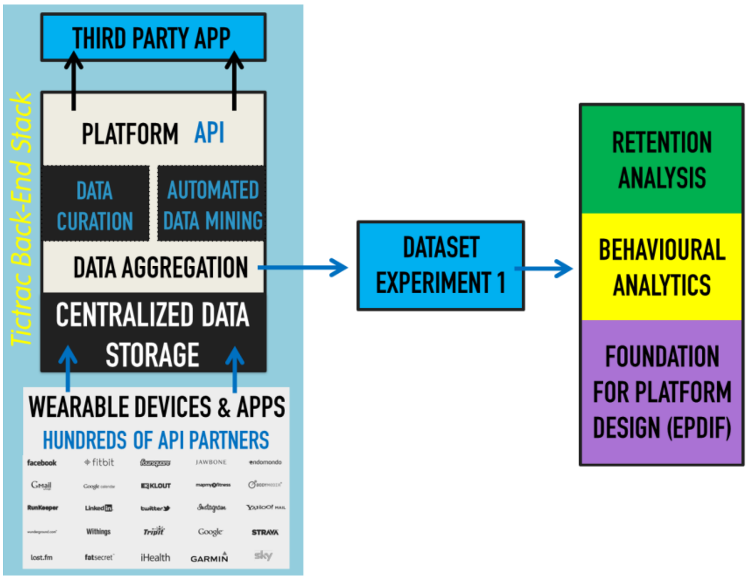


Figure Appendix.1.1 ***Preliminary work, computational platform for intervention: 'Capturing long-term behaviours with wearables'***

Research objectives

The main goal of the study was the analysis of data capture processes, behaviours displayed and assessment of the potential for a dedicated computational platform for intervention. This goal was translated into the following research objectives:

- Capturing Behaviours: determination of principles for describing the behaviours related to running and the engagement dynamics. Evaluating the potential of wearables for interventions
- Analytics: Determine the best features that describe running behaviour for measuring and monitoring progress. Use of analytics to identify segments based on performance. Determination of the value and limitations of the data collected
- Retention: Determination and analysis of the mechanics of retention and the use of wearables on a data aggregation platform
- Technological requirements: Determination of the requirements for a computational platform for the purpose of delivering behavioural interventions

Results

This experimental research required the determination of behaviours within the running events stored as data records on the wearables platform. The consolidated 'running events' (when a participant goes for a passively recorded run or walk) define unique 'Digital profiles' for each participant. The measurement and observation of engagement on the app enabled the analysis of the relationship between retention and data generation from wearables. The investigation of different analytics to measure performance through time validated the potential for segmentation by behavioural profiles.

Running speed as a key metric to segment behaviours:

'Speed' is a critical factor to classify distinctively a 'running event' –vs- a 'walking event'. This result is relevant because it indicates that there is a clear distinction between 'walking' and 'running' as recorded events, with different underlying behaviours (see Figure Appendix.1.2).

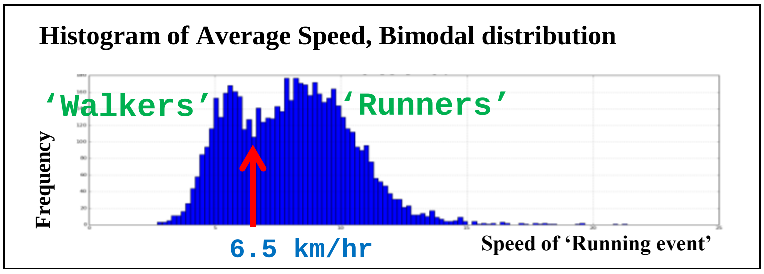


Figure Appendix.1.2 ***Histogram of average speed, bimodal distribution***

This finding implies that there are two clear populations using the dapp, as can be seen in the bimodal distribution of Average Speed. There is a clear valley around 6.5 km/h a natural limit in which an average human switches from 'walking' to 'jogging / running' due to biomechanical efficiencies of the human body.

<u>App engagement measured by retention</u>:

The retention rate has valuable information about thresholds for usage of the dapp (Figure Appendix.1.3.). There are two relevant findings for future interventions. (1) Short term interventions benefit from high engagement for a total duration of less than 6 weeks. There was a relatively high retention rate (above 30%) before completing week 6 / 1.5 months. (2) Medium term interventions using apps should not extend beyond 5 months. There is an inflection point at 20 weeks / 5 months in which the behaviour of power users becomes more distinct (high retention and increasing average number of data records).

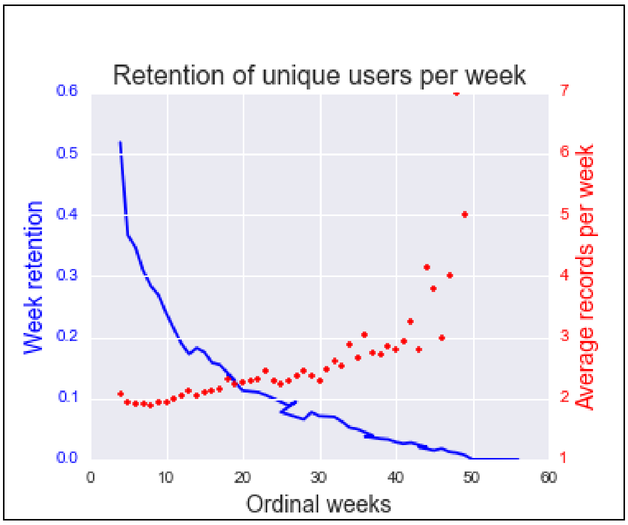


Figure Appendix.1.3 ***Retention per week and Average records per week for the clean / filtered dataset***

There is evidence about the presence and persistence of power users using the dapp beyond 30 weeks, in a context of continuous churn during 56 weeks. This can be seen in the contrast between: the decreasing retention and increasing average number of records (per user / week). This outcome although expected, is relevant because it highlights the importance of app engagement.

<u>Analytics for performance:</u>

The investigation on analytics for performance for running and walking was conducted by tagging the statistical quartiles on performance and evaluating multiple combinations of the variables of the dataset. As a result two sets of performance metrics were defined. The first captures the performance persistence between the periods of analysis: (*Average Speed*, *Total Runs*). The second describe the local nature of performance at the granularity of a running event: (*Total Distance (event), Average time (event)*). These two relationships can be used to identify performance change across individuals, cohorts, or the same sample (inclusive of n=1) to compare different periods, see Figures Appendix.1.4 (a) (b).

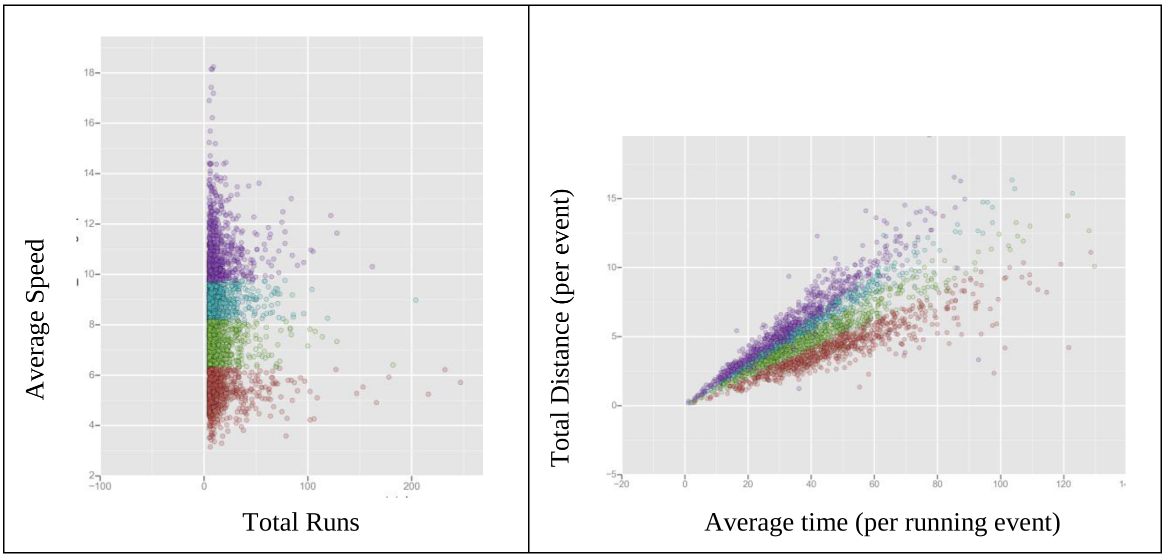


Figure Appendix.1.4 (a) & (b) ***Performance Analytics (Colours represent quantiles)***

Assessment

The dapp had limited reach and produced a relatively small amount of data, considering the high potential of collecting data streams from wearables and user interactions. The data itself had limited baseline characteristics of the users, which restricted the capacity for the development of behavioural analytics. There were many limitations as a result of using a third party's dapp, such limitations provide a space for improvement. Future experiments will require the use of computation platforms designed for the specific purpose of interventions. It will then be possible to plan and deploy the apps with intervention design and evaluation.

Conclusions & Future Work

<u>Behavioural Analytics:</u> There are two clear populations present in the bimodal distribution of Average Speed of running/ walking events recorded. The state transition is clearly defined in the data around 6.5 km/h, a biomechanical limit of the human body.

<u>Analytics for performance:</u> Performance can be effectively measured for walking and running, using the data passively collected with wearables. As a result two sets of performance metrics were defined: for performance persistence (*Average Speed*, *Total Runs*) and for a granular running event (*Total Distance (event), Average time (event)*). Further research is suggested on the relationship between engagement and improvement of target behaviours (or their outcome measures).

Use of wearable devices: The future use of wearables for behavioural interventions is promising. Additional research is required to make use of the potential of wearables for health and wellbeing. The effective use of wearables requires further study: target outcomes should be defined, tested and measured.

Behaviour Change Science & Behavioural Interventions: The behaviours of runners can be captured as a collection of running events and engagement analytics in 'digital profiles', as it was done in this study during a longitudinal study of one year. Future interventions require the re-contextualization of wearable devices as part of structured interventions. Further research is suggested to confirm the findings on the suggested duration of interventions delivered with apps or dapps: (1) Short term interventions should not last longer than 6 weeks and (2) Interventions using apps should not extend beyond 5 months.

Computational platforms for interventions: Future interventions will benefit greatly from principles and frameworks of applied Behaviour Change Science for the design, development and deployment of computational platforms as delivery mediums. These should include: intervention design, implementation and evaluation.

Data Science: Future interventions should include a Data Science workflow with an industrial standard with the capacity to ingest, process and wrangle millions of data points.

Data Analysis: The behavioural data passively generated from wearable devices has a Zipfian structure, with only a 30% useful for analysis. For practical matters this means that recruitment for future interventions should target over-subscription of 300% the target sample size.

Product management: Engagement affects positively or negatively the data generation, therefore it is suggested for future experiments to make use of the best practices for product design, UX / UI.

10. Appendix 2: Experiment 1

Large Scale Intervention on a Corporate Wellness Setting

Experiment 1 was a large scale multi-component intervention in a corporate wellness setting. As technology-based behaviour change intervention with a control group, the ‘Corporate Wellness Challenge’ was designed for the evaluation of intervention components’ effectiveness for increasing physical activity and weight loss.

Table Appendix 2.1 ***Corporate Challenge, Change in steps, 4 models: Descriptive stats***

Full dataset model

	Variable	Mean (SD)	Frequency
	y_outcome	788 (2849)	
	reg	6604 (3832)	
	all_logs	9 (11)	
	all_posts	3 (8)	
sex	Female_0	638 (2843)	455 (55.6%)
	Male_1	976 (2849)	363 (44.4%)
categ	Fitness_0	984 (2848)	409 (50%)
	Weightloss_1	591 (2839)	409 (50%)
team	Individual_0	719 (2789)	577 (70.5%)
	Team_1	954 (2987)	241 (29.5%)

Balanced dataset model

	Variable	Mean (SD)	Frequency
	y_outcome	915 (3027)	
	reg	6409 (3681)	
	all_logs	10 (12)	
	all_posts	5 (11)	
sex	Female_0	845 (3168)	193 (61.1%)
	Male_1	1024 (2800)	123 (38.9%)
categ	Fitness_0	1313 (3360)	158 (50%)
	Weightloss_1	516 (2603)	158 (50%)
team	Individual_0	892 (2803)	158 (50%)
	Team_1	937 (3245)	158 (50%)

Individuals dataset model

	Variable	Mean (SD)	Frequency
	y_outcome	719 (2789)	
	reg	6569 (3896)	
	all_logs	7 (7)	
	all_posts	1 (2)	
sex	Female_0	495 (2857)	301 (52.2%)
	Male_1	963 (2696)	276 (47.8%)
categ	Fitness_0	894 (2652)	247 (42.8%)
	Weightloss_1	587 (2884)	330 (57.2%)
team	Individual_0	719 (2789)	577 (100%)

Teams dataset model

	Variable	Mean (SD)	Frequency
	y_outcome	954 (2987)	
	reg	6688 (3682)	
	all_logs	14 (14)	
	all_posts	10 (13)	
sex	Female_0	919 (2804)	154 (63.9%)
	Male_1	1016 (3303)	87 (36.1%)
categ	Fitness_0	1122 (3128)	162 (67.2%)
	Weightloss_1	609 (2661)	79 (32.8%)
team	Team_1	954 (2987)	241 (100%)

Table Appendix 2.2 *Corporate Challenge, Change in steps, 4 models: Matrix plot*

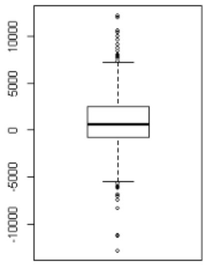
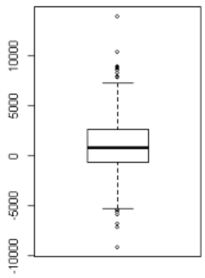
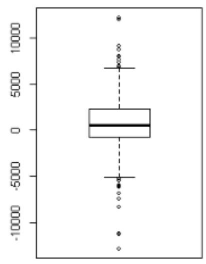
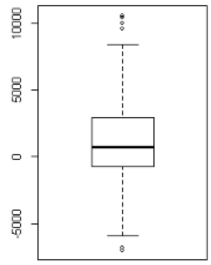
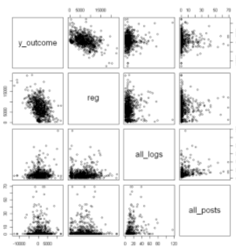
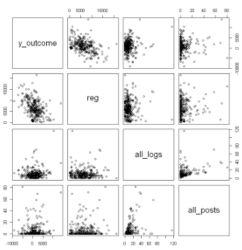
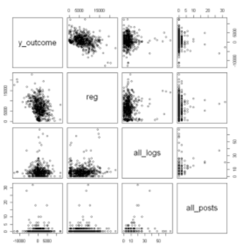
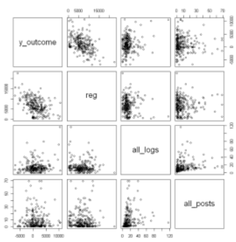
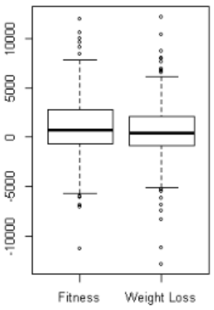
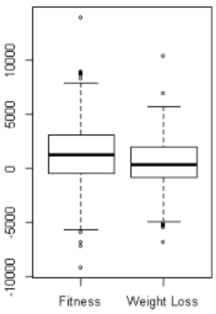
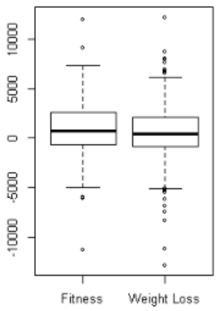
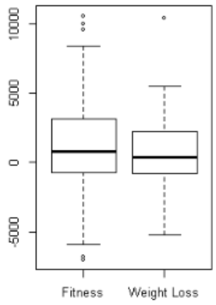
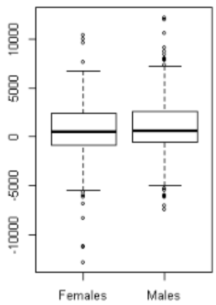
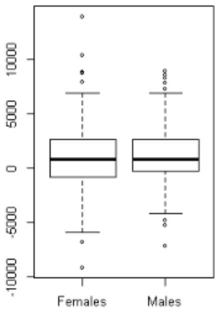
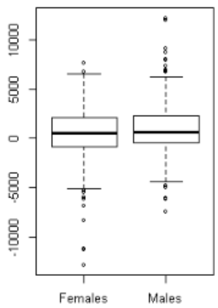
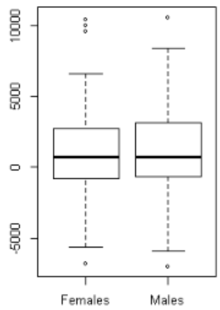
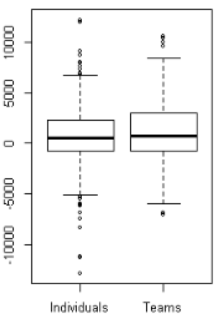
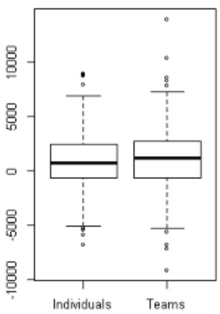
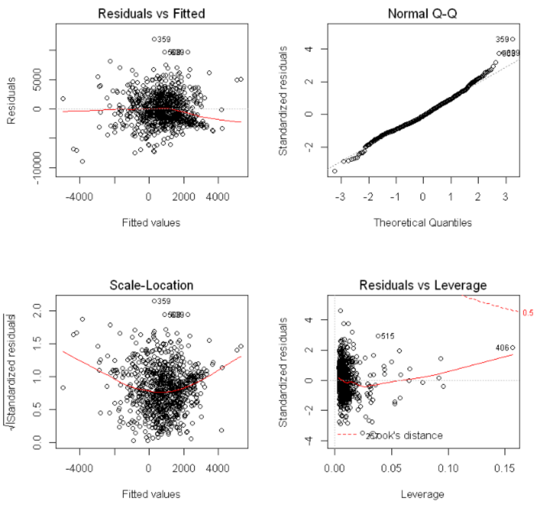
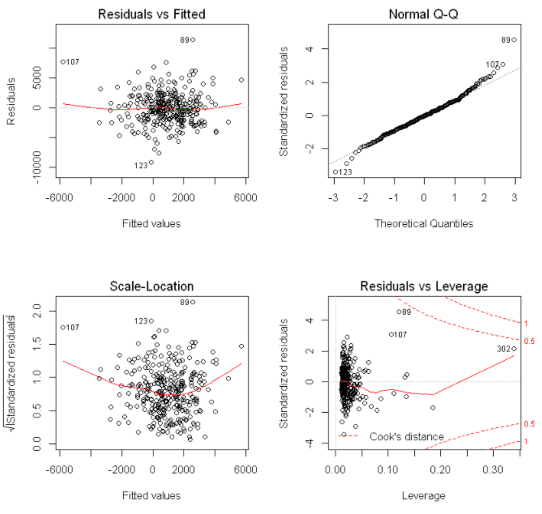
	Full dataset	Balanced dataset	Individuals dataset	Teams dataset
Y_outcome				
Continuous variables				
	Full dataset	**Balanced dataset**	**Individuals dataset**	**Teams dataset**
Category				
Sex				
Modality				

Figure Appendix 2.1 ***Corporate Challenge, Change in Steps: Diagnostic plots***

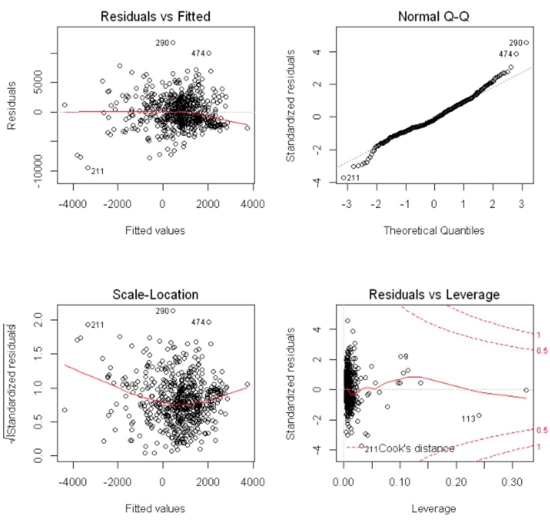
Full dataset model



Balanced dataset model



Individuals dataset model



Teams dataset model

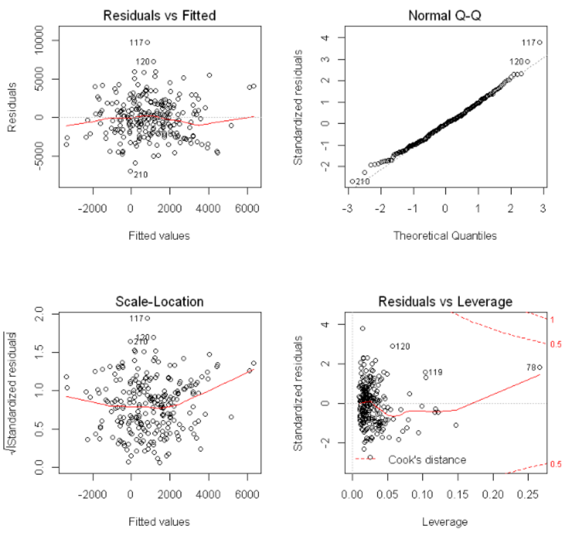


Table Appendix 2.3 *Corporate Challenge, Change in weight (%), 4 models: Descriptive stats*

Full dataset model

	Variable	Mean (SD)	Frequency
	y_outcome	-1.35 (3.87)	
	age	44.83 (9.29)	
	all_posts	3.07 (7.57)	
	comp	2.73 (1.48)	
sex	Female_0	-1.19 (3.92)	176 (56.8%)
	Male_1	-1.56 (3.8)	134 (43.2%)
categ	Fitness_0	-0.76 (3.19)	155 (50%)
	Weightloss_1	-1.94 (4.37)	155 (50%)
team	Individual_0	-1.18 (3.74)	223 (71.9%)
	Team_1	-1.79 (4.18)	87 (28.1%)
Team_1:Cptn			
	Cptn_0	-2.44 (4.31)	287 (92.6%)
	Cptn_1	0.02 (3.22)	23 (7.4%)

Balanced dataset model

	Variable	Mean (SD)	Frequency
	y_outcome	-1.66 (4.62)	
	age	44.13 (8.67)	
	all_posts	4.92 (8.36)	
	comp	2.88 (1.42)	
sex	Female_0	-1.18 (4.68)	69 (57.5%)
	Male_1	-2.31 (4.51)	51 (42.5%)
categ	Fitness_0	-0.6 (3.51)	60 (50%)
	Weightloss_1	-2.71 (5.34)	60 (50%)
team	Individual_0	-0.93 (4.45)	60 (50%)
	Team_1	-2.39 (4.71)	60 (50%)
Team_1:Cptn			
	Cptn_0	-3.09 (4.78)	106 (88.3%)
	Cptn_1	-0.07 (3.74)	14 (11.7%)

Females dataset model

	Variable	Mean (SD)	Frequency
	y_outcome	-1.19 (3.92)	
	age	44.11 (9.55)	
	all_posts	3.1 (6.64)	
	comp	2.8 (1.41)	
sex	Female_0	-1.19 (3.92)	176 (100%)
categ	Fitness_0	-0.55 (3)	83 (47.2%)
	Weightloss_1	-1.76 (4.52)	93 (52.8%)
team	Individual_0	-0.98 (3.87)	124 (70.5%)
	Team_1	-1.67 (4.01)	52 (29.5%)
Team_1:Cptn			
	Cptn_0	-2.55 (3.98)	160 (90.9%)
	Cptn_1	0.3 (3.45)	16 (9.1%)

Males dataset model

	Variable	Mean (SD)	Frequency
	y_outcome	-1.56 (3.8)	
	age	45.78 (8.88)	
	all_posts	3.04 (8.66)	
	comp	2.63 (1.56)	
sex	Male_1	-1.56 (3.8)	134 (100%)
categ	Fitness_0	-1 (3.4)	72 (53.7%)
	Weightloss_1	-2.22 (4.16)	62 (46.3%)
team	Individual_0	-1.43 (3.56)	99 (73.9%)
	Team_1	-1.96 (4.46)	35 (26.1%)
Team_1:Cptn			
	Cptn_0	-2.29 (4.77)	127 (94.8%)
	Cptn_1	-0.63 (2.75)	7 (5.2%)

Table Appendix 2.4 *Corporate Challenge, Change in weight (%), 4 models: Matrix plot*

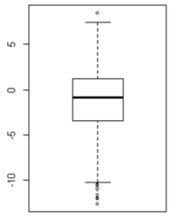
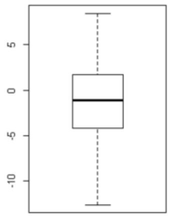
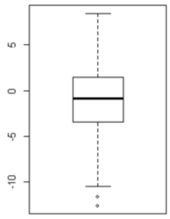
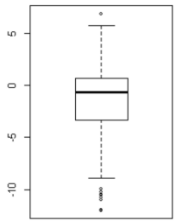
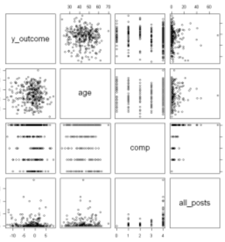
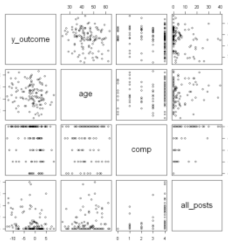
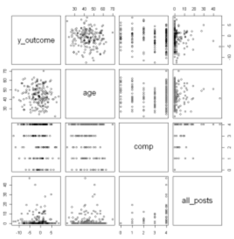
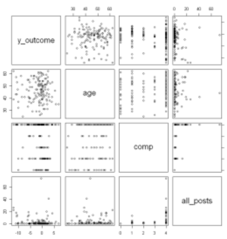
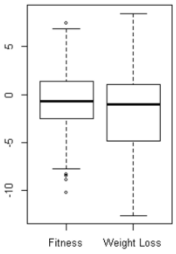
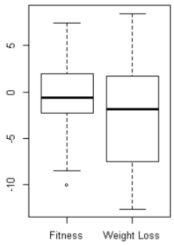
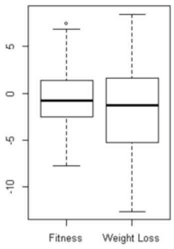
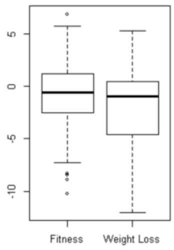
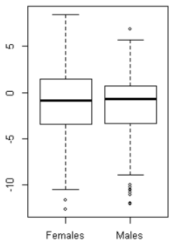
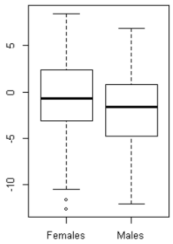
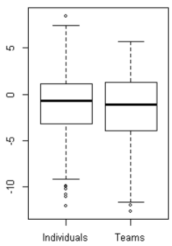
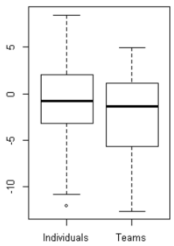
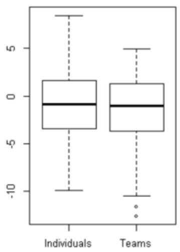
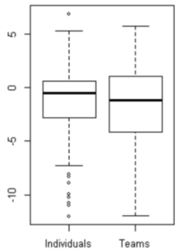
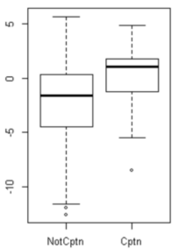
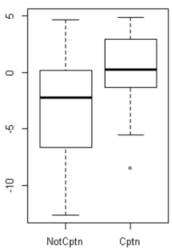
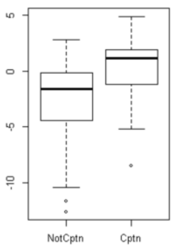
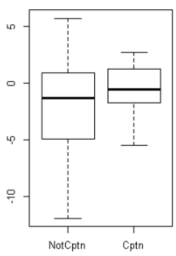
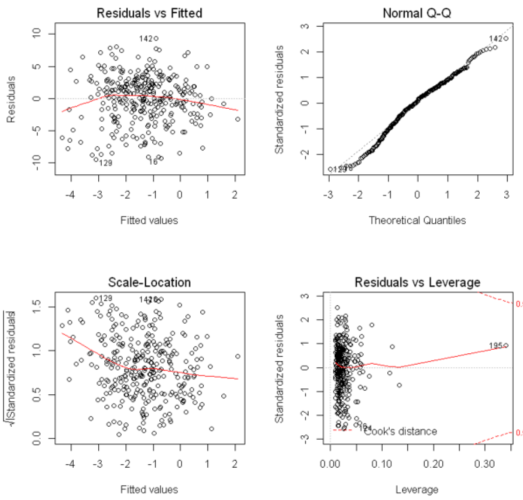
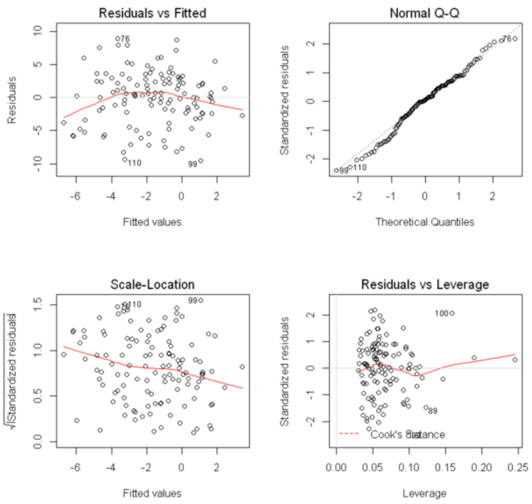
	Full dataset	Balanced dataset	Females dataset	Males dataset
Y_outcome				
Continuous variables				
	Full dataset	**Balanced dataset**	**Females dataset**	**Males dataset**
Category				
Sex				
Modality				
Captain (Team only)				

Figure Appendix 2.2 *Corporate Challenge, change in Weight: Diagnostic plots*

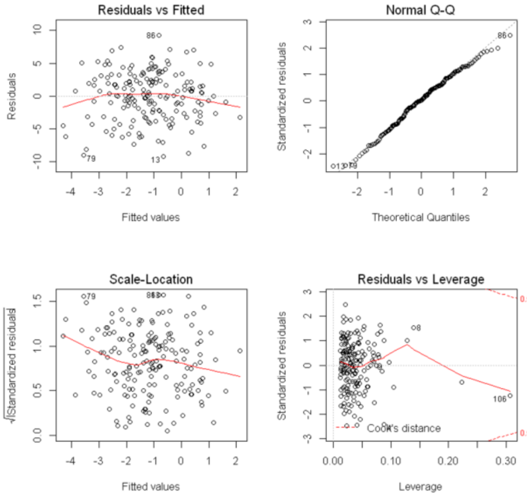
Full dataset model



Balanced dataset model



Females dataset model



Males dataset model

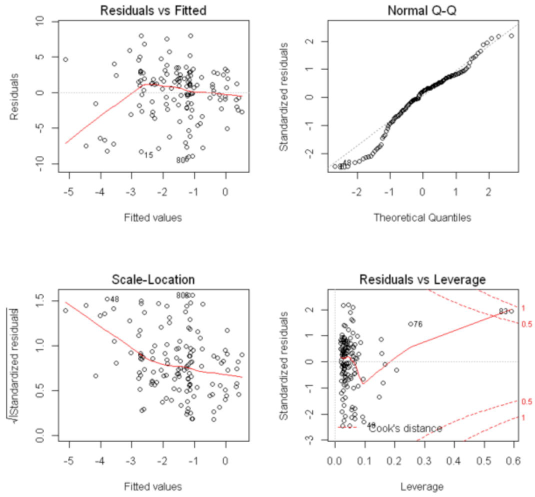


Table Appendix 2.5 ***Challenge effect, Change in steps, 5 models: Descriptive stats***

Balanced model

	Variable	Mean (SD)	Frequency
	y_outcome	590 (2728)	
	Age	42 (11)	
	Registration	6236 (4267)	
Sex	Female	605 (2704)	1062 (50%)
	Male	576 (2754)	1062 (50%)
Label	Challenge	684 (2905)	1062 (50%)
	Control	497 (2537)	1062 (50%)
Challenge	Category		
	Fitness	751 (2949)	819 (38.6%)
	Weightloss	459 (2746)	243 (11.4%)
Female	Label		
	Challenge	597 (2788)	531 (25%)
	Control	613 (2619)	531 (25%)
Male	Label		
	Challenge	771 (3018)	531 (25%)
	Control	380 (2449)	531 (25%)

Challenge model

	Variable	Mean (SD)	Frequency
	y_outcome	663 (2927)	
	Age	47 (10)	
	Registration	7690 (3595)	
Sex	Female	582 (2856)	709 (57.2%)
	Male	771 (3018)	531 (42.8%)

Control model

	Variable	Mean (SD)	Frequency
	y_outcome	349 (2278)	
	Age	38 (10)	
	Registration	4604 (4454)	
Sex	Female	318 (2456)	344 (27.7%)
	Male	360 (2207)	896 (72.3%)

Females model

	Variable	Mean (SD)	Frequency
	y_outcome	605 (2704)	
	Age	42 (11)	
	Registration	6158 (3966)	
Label	Challenge	597 (2788)	531 (50%)
	Control	613 (2619)	531 (50%)
Challenge	Category		
	Fitness	662 (2814)	404 (38%)
	Weightloss	390 (2704)	127 (12%)

Males model

	Variable	Mean (SD)	Frequency
	y_outcome	576 (2754)	
	Age	43 (11)	
	Registration	6314 (4549)	
Label	Challenge	771 (3018)	531 (50%)
	Control	380 (2449)	531 (50%)
Challenge	Category		
	Fitness	837 (3075)	415 (39.1%)
	Weightloss	533 (2800)	116 (10.9%)

Table Appendix 2.6 ***Challenge effect, Change steps, 5 models: Matrix plot***

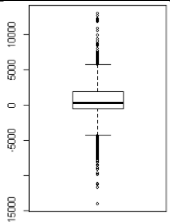
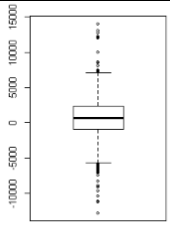
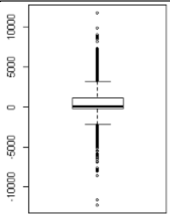
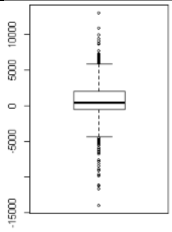
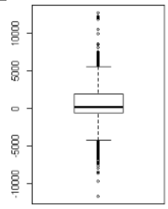
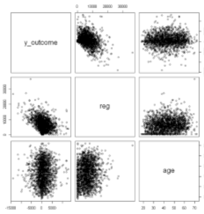
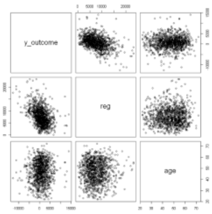
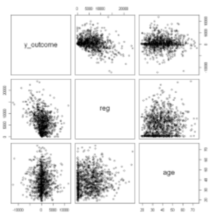
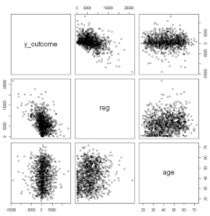
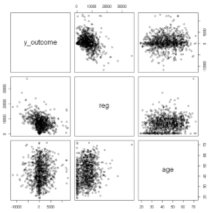
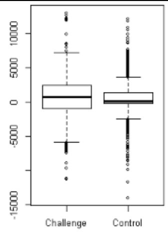
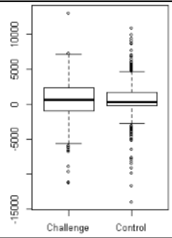
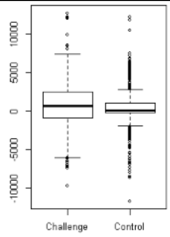
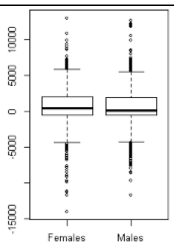
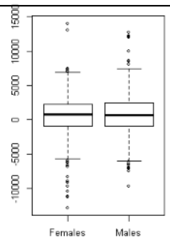
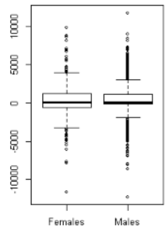
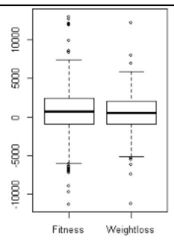
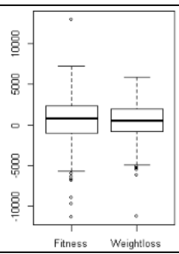
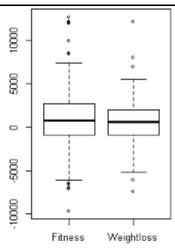
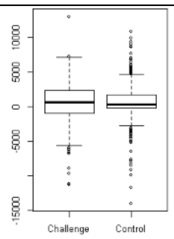
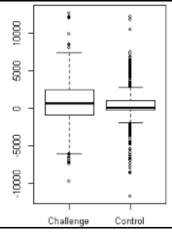
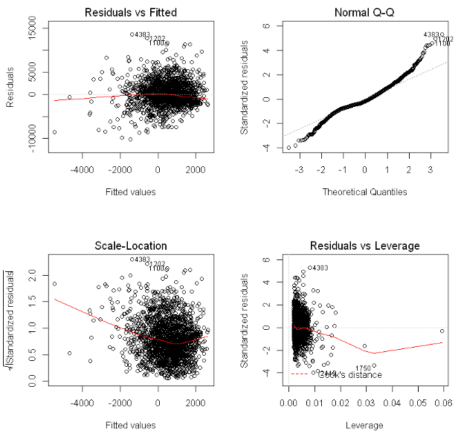
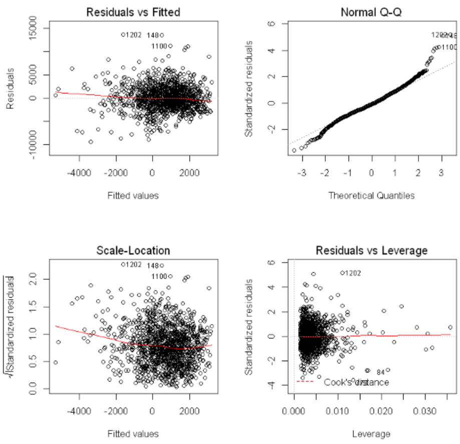
	Balanced	Challenge	Control	Females	Males
Y_outcome					
Continuous variables					
	Balanced	**Challenge**	**Control**	**Females**	**Males**
Label (Challenge, Control)					
Sex					
Category					
Females					
Males					

Figure Appendix 2.3 ***Challenge effect steps models, Balanced, Challenge, Control, Females, Males: Diagnostic plots***

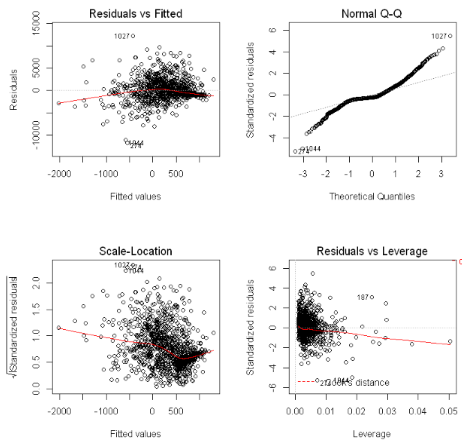
Balanced model



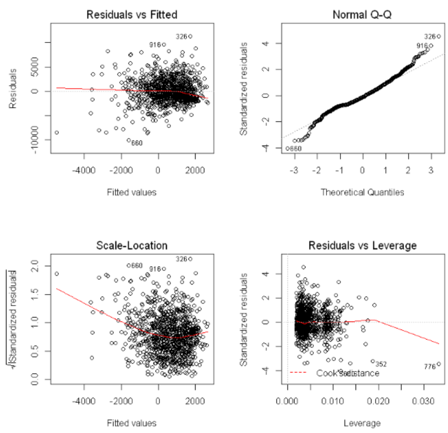
Challenge model



Control model



Females model



Males model

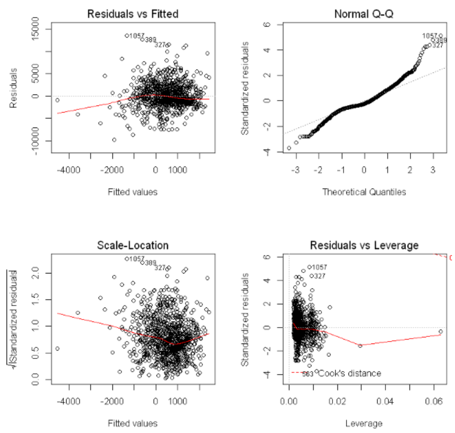


Table Appendix 2.7 ***Challenge effect, Change in weight (%), 5 models: Descriptive stats***

Balanced model

	Variable	Mean (SD)	Frequency
	y_outcome	-0.57 (3.78)	
	Age	41.24 (10.46)	
	Registration	190.41 (47.47)	
Sex	Female	-0.53 (4.1)	478 (50%)
	Male	-0.6 (3.44)	478 (50%)
Label	Challenge	-1.03 (3.92)	478 (50%)
	Control	-0.1 (3.58)	478 (50%)
Challenge	Category		
	Fitness	-0.64 (3.64)	140 (14.6%)
	Weightloss	-1.95 (4.4)	478 (50%)
Female	Label		
	Challenge	-0.83 (4.17)	239 (25%)
	Control	-0.24 (4.01)	239 (25%)
Male	Label		
	Challenge	-1.22 (3.65)	239 (25%)
	Control	0.03 (3.1)	239 (25%)

Challenge model

	Variable	Mean (SD)	Frequency
	y_outcome	-1.06 (3.95)	
	Age	45.49 (9.36)	
	Registration	196.28 (47.86)	
Sex	Female	-0.93 (4.17)	312 (56.6%)
	Male	-1.22 (3.65)	239 (43.4%)

Control model

	Variable	Mean (SD)	Frequency
	y_outcome	0.11 (3.37)	
	Age	37.27 (9.21)	
	Registration	190.62 (46.5)	
Sex	Female	0.11 (3.58)	153 (27.8%)
	Male	0.11 (3.29)	398 (72.2%)

Females model

	Variable	Mean (SD)	Frequency
	y_outcome	-0.53 (4.1)	
	Age	40.79 (10.93)	
	Registration	176.45 (44.69)	
Label	Challenge	-0.83 (4.17)	239 (50%)
	Control	-0.24 (4.01)	239 (50%)
Challenge	Category		
	Fitness	-0.47 (4.03)	77 (16.1%)
	Weightloss	-1.57 (4.39)	239 (50%)

Males model

	Variable	Mean (SD)	Frequency
	y_outcome	-0.6 (3.44)	
	Age	41.68 (9.95)	
	Registration	204.38 (46.08)	
Label	Challenge	-1.22 (3.65)	239 (50%)
	Control	0.03 (3.1)	239 (50%)
Challenge	Category		
	Fitness	-0.8 (3.25)	63 (13.2%)
	Weightloss	-2.42 (4.41)	239 (50%)

Table Appendix 2.8 ***Challenge effect, Change in weight (%), 5 models: Matrix plot***

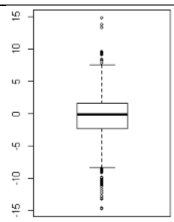
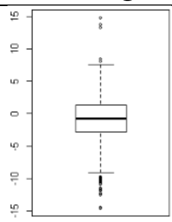
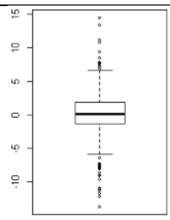
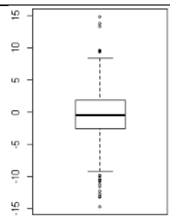
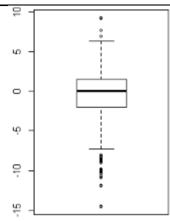
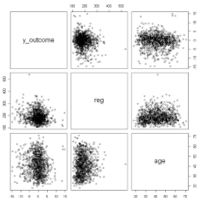
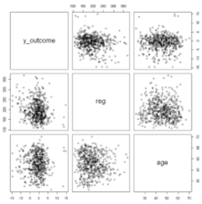
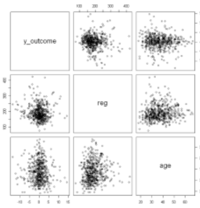
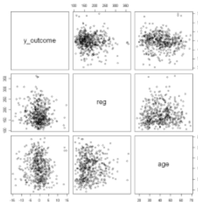
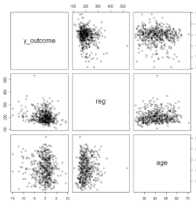
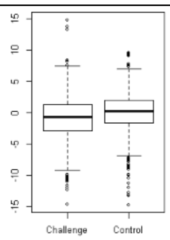
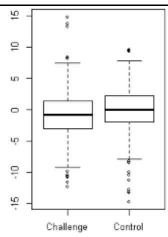
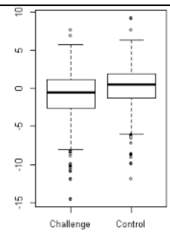
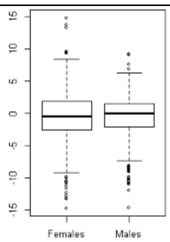
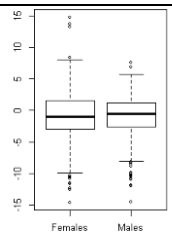
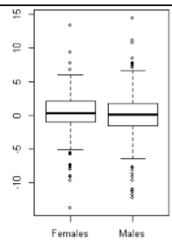
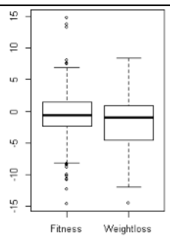
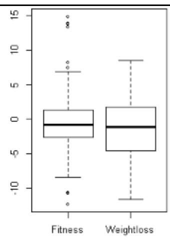
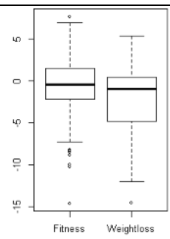
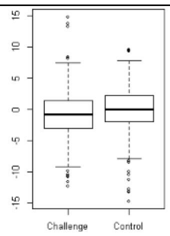
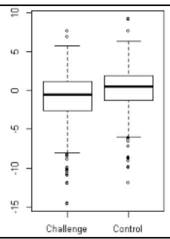
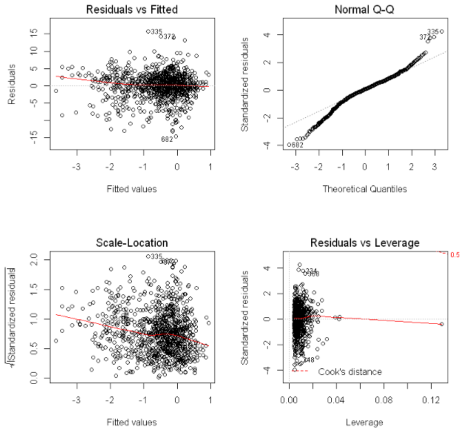
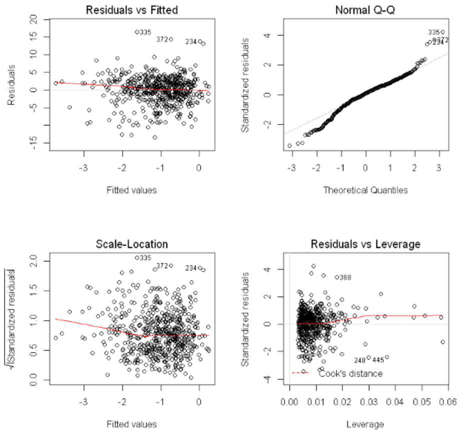
	Balanced	Challenge	Control	Females	Males
Y_outcome					
Continuous variables					
	Balanced	**Challenge**	**Control**	**Females**	**Males**
Label (Challenge, Control)					
Sex					
Category					
Females					
Males					

Figure Appendix 2.4 ***Challenge effect weight (%) models Balanced, Challenge, Control, Females, Males: Diagnostic plots***

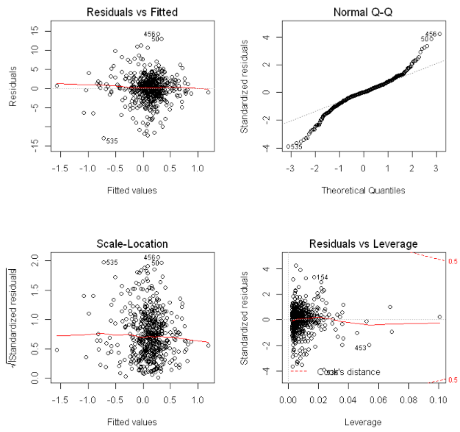
Balanced model



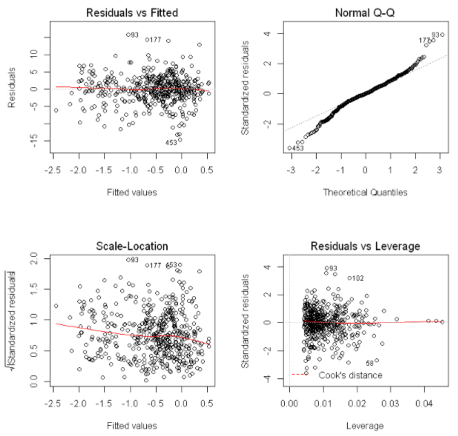
Challenge model



Control model



Females model



Males model

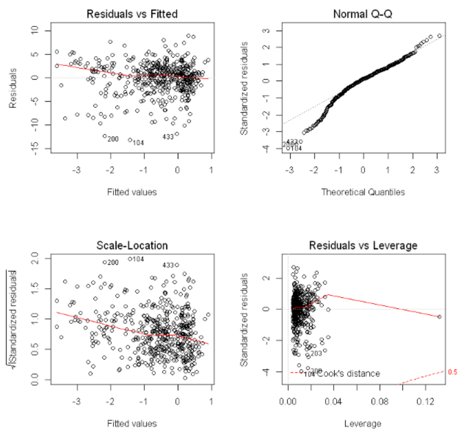
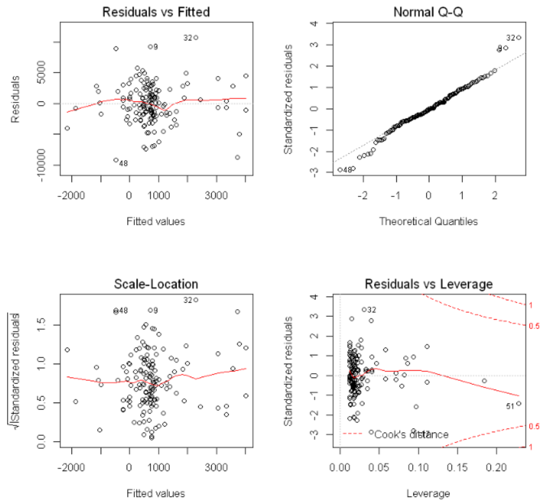
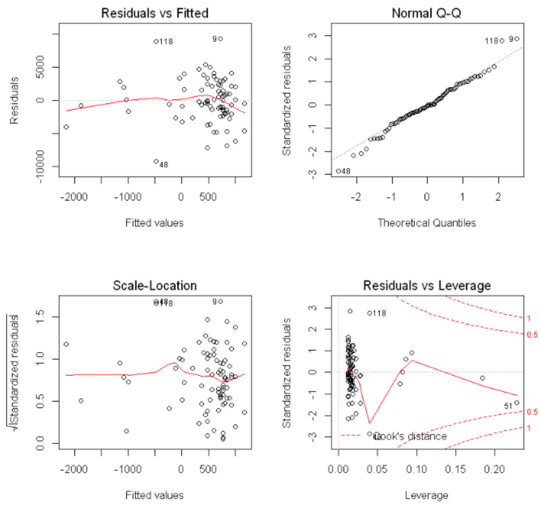


Figure Appendix 2.5 ***Change in steps, Social interaction model and subgroups: Diagnostic plots***

Social interaction model



Social, low degree model



Social, high degree model

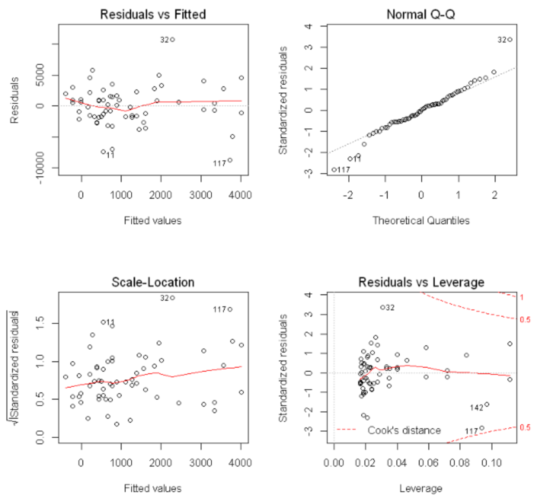
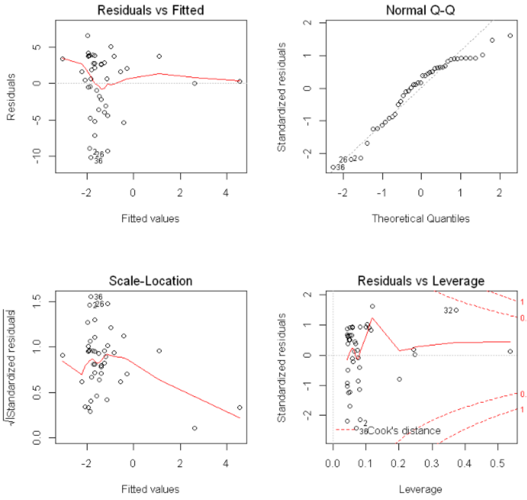
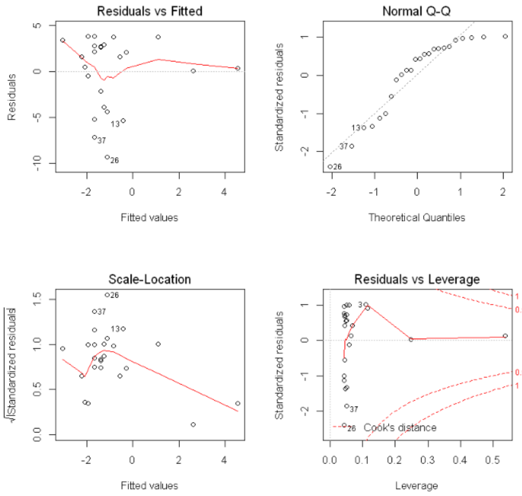


Figure Appendix 2.6 ***Change in weight, Social interaction model and subgroups: Diagnostic plots***

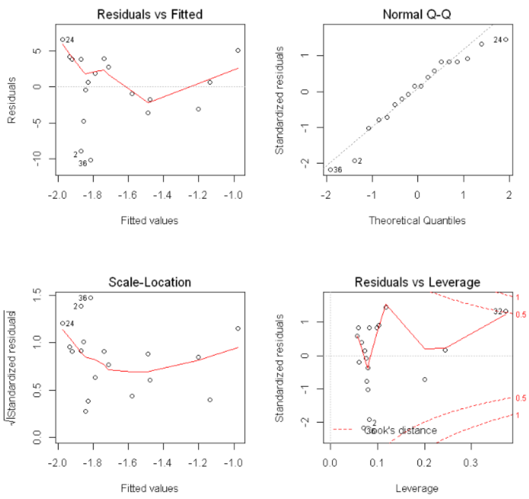
Social interaction model



Social, low degree model



Social, high degree model



11. Appendix 3: Experiment 2

Identification of Critical Factors of an Intervention for Weight Loss and Physical Activity

Experiment 2, the 'Health & Nutrition' study (H&N), was an academic exercise on the identification of the effective components of a technology-based behavioural intervention on improving the target habits of nutrition and physical activity (steps count), measuring the change in weight as an outcome.

Table Appendix 3.1 ***Health & Nutrition study: Ethical Approval***

UCL RESEARCH ETHICS COMMITTEE
ACADEMIC SERVICES

26th August 2016

Professor Philip Treleaven
Department of Computer Science
UCL

Dear Professor Treleaven

Notification of Ethical Approval
Re: Ethics Application 9429/002: Behaviour Change Health and Nutrition Study

I am pleased to confirm in my capacity as Chair of the UCL Research Ethics Committee that I have ethically approved your study until 26th August 2017.

Approval is subject to the following conditions.

1. You must seek Chair's approval for proposed amendments to the research for which this approval has been given. Ethical approval is specific to this project and must not be treated as applicable to research of a similar nature. Each research project is reviewed separately and if there are significant changes to the research protocol you should seek confirmation of continued ethical approval by completing the 'Amendment Approval Request Form': http://ethics.grad.ucl.ac.uk/responsibilities.php

2. It is your responsibility to report to the Committee any unanticipated problems or adverse events involving risks to participants or others. The Ethics Committee should be notified of all serious adverse events via the Ethics Committee Administrator (ethics@ucl.ac.uk) immediately the incident occurs. Where the adverse incident is unexpected and serious, the Chair or Vice-Chair will decide whether the study should be terminated pending the opinion of an independent expert. The adverse event will be considered at the next Committee meeting and a decision will be made on the need to change the information leaflet and/or study protocol.

3. For non-serious adverse events the Chair or Vice-Chair of the Ethics Committee should again be notified via the Ethics Committee Administrator (ethics@ucl.ac.uk) within ten days of an adverse incident occurring and provide a full written report that should include any amendments to the participant information sheet and study protocol. The Chair or Vice-Chair will confirm that the incident is non-serious and report to the Committee at the next meeting. The final view of the Committee will be communicated to you.

On completion of the research you must submit a brief report of your findings/concluding comments to the Committee, which includes in particular issues relating to the ethical implications of the research.

Yours sincerely

[redacted]

Professor John Foreman
Chair of the UCL Research Ethics Committee

Academic Services, 1-19 Torrington Place (9th Floor),
University College London
Tel: +44 (0)20 3108 8216
Email: ethics@ucl.ac.uk
http://ethics.grad.ucl.ac.uk/

Table Appendix 3.2 *Health & Nutrition study: Behaviour Change Techniques encoded in the four Interventions*

BCT´s Category	Coach BCT's	Challenge BCT's	Action Plans BCT's	Forum BCT's
Goals & Planning	• Review of behavioral goals • Discrepancy between current behaviour and goal • Review outcome goal		• Goal Setting • Action Planning • Prompt practice • Provide instruction	
Feedback & monitoring	• Feedback on behaviour • Feedback on outcome(s) of behaviour	• Self-monitoring of behaviour • Self-monitoring of outcomes(s) of behaviour • Feedback on outcome(s) of behaviour		
Social Support	• Social support (emotional)	• Social support (practical)		• Social support (practical)
Shaping knowledge	• Instruction on how to perform behaviours			• Instruction on how to perform behaviours
Natural Consequences	• Information about health consequences			• Information about health consequences
Comparison of Behaviour		• Social comparisons		
Repetition & substitution	• Habit formation • Behaviour substitution	• Habit formation	• Habit formation • Graded tasks	
Comparison of outcomes	• Credible source			
Reward and threat		• Non-specific reward		
Self-belief	• Focus on past successes			

Table Appendix 3.3 ***Health & Nutrition study: Chronology***

	Mon	Tues	Wed	Thurs	Fri	Sat	Sun
August					5	6	7
	8	9	10	11	12	13	14
	15	16	17	18	19	20	21
	22	23	24	25	26 *EA*	27 *CA*	28
	29	30	31				
September				1	2	3	4
	5	6	7	8	9 *S1*	10	11
	12	13 *FE ON*	14	15	16 *S2,CH*	17	18 *C1-1*
	19 *C1-2*	20 *C1-3*	21	22	23 *S3*	24	25
	26	27	28	29	30 *S4*		
October						1	2 *C2-1*
	3 *C2-2*	4 *C2-3*	5	6	7 *S5*	8	9
	10	11	12	13	14	15	16 *C3-1*
	17 *C3-2*	18 *C3-3*	19	20	21 *S6*	22	23
	24	25	26	27	28 *OFF*	29	30
	31 *DA*						
November		1	2	3	4 *S7*	5	6
	7 *END*	8	9	10	11	12	13
	14	15	16	17	18	19	20
	21	22	23	24	25	26	27
	28	29	30				
December				1	2	3	4
	5	6	7	8	9	10	11
	12	13	14	15 *V*	16	17	18
	19	20	21	22	23	24	25
	26	27	28	29	30	1	*(...)*

EA	Ethical Approval
CA	Campaigning period
S1	Survey 1 (baseline)
FE ON	Features turned on (study starts)
CH	Challenge starts
S2	Survey 2
C1-1,2,3	First Coaching Session
S3	Survey 3
S4	Survey 4
C2-1,2,3	Second Coaching Session
S5	Survey 5
C3-1,2,3	Third Coaching Session
S6	Survey 6
OFF	Platform Switch off
DA	Data Analysis starts
S7	Follow-up survey
END	End of the study
V	Amazon gift voucher
(...)	Data Analysis continues

Table Appendix 3.4 ***Health & Nutrition study: Factorial Design (PLANNED)***

	Combination Name	16 combinations								Size
1	1	AP_TT	+	Team	+	Coach	+	Forum		**28**
2	2	AP_TT	+	Team	+	Coach	+			**25**
3	3	AP_TT	+	Team	+		+	Forum		**27**
4	4	AP_TT	+	Team	+		+			**23**
5	5	AP_TT	+	Individual	+	Coach	+	Forum		**27**
6	6	AP_TT	+	Individual	+	Coach	+			**27**
7	7	AP_TT	+	Individual	+		+	Forum		**27**
8	8	AP_TT	+	Individual	+		+			**29**
9	13	Expert	+	Team	+	Coach	+	Forum		**29**
10	14	Expert	+	Team	+	Coach	+			**27**
11	15	Expert	+	Team	+		+	Forum		**27**
12	16	Expert	+	Team	+		+			**26**
13	17	Expert	+	Individual	+	Coach	+	Forum		**34**
14	18	Expert	+	Individual	+	Coach	+			**25**
15	19	Expert	+	Individual	+		+	Forum		**26**
16	20	Expert	+	Individual	+		+			**25**
Total		AP_TT	213	Team	212	Coach	222	Forum	225	**432**
		Expert	219	Individual	220		210		207	

INTERVENTION 1: COACH

COACHED	Coach
NOT COACHED	N.A.

INTERVENTION 2: WALKING CHALLENGE

TEAM CHALLENGE	Team
INDIVIDUAL CHALLENGE	Individual

INTERVENTION 3: ACTION PLANS

TICTRAC's ACTION PLANS	AP_TT
COACH ACTION PLAN	Expert

INTERVENTION 4: DISCUSSION FORUM

DISCUSSION FORUM	Forum
NO FORUM	N.A.

Table Appendix 3.5 *Health & Nutrition study: Factorial Design (EFFECTIVE)*

	Combination Name	16 combinations							Size
1	1	AP_used	+	Team	+	Coach	+	Forum	**12**
2	2	AP_used	+	Team	+	Coach	+		**9**
3	3	AP_used	+	Team	+		+	Forum	**12**
4	4	AP_used	+	Team	+		+		**13**
5	5	AP_used	+	Individual	+	Coach	+	Forum	**9**
6	6	AP_used	+	Individual	+	Coach	+		**2**
7	7	AP_used	+	Individual	+		+	Forum	**3**
8	8	AP_used	+	Individual	+		+		**13**
9	13		+	Team	+	Coach	+	Forum	**3**
10	14		+	Team	+	Coach	+		**11**
11	15		+	Team	+		+	Forum	**26**
12	16		+	Team	+		+		**48**
13	17		+	Individual	+	Coach	+	Forum	**8**
14	18		+	Individual	+	Coach	+		**9**
15	19		+	Individual	+		+	Forum	**2**
16	20		+	Individual	+		+		**41**
Total		AP_used	73	Team	134	Coach	63	Forum 75	**221**
			148	Individual	87		158	146	

INTERVENTION 1: COACH

COACHED AT LEAST ONCE	Coach
NOT COACHED + DID NOT USE	N.A.

INTERVENTION 2: WALKING CHALLENGE

TEAM CHALLENGE	Team
INDIVIDUAL CHALLENGE	Individual

INTERVENTION 3: ACTION PLANS

USED AN ACTION PLANS	AP_used
DID NOT USE ACTION PLAN	N.A.

INTERVENTION 4: DISCUSSION FORUM

DISCUSSION FORUM	Forum
NO FORUM + DID NOT USE	N.A.

Table Appendix 3.6 ***Health & Nutrition study: Recruitment Funnel***

Channel	*Digital Impressions / Landing Page*	*Screening survey*	*Percentage*	*Consent form signed (effective recruitment)*
By word of mouth	n.a.	204	23%	113 (55%)
Facebook	X > 6,000, from WSI	167	19%	83 (50%)
Twitter	X > 26,000	142	16%	72 (51%)
LinkedIn	Unmeasured	79	9%	46 (58%)
LBS alumni network	X > 2,000	53	6%	38 (72%)
Email	X > 1,000	47	5%	24 (51%)
gumtree	5,321	44	5%	26 (59%)
callforparticipants.com	6,500	37	4%	24 (65%)
Posters	n.a.	34	4%	17 (50%)
Instagram	n.a.	25	3%	12 (48%)
Craigslist	n.a.	19	2%	9 (47%)
Others	n.a.	15	2%	8 (53%)
Tictrac direct channels	n.a.	9	1%	5 (56%)
Googleplus	Unmeasured	5	1%	3 (60%)
TOTAL	X > 35,000	880 *(**811**: Without channel repetitions)*	100%	480 *(**432**: Without channel repetitions)*

The digital campaign was launched across 14 main channels heavily concentrated on Twitter, Facebook, LinkedIn and making use of callforparticipants.com. The actual conversion rate overall was low. More than 35,000 digital impressions were required to receive 811 applications.

Key lessons of campaigning for future interventions:

- Personal reference supports a high conversion rate (trust?).
- LinkedIn works better during the week and provides access to highly educated and qualified individuals.
- Writing article posts in LinkedIn generates trust and interest, while validating the campaign as serious. The LinkedIn article can effectively be re-posted on Twitter and Facebook.
- Twitter provides the reach to a network of interested individuals through groups of interest and hashtags. Campaigning in this channel is effective when it is tailored to the specific target group. The big numbers of digital impressions were possible to the connection with influencers by trading content (tweet their message, befriend them, get retweets)
- Facebook works better during the weekends
- The scientific angle of the campaign was a foundation to attract interest.
- It was critical to make collaboration agreements with different parties to access other audiences

Table Appendix 3.7 (a) ***Health & Nutrition study, Weight change (%): Matrix plot***

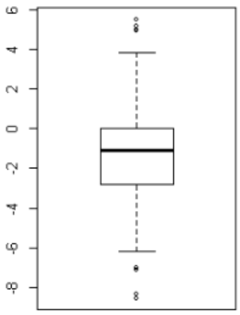
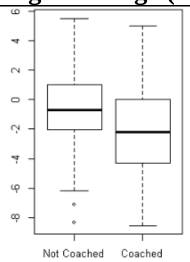
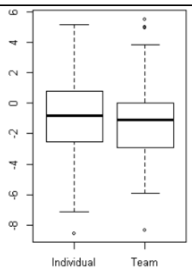
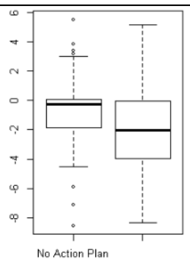
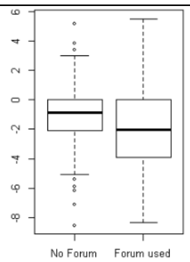
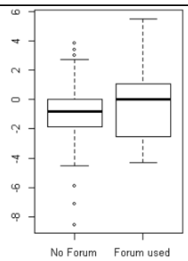
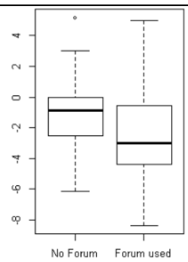
	Weight Change (%)		
Y_outcome			
	Weight Change (%)		
Coach			
Challenge			
Action Plan			
Forum			
	Forum only	*Forum (No Action Plan)*	*Forum (Used Action Plan)*

Table Appendix 3.7 (b) ***Health & Nutrition study, Weight change (%): Matrix plot***

Continuous variables

Continuous variables

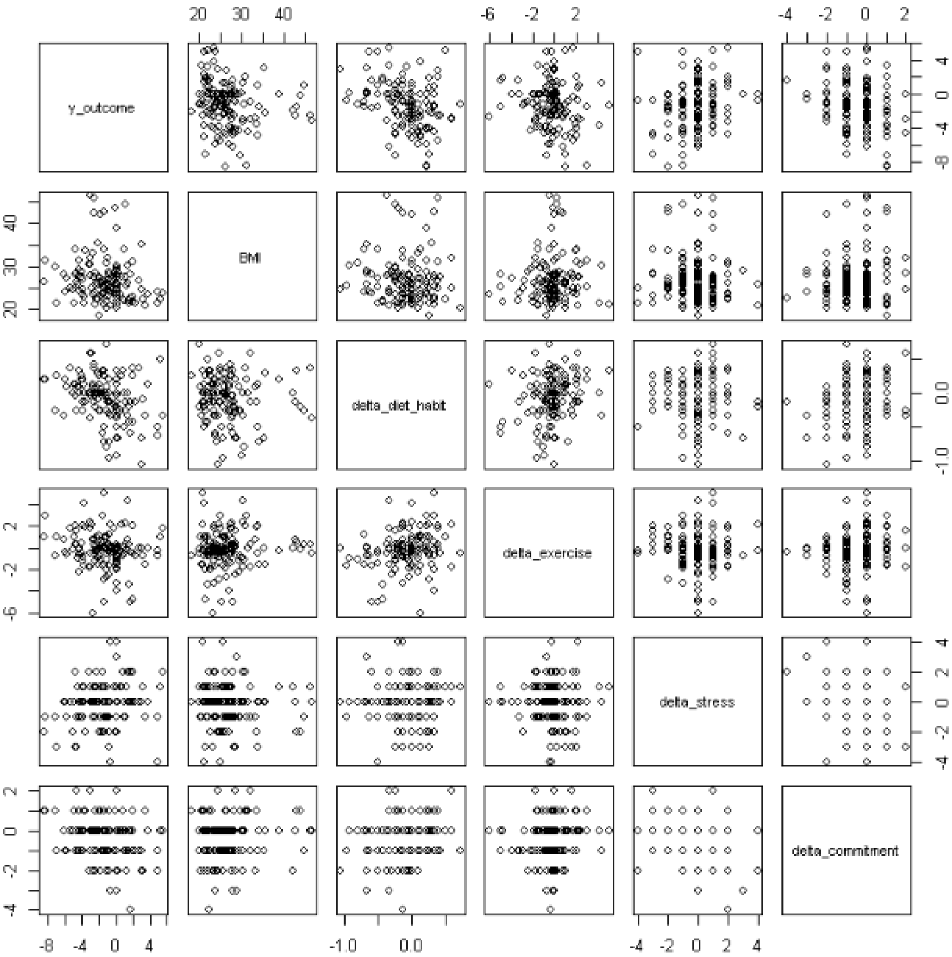


Figure Appendix 3.1 ***H&N:*** **OPENNESS TO EXPERIENCE (O)** ***Diet habit change model***

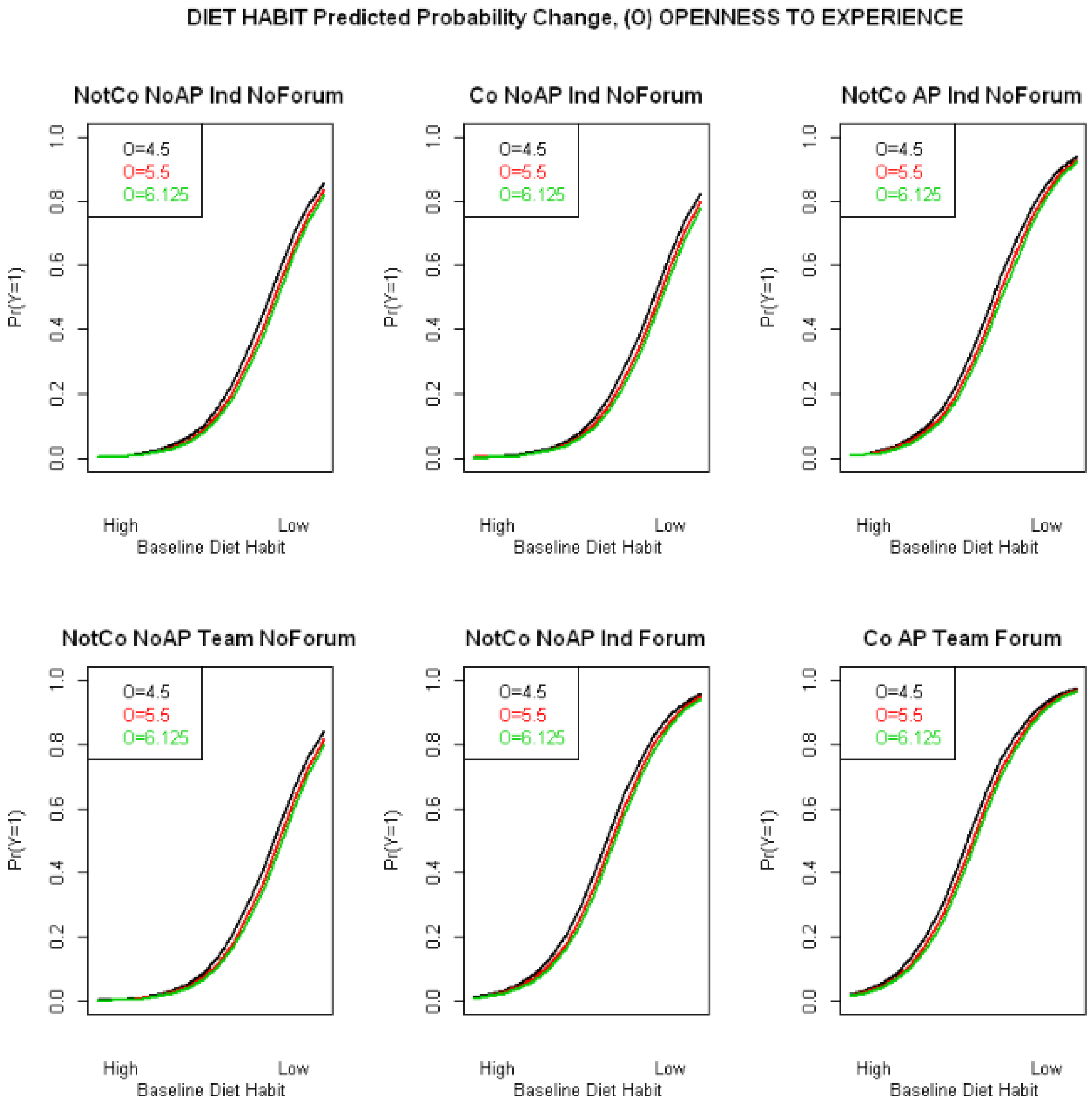


Figure Appendix 3.2 ***H&N:*** **CONSCIENTIOUSNESS (C)** ***Diet habit change model***

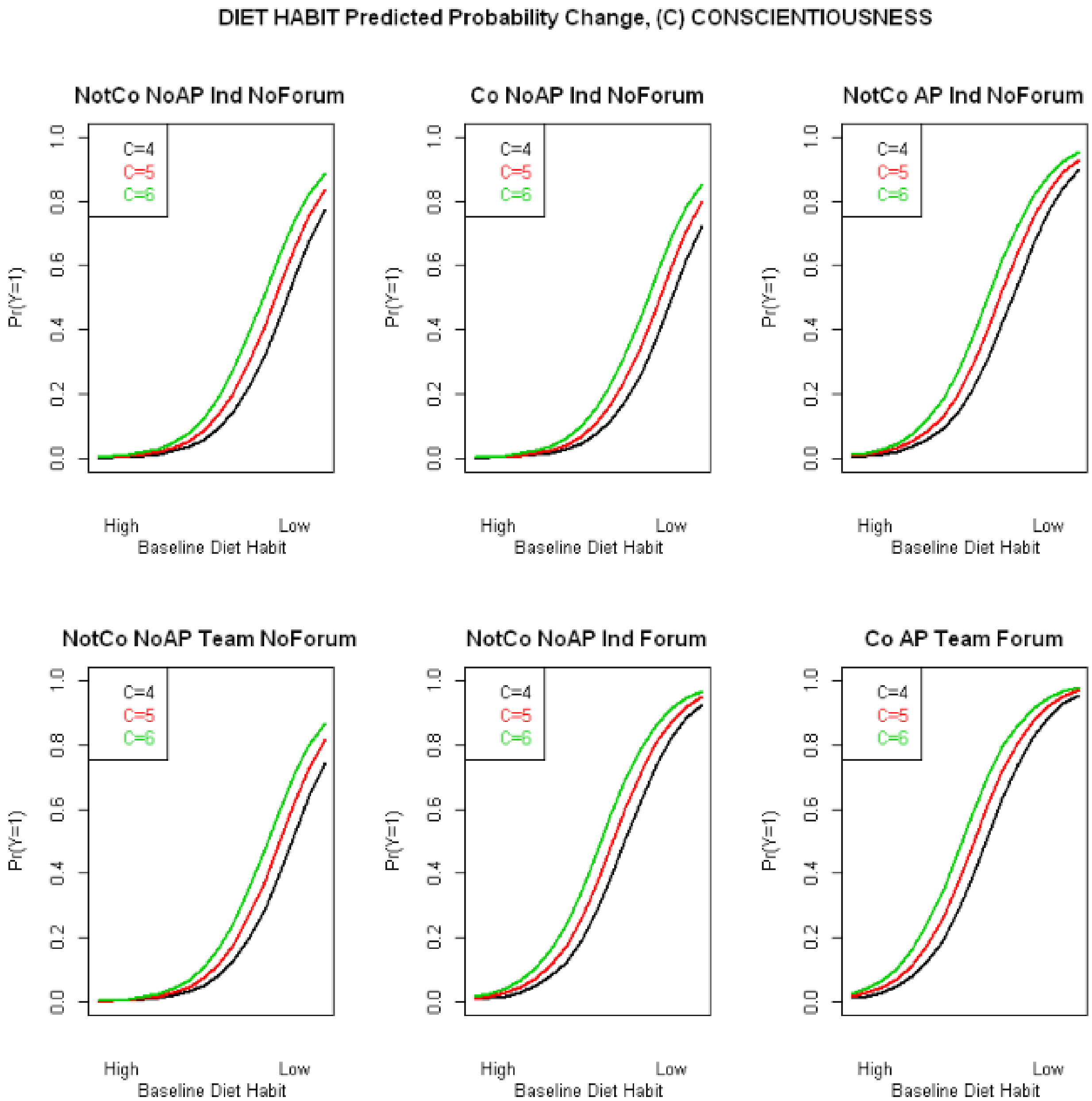


Figure Appendix 3.3 ***H&N:*** **EXTRAVERSION (E)** ***Diet habit change model***

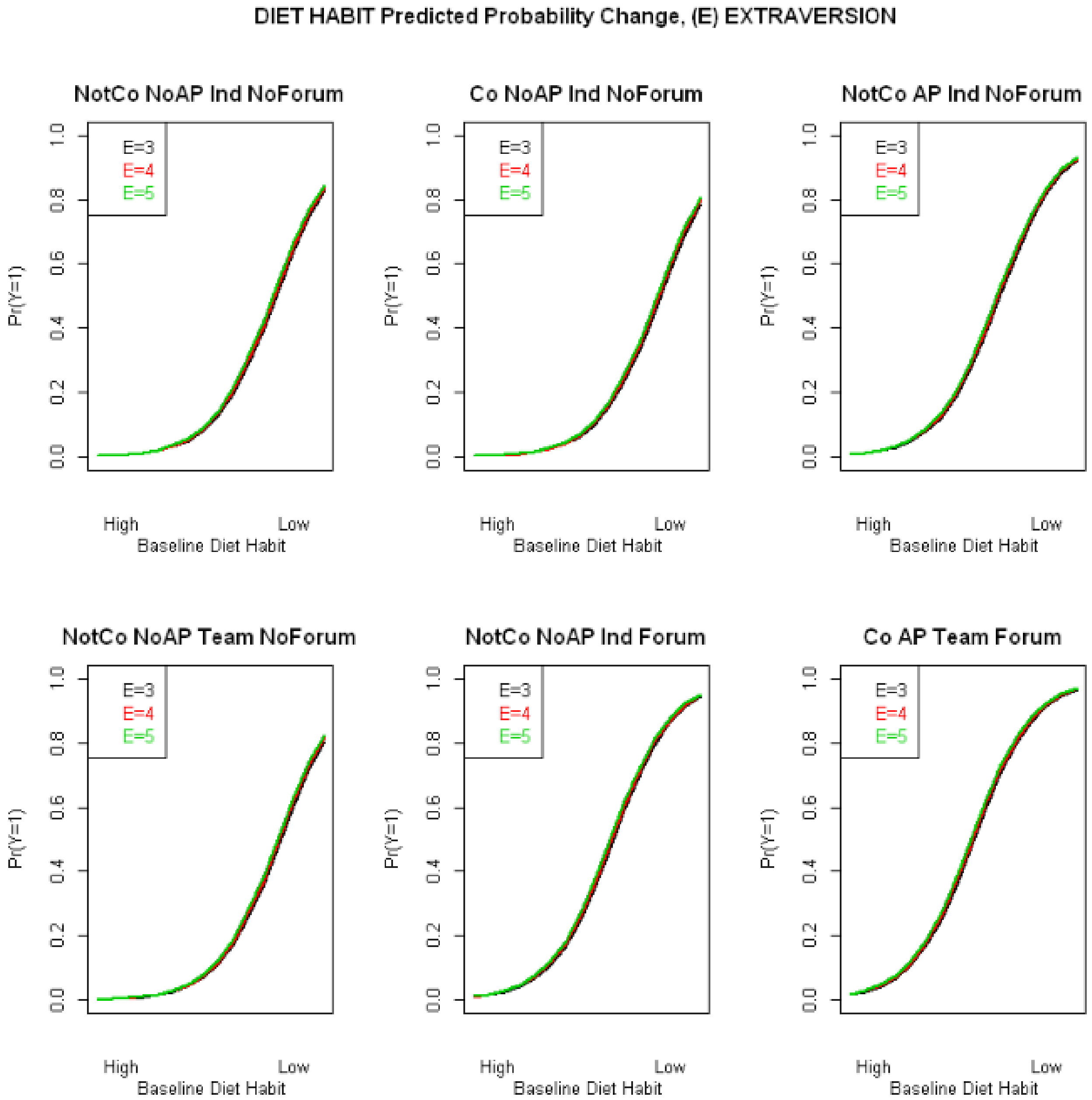


Figure Appendix 3.4 ***H&N:*** **AGREEABLENESS (A)** ***Diet habit change model***

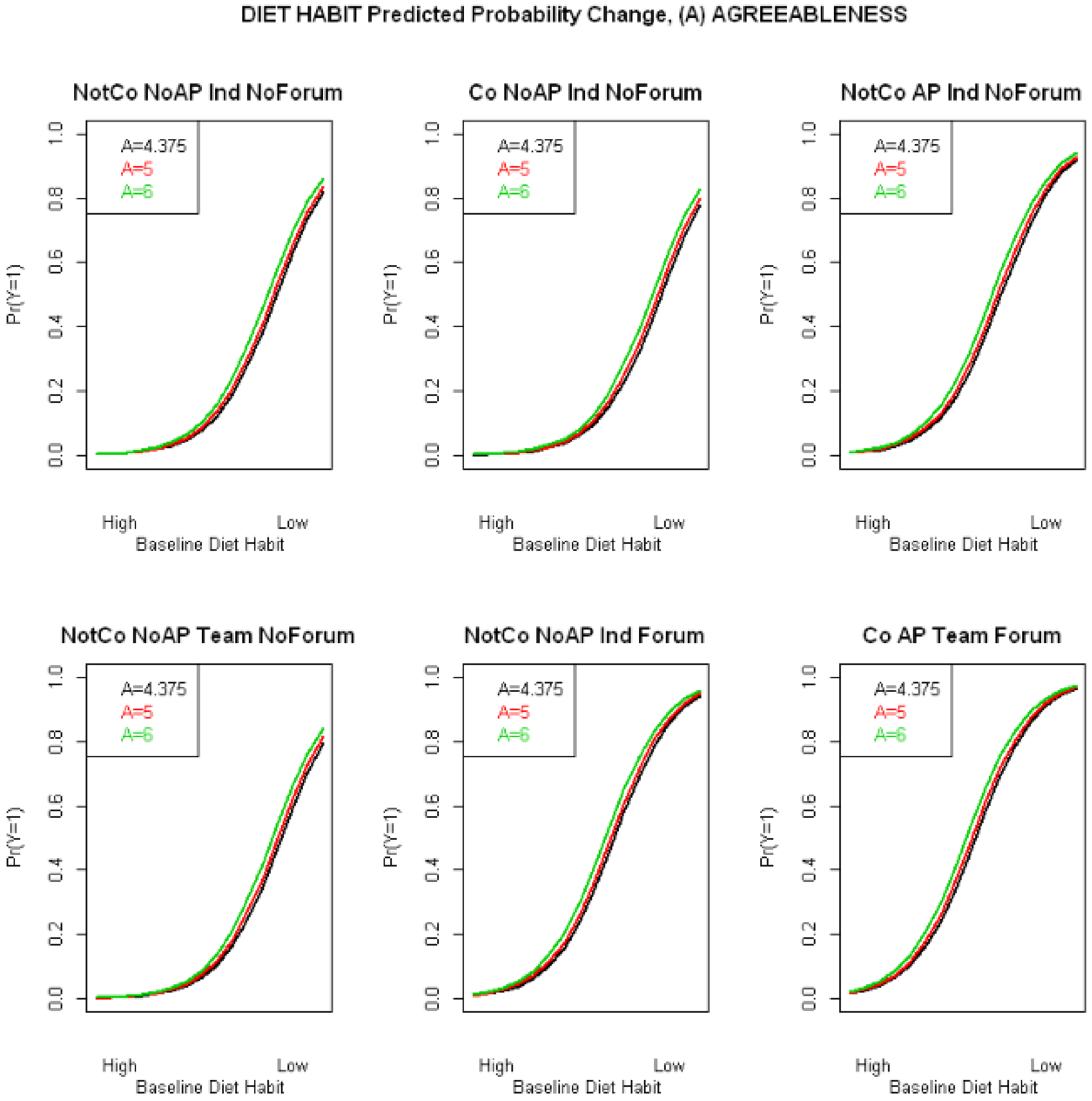


Figure Appendix 3.5 ***H&N:*** **NEUROTICISM (N)** ***Diet habit change model***

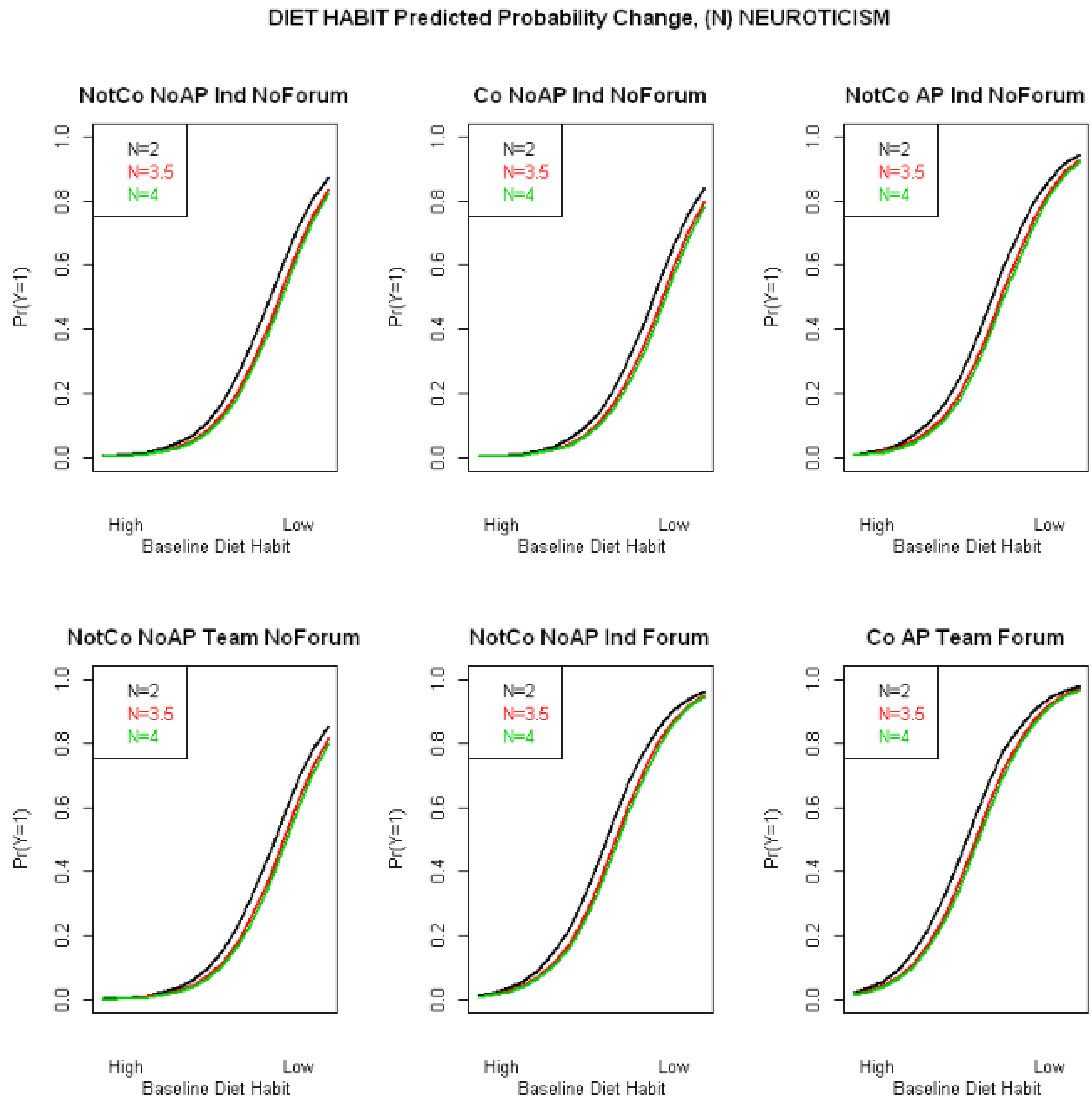


Figure Appendix 3.6 ***H&N:*** **OPENNESS TO EXPERIENCE (O)** ***Exercise habit change model***

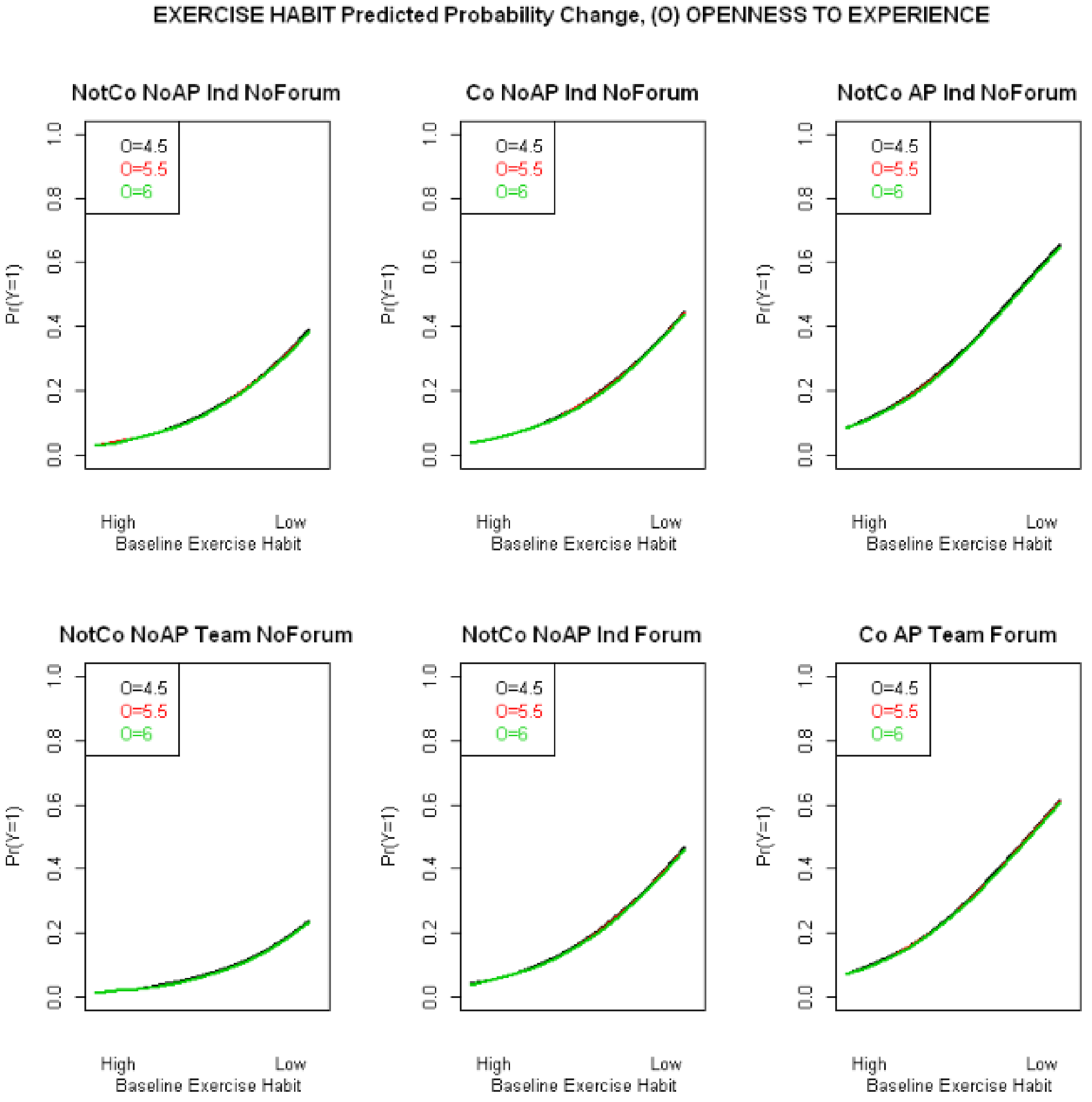


Figure Appendix 3.7 ***H&N:*** **CONSCIENTIOUSNESS (C)** ***Exercise habit change model***

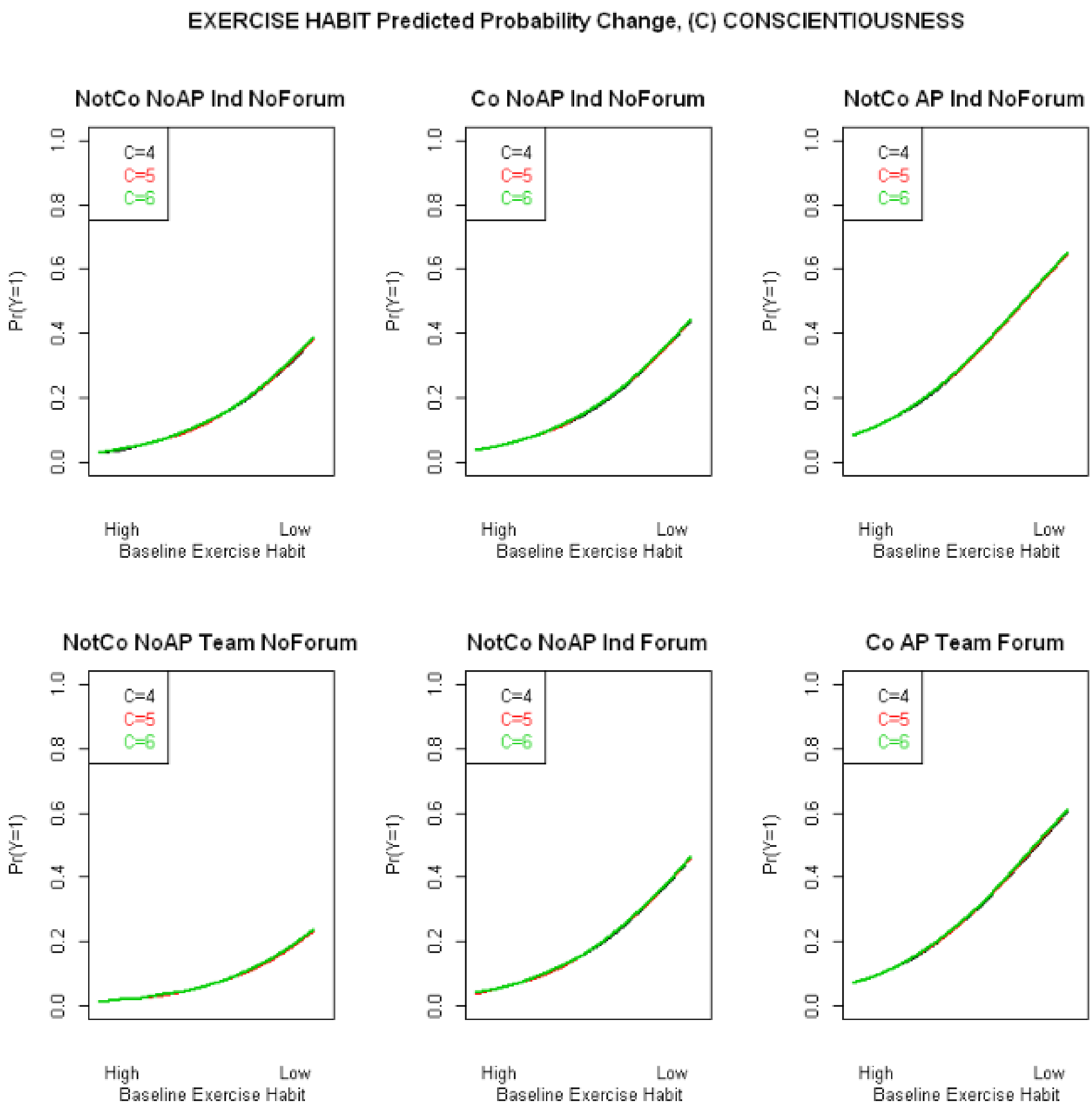


Figure Appendix 3.8 ***H&N:*** **EXTRAVERSION (E)** ***Exercise habit change model***

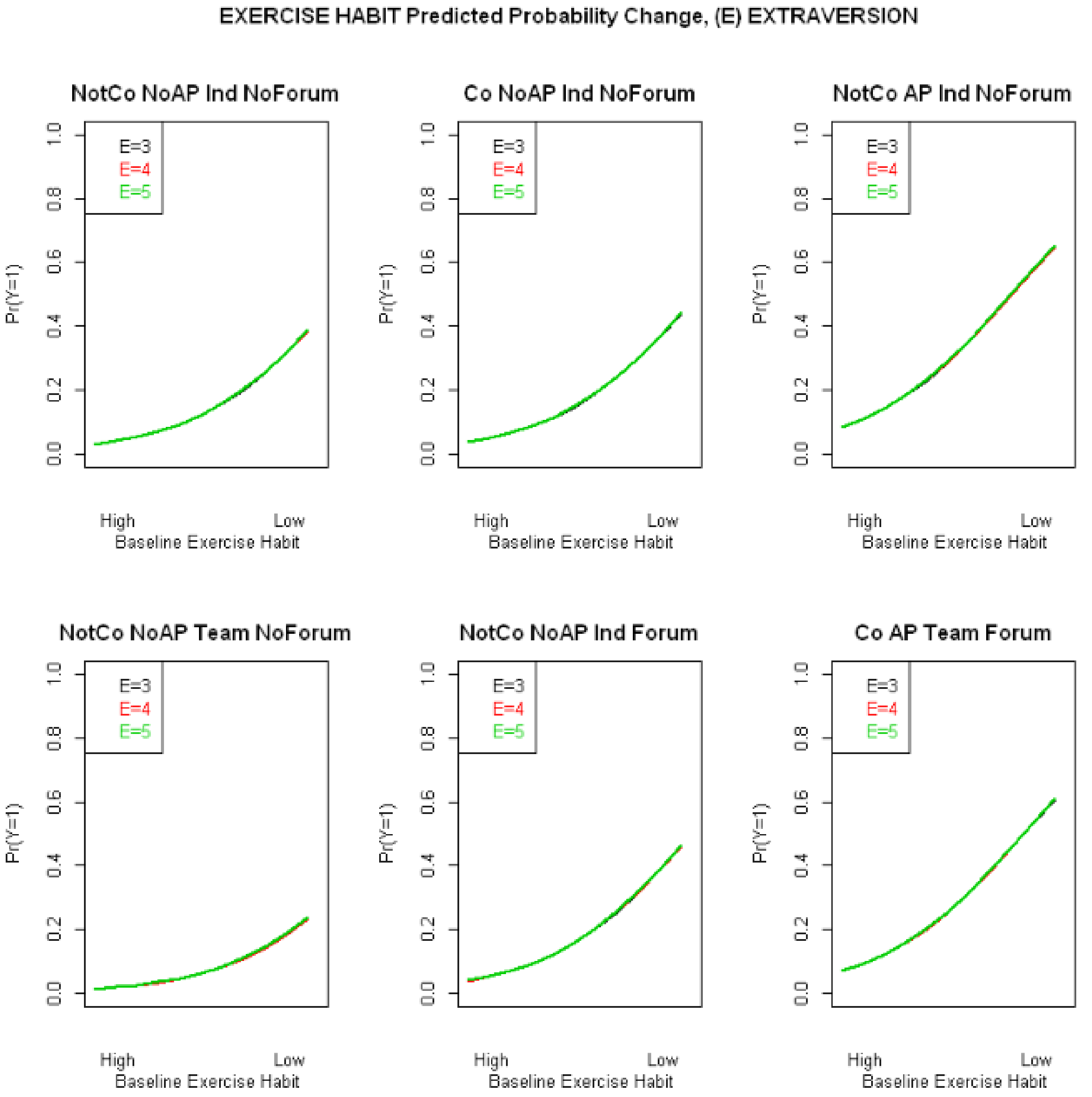


Figure Appendix 3.9 ***H&N:*** **AGREEABLENESS (A)** ***Exercise habit change model***

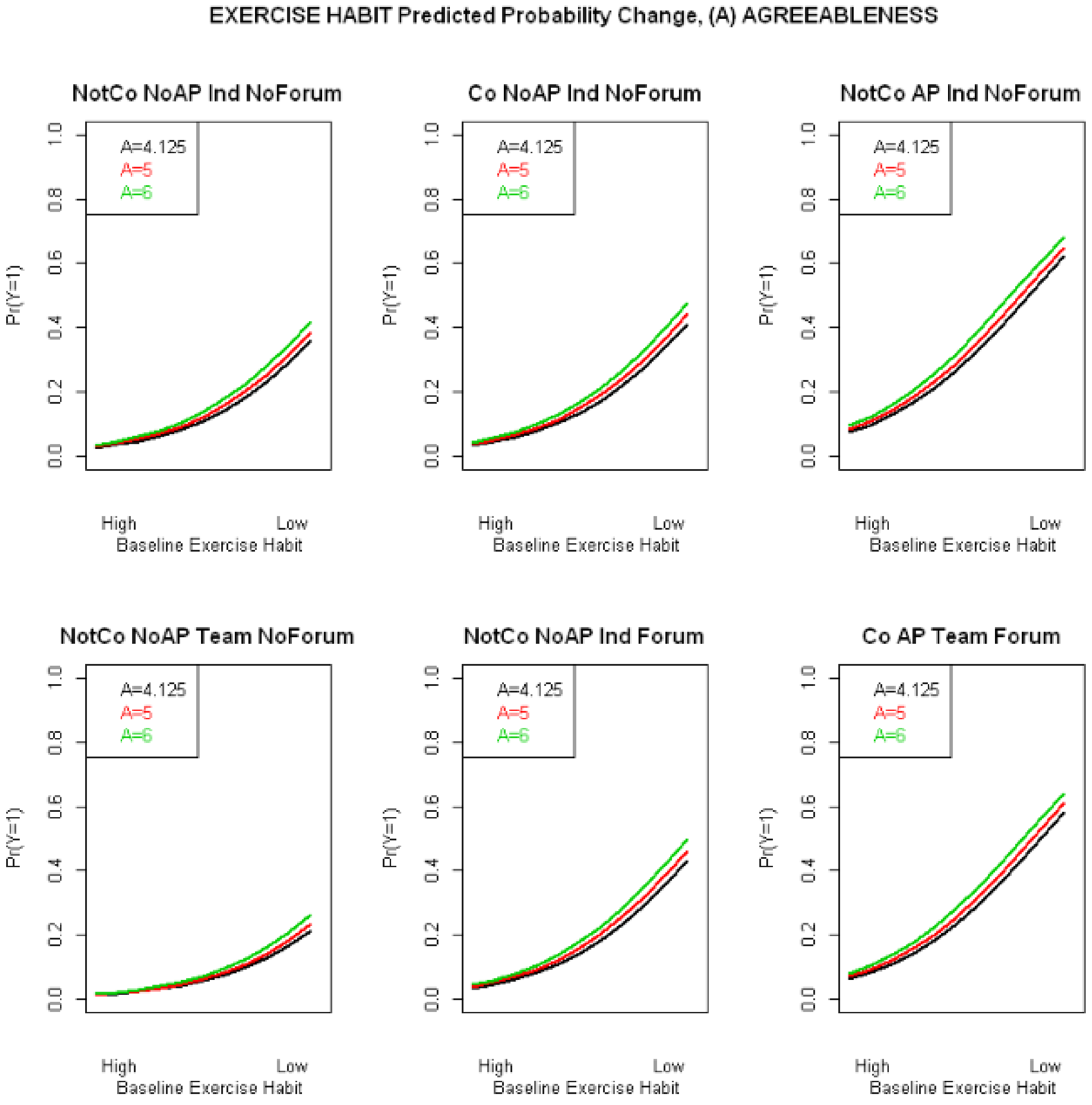
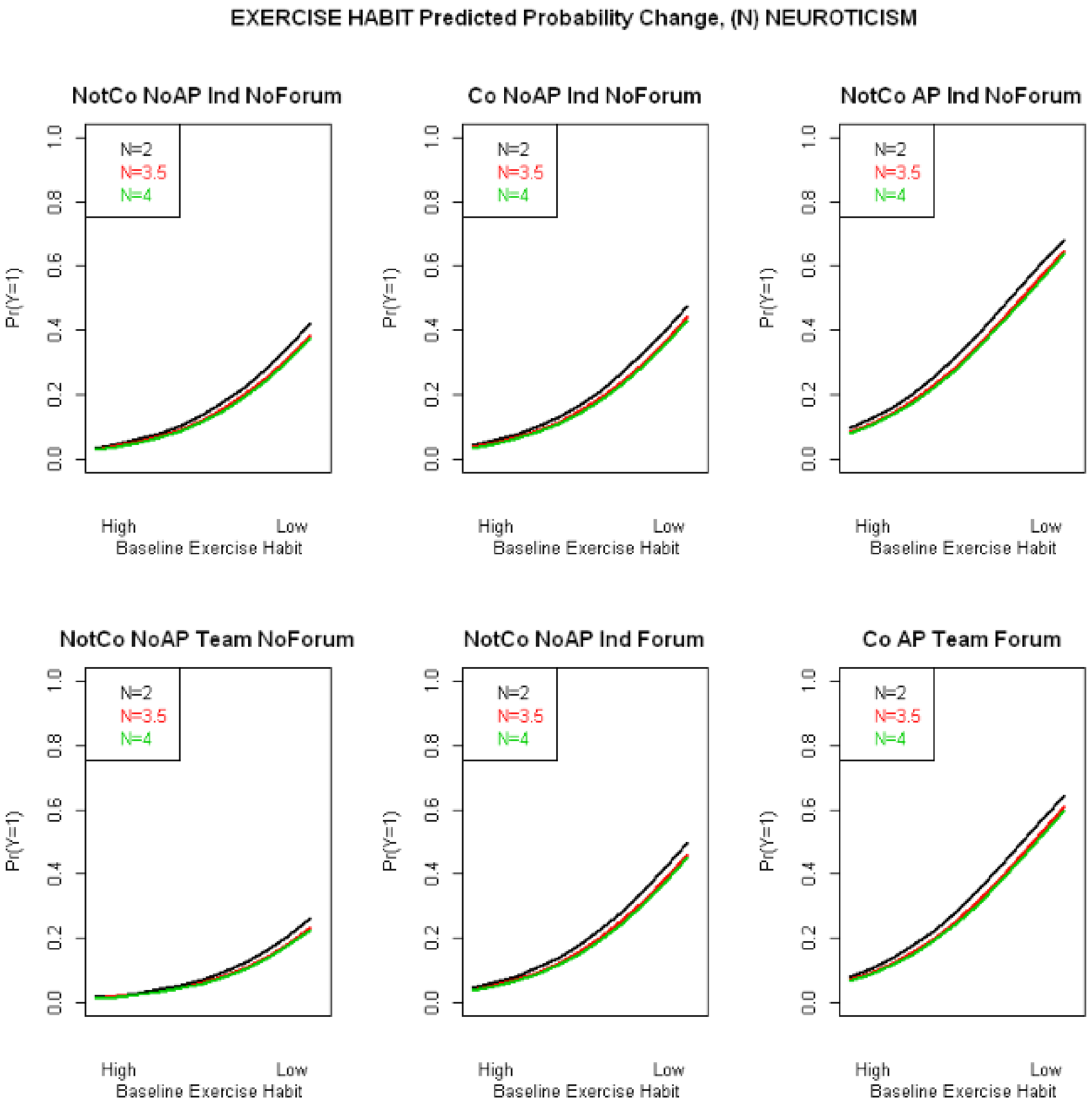


Figure Appendix 3.10 ***H&N:*** **NEUROTICISM (N)** ***Exercise habit change model***

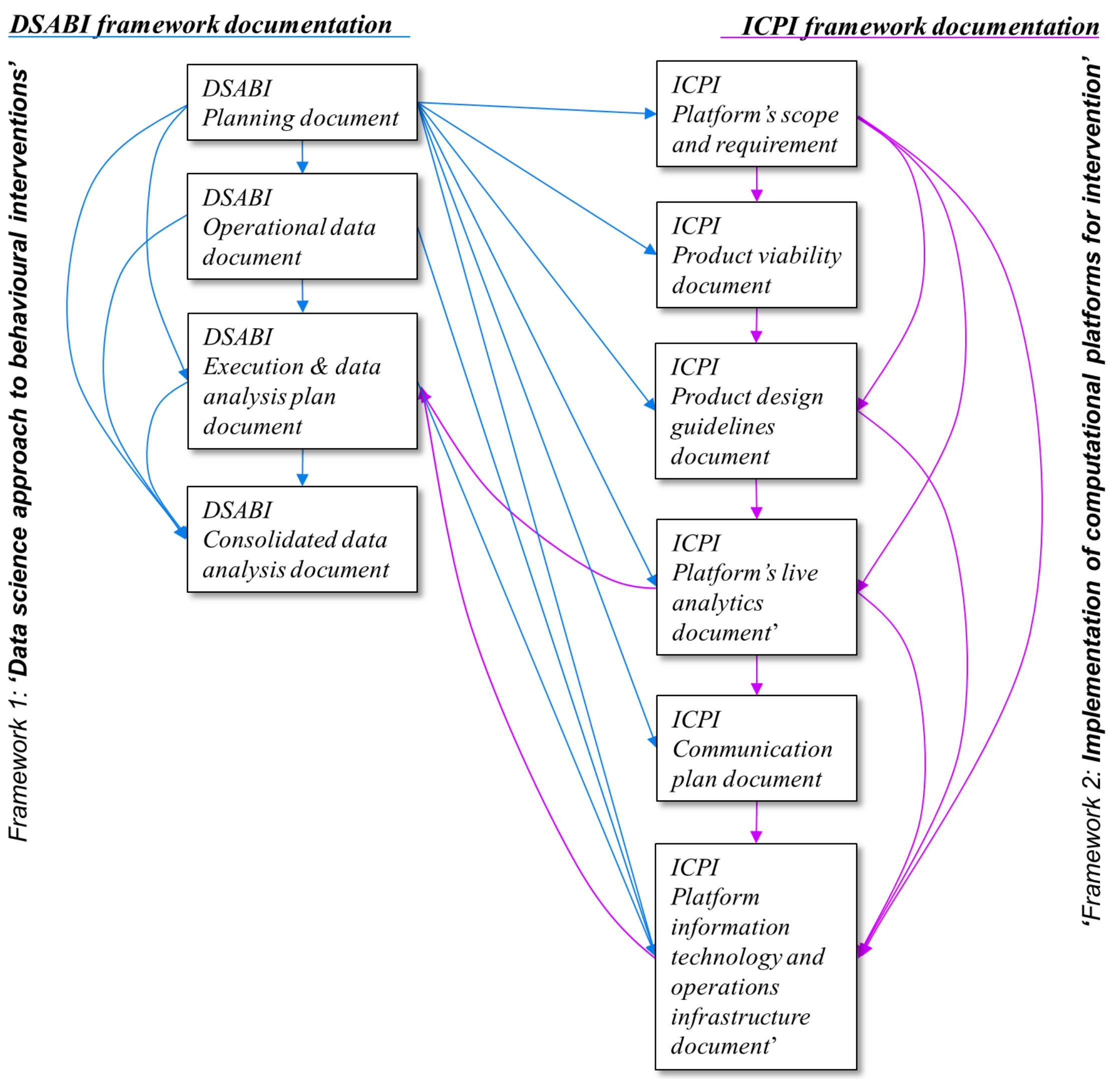


12. Appendix 4: Proposed Frameworks for Future Large Scale BCIs

DSABI and ICPI in practice, complementary workflows

The sequence of the interlocking documentation for the DSABI and ICPI frameworks is represented in Figure Appendix 4.1, showing how both frameworks used in practice as complementary workflows. A researcher(s) or a practitioner(s) would make use of the frameworks as described on this chapter and produce the documents of DSABI and ICPI facilitating the whole process from ideation to intervention delivery and the subsequent data analysis.

Figure Appendix 4.1 ***DSABI & ICPI, Interlocking documentation for both frameworks***



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