Characterising Habitual Health Behaviour Patterns for Physical Activities in Constrained Settings

by

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TABLE OF CONTENTS

Table of Contents ... **3**
i. List of Figures ... 5
ii. List of Tables ... 6
iii. List of Appendices ... 7
iii.a. Publications ... 7

Abstract ... **9**

Declaration ... **11**

Acknowledgements ... **13**

1. Introduction ... **15**
1.1. Overview ... 15
1.2. Background to this Research ... 16
1.3. Why Habits and Behaviour Matter? ... 18
1.4. Why Step Counts Matter? ... 19
1.5. Research Aim and Research Objectives ... 20
1.6. Research Process ... 21
1.7. Approach to Analysis ... 22
1.8. Key Contributions, Outcomes, and Findings ... 22
1.9. Outline of the Thesis ... 22

2. Literature Review ... **24**
2.1. Introduction ... 24
2.2. Health Behaviour and Behaviour Change ... 25
2.2.1. Definition of a Behaviour ... 25
2.2.2. Definition of a Habit ... 26
2.2.3. Behaviour Change Theories and Models of Behaviour ... 27
2.2.3.1. Theory of Expanded, Extended, and Enhanced Opportunities (TEO) ... 27
2.2.3.2. Theory of Reasoned Action (TRA) and Theory of Planned Behaviour (TPB) ... 28
2.2.3.3. The COM-B Simple Model of Behaviour (change) ... 29
2.3. Human Activity and Measurement ... 30
2.3.1. Properties of a Step ... 30
2.3.2. Daily Step Count Goals ... 31
2.3.3. Wearable Devices ... 31
2.3.4. Habits in Context ... 33
2.3.5. Types of Environments ... 33
2.3.5.1. Structured Environments ... 33
2.3.5.2. Unstructured Environments ... 33
2.3.5.3. Constrained Settings ... 34
2.3.6. The Influence of Environments on Habits ... 34
2.3.7. Daily Activity Types ... 35
2.3.7.1. Mandatory Activities ... 35
2.3.7.2. Optional Activities ... 36
2.4. Increasing Human Activity ... 36
2.4.1. Point-in-time Interactions ... 36
2.4.2. The benefits of point-in-time Interactions ... 37
2.4.3. The challenges of detecting Point-In-Time interaction opportunities ... 37
2.5. Conclusion ... 37

3. Methodology ... **38**
3.1. A Pragmatic Approach – The Design Science Research Methodology ... 38
3.2. Applying the Design Science Research Methodology ... 39
3.2.1. Identify Problem & Motivate ... 40
3.2.2. Define Objectives of a Solution ... 40

3.2.3. Design & Development ... 40
3.2.4. Demonstration ... 41
3.2.5. Evaluation ... 41
3.2.6. Communication ... 41
3.3. Data Collection Process ... 42
3.4. Determining Data Relevance ... 42
3.5. Processing Pipeline ... 43
1. Describe Expected Health Habit ... 44
2. Hypothesise Health Habit Envelope ... 45
3. Identify Health Habit Instances ... 45
4. Finalise Health Habit Characterisation ... 45
3.6. Health Habit Variants ... 46
3.7. Example Application of the DHIF-PP Artefact ... 47
3.7.1. Describe Expected Health Habit ... 47
3.7.2. Hypothesize Health Habit Envelope ... 47
3.7.3. Identify Health Habit Instances ... 48
3.7.4. Finalise Health Habit Characterisation ... 49
3.8. Pareto Analysis ... 50
3.9. Limitations ... 53
3.10. Conclusion ... 53

4. Case Study 1 – Simulated Workplace Tasks ... 54
4.1. Overview ... 54
4.2. Aim ... 54
4.3. Methodology ... 55
4.4. Results & Analysis ... 57
4.5. Limitations ... 67
4.6. Conclusion ... 68

5. Case Study 2 – Open-plan Workplace Tasks ... 69
5.1. Overview ... 69
5.2. Aim ... 69
5.3. Methodology ... 70
5.4. Results & Analysis ... 71
5.4.1. Participant Health Habits Overview ... 72
5.4.2. Coffee Health Habit ... 74
5.4.3. Bathroom Health Habit ... 77
5.5. Limitations ... 80
5.6. Conclusion ... 80

6. Case Study 3 – Working From Home Versus Office ... 81
6.1. Overview ... 81
6.2. Aim ... 81
6.3. Methodology ... 81
6.3.1. Acceptance/Rejection Criteria ... 82
6.4. Results & Analysis ... 83
6.4.1. Health Habit Instances for Participant A ... 84
6.4.2. Health Habit Instances for Participant B ... 89
6.4.3. Health Habit Comparison Participant A to Participant B ... 93
6.5. Limitations ... 95
6.6. Conclusion ... 95

7. Discussion & Conclusion ... 97
7.1. Summary ... 97
7.2. Limitations ... 98
7.3. Recommendations ... 99
7.4. Future Considerations ... 100

8. Appendix ... 102

9. References 132

i. List of Figures

Figure 1: Research Process 21
Figure 2: Mapping for Literature Review 25
Figure 3: Theory of Reasoned Action and Theory of Planned Behaviour 29
Figure 4: COM-B Model of Behaviour 30
Figure 5: Design Science Research Methodology Cycles (Hevner, A.R., 2007) 39
Figure 6: Design Science Research Methodology Process Model (Peffers, K., Tuunanen, T., Rothenberger, M.A., et al. 2007) 40
Figure 7: Determining Data Relevance 43
Figure 8: The Four Phases of the Processing Pipeline 44
Figure 9: Health Habit Exemplar 49
Figure 10: Health Habit Line Exemplar 49
Figure 11: Pareto Chart Exemplar 51
Figure 12: Pareto Chart Exemplar Magnified 52
Figure 13: Step and Time data for Long Walk activity (respectively for participants A, B, C) 59
Figure 14: Step and Time data for Short Walk activity (respectively for participants A, B, C) 62
Figure 15: Step and Time data for Stair's activity (respectively for participants A, B, C) 64
Figure 16: Step and Time data for Meeting activity (respectively for participants A, B, C) 66
Figure 17: Office building layout with Bluetooth beacons (Flinders University, Tonsley Campus Map with Bluetooth beacon markings, 2019) 71
Figure 18: Coffee Health Habit Instance 1 75
Figure 19: Coffee Health Habit Instance 2 75
Figure 20: Coffee Health Habit Instance 3 76
Figure 21: Coffee Health Habit Instance 4 76
Figure 22: Coffee Health Habit Instance 5 77
Figure 23: Bathroom Health Habit Instance 1 78
Figure 24: Bathroom Health Habit Instance 2 78
Figure 25: Bathroom Health Habit Instance 3 79
Figure 26: Bathroom Health Habit Instance 4 79

ii. List of Tables

Table 1: Expanded, Extended, and Enhanced examples (Beets, M.W., Okely, A., Weaver, R.G., et al. 2016)........ 28
Table 2: Steps per day classification (Tudor-Locke, C., Craig, C.L., Brown, W.J., et al. 2011) 31
Table 3: Raw Data Example 43
Table 4: Predefined activity descriptions 57
Table 5: Parameters for Long Walk Characterisation 60
Table 6: Parameters for Short Walk Characterisation 63
Table 7: Parameters for Stairs Task Characterisation 65
Table 8: Parameters for Meeting Task Characterisation........ 67
Table 9: Participant data collection days 71
Table 10: Office -> Coffee Area -> Office Health Habit........ 72
Table 11: Office -> Bathroom -> Office Health Habit 72
Table 12: Instances of health habits found across all participants, over the observation period 72
Table 13: Participant A health habits........ 73
Table 14: Participant B health habits........ 73
Table 15: Participant C health habits........ 73
Table 16: Participant D health habits........ 73
Table 17: Participant E health habits........ 74
Table 18: Participant F health habits........ 74
Table 19: Participant G health habits 74
Table 20: Parameters for Coffee Area trip characterisation........ 74
Table 21: Parameters for Bathroom trip characterisation 77
Table 22: Sedentary Health Habit Types........ 82
Table 23: Overall Sedentary Health Habit Instances 83
Table 24: Working from Home Sedentary Health Habit Instances........ 83
Table 25: Working from Office Sedentary Health Habit Instances 84
Table 26: Task Instances participant A, week 1 work from home 84
Table 27: Task Instances Parameter Characterisation, participant A, week 1 work from home 84
Table 28: Task Instances participant A, week 2 work from home 85
Table 29: Task Instances Parameter Characterisation, participant A, week 2 work from home 85
Table 30: Task Instances participant A, week 3 work from home 85
Table 31: Task Instances Parameter Characterisation, participant A, week 3 work from home 85
Table 32: Task Instances participant A, week 4 work from home 86
Table 33: Task Instances Parameter Characterisation, participant A, week 4 work from home 86
Table 34: Task Instances participant A, week 1 work from office 86
Table 35: Task Instances Parameter Characterisation, participant A, week 1 work from office 86
Table 36: Task Instances participant A, week 2 work from office 87

Table 37: Task Instances Parameter Characterisation, participant A, week 2 work from office 87
Table 38: Task Instances participant A, week 3 work from office 87
Table 39: Task Instances Parameter Characterisation, participant A, week 3 work from office 87
Table 40: Task Instances participant A, week 4 work from office 88
Table 41: Task Instances Parameter Characterisation, participant A, week 4 work from office 88
Table 42: Task Instances participant B, week 1 work from home 89
Table 43: Task Instances Parameter Characterisation, participant B, week 1 work from home 89
Table 44: Task Instances participant B, week 2 work from home 89
Table 45: Task Instances Parameter Characterisation, participant B, week 2 work from home 89
Table 46: Task Instances participant B, week 3 work from home 90
Table 47: Task Instances Parameter Characterisation, participant B, week 3 work from home 90
Table 48: Task Instances participant B, week 1 work from office 91
Table 49: Task Instances Parameter Characterisation, participant B, week 1 work from office 91
Table 50: Task Instances participant B, week 2 work from office 91
Table 51: Task Instances Parameter Characterisation, participant B, week 2 work from office 91
Table 52: Task Instances participant B, week 3 work from office 92
Table 53: Task Instances Parameter Characterisation, participant B, week 3 work from office 92
Table 54: Task Instances participant B, week 4 work from office 92
Table 55: Task Instances Parameter Characterisation, participant B, week 4 work from office 92
Table 56: Week 2 - Work from Home Comparison 93
Table 57: Week 2 - Work from Office Comparison 94

iii. List of Appendices

iii.a. Publications

Some of the developmental work was published during the progress of the doctorate (available in full in the appendix). A journal paper providing a comprehensive methodology and its application is in review (Appendix D).

A. "Habitual Personal Movement Patterns in a Structured Environment", Nathan Poultney and Anthony Maeder. *Transforming Healthcare through Innovation in Digital Health. Global Telehealth (GT2018) Conference, Colombo, Sri Lanka, 2018.*

B. "Detecting Personal Movement Patterns in a Structured Environment", Anthony Maeder and Nathan Poultney. *IEEE Engineering in Medicine and Biology Conference (EMBC), Honolulu, USA, 2018.*

C. "Design of a Flexible Template Approach for Characterising Health Activity Habits Using Step Count Data", Nathan Poultney and Anthony Maeder. *The PErvasive*

Technologies Related to Assistive Environments (PETRA) Conference, Corfu, Greece, 2021.

D. “Characterising Health Activity Habits Using Step Count Data: A Flexible Template Approach”, Nathan Poultney and Anthony Maeder. *Multidisciplinary Digital Publishing Institute (MDPI) – “Technologies” journal. Selected Papers from the PETRA Conference Series, Journal Articles, 2021.* – In review.

ABSTRACT

Successful outcomes for health behaviour change interventions rely in part on the engagement of the subjects in the context of their everyday life. When the context in which the intervention is to be implemented is relatively structured, better engagement might be achieved if the intervention is delivered in harmony with the context. In the design of health behaviour change interventions it would be desirable to instigate the subject's expected interaction with interventions at a "point-in-time" when an instance of repeated behaviour is occurring or about to occur, rather than inserting disconnected and disruptive new activities. Such structured contextual behaviours that are being practiced repeatedly are deemed "habits". For example, if the pattern is a short walk to reach some endpoint and then return, the subject may be nudged to extend the length of the walk by varying the return route. Typically, structured settings where this approach may be applicable exist in several free-living situations, such as home, workplace, daily routines, to name a few.

The motivation behind this research was to devise a method for identifying and characterising repeated habitual patterns of health behaviours, specifically for the class of walking and associated sedentary activity in workplace settings, as determined by the collection and analysis of step count data and periods of inactivity from commercially available mobile or wearable consumer fitness devices. This work was confined to the type of information typically provided by these basic sources to provide a utilitarian solution. A few different actual settings, with associated variations in structure and health habits, were selected for application of the research to enable the stability and reliability of the method to be tested.

Generally, consumer fitness devices do not identify habitual patterns of behaviour but provide only aggregate step counts at predetermined time intervals, without fine-grained information on step-to-step variations such as data on speed or stride. They may provide some adjunct physiological information such as heart rate and environmental information such as vertical displacement, which may be useful in broad terms for recognising patterns without the need for precise information on other more nuanced details of the physical activity or environment.

The main contribution of this work is the specification of a staged template procedure that has been devised using the Design Science Research methodology for characterising and identifying habitual patterns of health behaviour. Initially, the Relevance Cycle identifies the data that is of interest by describing the tasks to identify and removing noise. The Design Cycle then characterises the tasks by defining boundaries to focus the scope. Then the Rigor Cycle refines the characterisations in an iterative process to increase the accuracy of the health habit detection. Once the habitual behaviour patterns have been identified, statistical models for the patterns can be constructed so that their subsequent effect on behaviour change interventions can be quantified. The primary effort in the Design Science Research approach was concentrated on the development

of the procedural pipeline to provide a universal template for step count activity data analysis. The initial prototype was refined through feedback from a trial application on simulated activity data, as detailed in the first case study.

This research has been trialled in three different constrained environment situations. Case study 1 (Simulated Workplace Tasks) was carried out in an open-plan multi-story workplace setting by most of the participants at Flinders University Tonsley campus and one participant at Western Sydney University Werrington South campus. Case study 2 (Open-Plan Workplace Tasks) was carried out in the same two environments as the Simulated Workplace Tasks case study. Case study 3 (Working from Home Versus Office) was undertaken in both environments from the first two case studies for the working from office part of the study, and in a modern residential apartment environment for the working from home part, during the SARS-CoV-2 pandemic lockdowns in Australia.

In each case study, multiple habitual behavioural patterns were identified and characterised using the proposed method. The resulting characterisation provided a baseline for further experimental work involving health behaviour change.

Through the understanding of these patterns in daily activities (including sedentary behaviour), specific points in the day could subsequently be chosen as appropriate for interventions to increase physical activity. For instance, if points of interest associated with walking could be identified in real-time, subjects could be notified of an opportunity for them to increase their step count immediately and unobtrusively, so that they could maximise their overall daily step count without feeling coerced or requiring them to consciously change to new health habits. In the three case studies reported, a total of 9 different types of patterns which could be used for such nudge type behaviour change interventions were identified and characterised.

DECLARATION

I certify that this thesis does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any university; and that to the best of my knowledge and belief it does not contain any material previously published or written by another person except where due reference is made in the text.

Signed...

Date...

To my late father whose own successes inspired mine.

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The pursuit of knowledge is a long journey, it is best travelled with the support of others. The journey I have undertaken in the past few years has been one of great triumphs and tribulations and I am extremely appreciative of those who were with me to celebrate the good and support me through the bad.

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1. INTRODUCTION

1.1. Overview

The health and wellbeing benefits of regular exercise with moderate to vigorous physical activity are well established (Penedo, F.J., Dahn, J.R., 2005) but have proved difficult to achieve at a population level (Long, G., Watkinson, C., Brage, S., et al. 2015). In recent years there has been a growing trend of expressing an implied benefit to one's health from the measurement of one's daily step count total. The ambition of working towards a total step count goal of 10,000 steps daily (De Cocker, K., De Bourdeaudhuijm, I., Brown, W., et al. 2009) has become a norm, regardless of the level of energy, the mood, the weather, the activeness, and many other factors that impact on an individual at any given time (Tudor-Locke, C., Craig, C.L., Brown, W.J., et al. 2011). If one's daily routine naturally involves a lot of walking or whole-of-body movement, this step goal may be attainable opportunistically. Greater challenge exists in low mobility situations where one must find ways to work proactively towards the step goal (Saint-Maurice, P.F., Troiano, R.P., Bassett, D.R., 2020), (Wilde, B., Sidman, C., Corbin, C., 2001). Health behaviour change interventions are a common approach to address this need, but often adoption and adherence for these interventions are low, with retention rates dropping after the initial intervention period is completed. It is widely held that strong engagement of the subject during an intervention leads to a more successful longer-term outcome of sustained behaviour change (Hargreaves, E.A., Mutrie, N., Fleming, J.D., 2016). But finding ideal ways for achieving this has proven to be elusive (Eckerstorfer, L.V., Tanzer, N.K., Vogrincic-Haselbacher, C., et al. 2018).

The intention behind this research is the characterisation of habitual behaviour patterns that are associated with either active or inactive movements which are primarily detectable in step count data. With the characterisation and subsequent identification of these health habits, this research provides a template approach which will be useful for behaviour change researchers and behaviour change related interventions. The work is also relevant to the quantified-self domain where personal movement logging and "self-knowledge through numbers" is established in popularity (Hoy, M B., 2016). An example of habitual behaviour could be an individual in an open plan office walking from their office desk to a meeting room where they remain sedentary for a period before returning to their office desk. Some similar attempts at detecting such habits have been proposed in the past (Shoaib, M., Bosch, S., Scholten, H., et al. 2015) but with lesser capacity to cater for pattern complexity than would be desirable. Health behaviour change researchers may use this template approach to identify that an individual or group of people frequently proceed to the meeting room via an elevator. In this scenario a health behaviour change intervention may prompt the individuals to use the stairs instead of the elevator to increase their overall daily step count. The template approach to characterising habitual behaviour patterns thus focuses on the repetition of patterns in step count data that could potentially be attributed to a set or subset of intervenable actions by subjects in health behaviour change interventions.

With the characterisation of habitual behaviour patterns, health behaviour change interventions can potentially inform points-in-time for interacting with an individual to increase their step counts, further encouraging health behaviour change. This research can also inform future health interventions to be better tailored to suit individuals for more effective health outcomes. The behaviour change aspect in this approach is focused on the improvement of existing health habits by extending or enhancing the relevant physical activity, as opposed to the creation of entirely new health habits which are often not sustained long term (Hargreaves, E.A., Mutrie, N., Fleming, J.D., 2016).

1.2. Background to this Research

The rationale to undertake this research stems from the lack of a general purpose and easily accessible approach to identify and characterise a person's habitual walking movements or degree of sedentary behaviour throughout a typical day. The focus is often on recognising activities of daily living (ADLs) and detection of instances of abnormal behaviour. These approaches are limiting in that they can involve complex parameter tuning or obtrusive data collection, and in some cases training data (Meng, L., Miao, C., Leung, C., 2017). Existing research in analysing consumer step counts has largely examined daily step count totals and averages, and whether an individual has been increasing their step count total and sustaining that increase over time e.g., the 10k daily steps challenge (McCormack, G., Giles-Corti, B., Milligan, R., 2006). Previous research in the area of consumer step count activity-based interventions has primarily focused on the creation of new health habits for individuals to sustain in the long-term using physical activity tracking devices (Maher, C., Ryan, J., Ambrosi, C., et al. 2017). This approach has been found to have low long-term sustainability. By contrast the research presented in this thesis explores pattern structures within step count data down to a 1-minute resolution across an entire day (either whole day or typical work hours), and over several comparable days (Nicolai, S., Benzinger, P., Skelton, D.A., et al. 2010). The identified patterns can be harnessed to improve the success of interventions to increase daily step count totals in a way which is to be less intrusive (Steinhauer, H.J., Sook-Ling, C., Guesgen, H.W., et al. 2010) and can be better sustained long term.

Presented in this thesis is a template-based approach to identify and characterise existing physical activity related health habit patterns. This template approach for characterising habitual behaviour has the potential for informing interventions such as just-in-time nudges, so that improvements can be made to those habits. By modifying existing health habits (Tuong, W., Larsen, E.R., Armstrong, A.W., 2014), it is proposed that those changes are more likely to be sustained long term in comparison to the introduction of new health habits. The challenge lies in the initial detection and associated profiling of the suspected health habits.

Previous research on characterising step count based activities (Chaudhry, U.A.R., Wahlich, C., Fortescue, R., et al. 2020) has analysed daily step count totals and averages and taken a high-level overview approach to summarisation (De Cocker, K.A., De Bourdeaudhuij, I.M., Cardon, G.M., 2010). Additionally, habitual walking movements have been monitored in laboratory-type settings with an array of monitoring tools utilised for very high precision data collection (Krishnan, N., Cook, D J., 2014). With the former approach it is extremely difficult to distil any habitual walking movements from individuals' daily step count totals. Interventions in this mode are highly cost effective and non-invasive for the participants that use a consumer-grade wearable device for counting their steps (Patel, M., Asch, D., Volpp, K., 2015), particularly as wearable devices are becoming more affordable, more accessible, and offer more variety (Andre, D., Wolf, D L., 2007). With the latter approach, whilst the various monitoring tools allow for very high-resolution data collection of participants, it can be far more intrusive to participants and expensive to conduct research in this mode. A laboratory-type setting also presents the possibility of participants behaving in a non-natural manner compared to the way they usually would in their regular day-to-day endeavours, possibly affecting the results as they may not accurately reflect natural movements and behaviours (Hillel, I., Gazit, E., Nieuwboer, A., et al. 2019). Both options can thus be rather impractical for streamlining and automating the identification and analysis of habitual walking movements of individuals. While step count data analysis has been used as a metric in research involving participants with ambulatory, chronic disease related illnesses or injuries, or disease prevention (Ayabe, M., Brubaker, P., Miller, H., et al. 2008), the focus of this research is rather on typically healthy individuals within the population to allow for general societal applicability.

The approach outlined in this thesis attempts to find a practical and minimally invasive middle ground for identifying habitual walking movements of individuals. This is undertaken in such a way as to provide enough resolution to accurately identify patterns of habitual behaviour without causing any untoward observational stress or burden on participants that could potentially affect the accuracy of the results (Gomersall, S., Ng, N., Burton, N., 2016), (Krishnan, N., Cook, D J., 2014). This approach will allow far greater sample sizes of participants and large data collection periods for longitudinal observations to be considered.

An emerging area in health behaviour change, exemplified in the quantified self (Hoy, M B., 2016), and citizen science (Silvertown, J., 2009), (King, A C., Winter, S J., Sheats, J L., et al. 2016) domains, is the popularity of consumer-driven physical activity monitoring and activity modification. Consumer grade wearable device use and its potential in health interventions is becoming increasingly more viable (Strath, S., Rowley, T., 2018), with the purpose of small-scale modification of health habits through the analysis of large volumes of granular data. This type of data is challenging to analyse as the patterns are hard to identify due to the unstructured nature of the typical day of an individual and the various environments they are likely to move between (e.g., home environment and workplace environment). Within a laboratory setting, a wide array of instruments can be utilised to monitor many aspects of an individual's physical activity, which cannot be so easily achieved outside of a laboratory environment.

This research thus aims to identify similar types of habitual behaviour patterns that typically can be easier to identify within a laboratory environment, but instead identifying those patterns in a constrained environment with a bare minimum of monitoring instrumentation. In this research for reasons of practicality it was decided to focus on workplace and walking/sedentary habitual behaviour as this was seen as a major domain for the types of habitual behaviour and interventions of interest. Measuring physical activity outside of the laboratory in free-living conditions with consumer grade physical activity trackers has been found to be a viable method of measurement (Tudor-Locke, C., Williams, J., Reis, J., et al. 2002). At a minimum, this approach requires two variables: step counts or locations, and timestamps, ideally each of them at 1-minute resolution (Storm, F.A., Heller, B.W., Mazzà, C., 2015) as a rule of thumb based on the usual relaxed walking speed of individuals on short trips i.e., on average <100 steps per minute as >100 steps per minute has been found to be a reasonable floor value indicating moderate intensity walking (Tudor-Locke, C., Craig, C.L., Brown, W.J.,), (Ayabe, M., Aoki, J., Kumahara, H., 2011). Consumer grade wearable devices can record some of the variables, and the data is often simple to extract through the device brand website using available APIs, often at 1-minute resolution for step counts and with their associated timestamps. Additional variables such as using location data as well as step count can enhance the accuracy of the characterisation and identification of habitual health behaviour patterns.

1.3. Why Habits and Behaviour Matter?

This research is looking at temporal patterns in step count data, it allows us to identify habitual behaviour of an individual within a constrained setting, with a sufficient degree of accuracy to provide us with sub-daily behavioural constructs. These habitual behaviours would not normally be identifiable looking at daily step count totals alone or even at a coarse granular level such as hourly intervals. An approach for characterising and identifying habitual behaviour in step count/movement data would allow for better informed health behaviour change interventions. For example, they would assist interventions targeting the reduction of sedentary behaviour (Conroy, D.E., Maher, J.P., Elavsky, S., et al. 2013), (Brickwood, K.-J., Watson, G., O'Brien, J., et al. 2019).

Individuals exhibit particular habits and behaviours in relation to their surroundings, their interactions, and their objectives (Verplanken, B., Aarts, H., 1999). This directly affects the quantity of steps and duration of active periods of walking taken during a typical day as well as the frequency of activity. More mindful appreciation of habitual behaviour can be leveraged to overcome such environmental negatives, which is one justification for using nudges (Toner, J., Allen-Collinson, J., Jones, L., 2021).

1.4. Why Step Counts Matter?

Step count data is often looked at in terms of the daily step totals (McCormack, G., Giles-Corti, B., Milligan, R., et al. 2006). One issue that can present itself is of noise in the collected data from wearable fitness devices to be considered. While the granular level of data greatly assists in the identification of patterns there can be a large degree of uncertainty due to the variability in data quality that is exhibited in a typical step count data set when it is at 1-minute resolution. Each wearable device will at times detect steps when there are none (Evenson, K., Goto, M., Forsberg, R., 2015). The degree to which erroneous steps are recorded differs from device to device (Feehan, L., Geldman, J., Sayre, E., et al. 2018). Wearable devices worn on the wrist will record some steps when using hand gestures for example, as will ankle-worn wearable devices when tapping your feet in a seated position (Alinia, P., Cain, C., Fallahzadeh, R., et al. 2017). The opposite can also be true in that steps will not be logged for wrist-worn wearable devices when pushing a pram or trolley as the wrist will have a negligible level of movement for the movement to be counted as a step (Winfree K., Dominick, G., 2018).

Complications in the data can also present themselves when expected data points are missing, such as when location data is available and has been collected from an RFID or Bluetooth device. There is the possibility that some locations are not accurately recorded as an individual passes by a beacon device or RFID chip. This can result in anomalies in the data where individuals may appear to have moved from one location to another without having passed an unavoidable location or checkpoint in between two locations (Cambo, S.A., Avrahami, D., Lee, M.L., 2017).

To reduce problems in later data analysis, the data cleansing that typically happens prior to the analysis may require sensible cut off points to reduce the risk of noise interfering with the identification of health habits in the data, as well as a reliable and thorough data cleansing routine. For example, when looking at health habits in a workplace environment between 9am to 5pm work hours, some data points immediately after 9am and immediately prior to 5pm may need to be excluded where reliable contextual information is not present due to those time cut off points.

1.5. Research Aim and Research Objectives

The primary aim of the research is to define a systematic approach for identifying and characterising patterns of habitual movement or sedentary periods in a typical day of a person working in a structured, constrained setting. A constrained setting is defined as an indoor environment with physical areas of interest in which time is purposefully spent to perform a task e.g., making a coffee in a kitchen space. The defined areas of interest can include transit areas for traversal such as hallways or stairs. A typical office environment is often structured in such a way as to separate the areas in which work is carried out at a desk from the communal kitchen area, meeting rooms, or bathrooms. Each of these areas serve different purposes and are what constitute a structured, constrained, free-living setting.

This aim presents several research objectives to be explored within the thesis:

- What are the current approaches to identifying and characterising patterns of habitual movement, with their limitations and implications?
- What are the fundamental characteristics of the patterns for typical movement related health habits, which can lead to comparing and understanding these patterns?
- How can an information model for such health habit patterns be framed which is simple in nature while yielding useful results for informing future interventions?

For the purpose of this research, we are interested in the habits of the individuals in their settings or environments (Neal, D., Wood, W., Quinn, J., 2006). This includes understanding what activities or interactions the individual has with their setting but does not include analysing what the individual is doing once they have moved to a new location within their setting. For instance, if they have walked to a printer then the action of printing is irrelevant to this research, whereas the details of the walk itself, any static or sedentary duration at the destination, and the frequency of this walk is what is of interest. The trips between one identified location and another are in general of interest, as are sedentary periods and the frequency of trips.

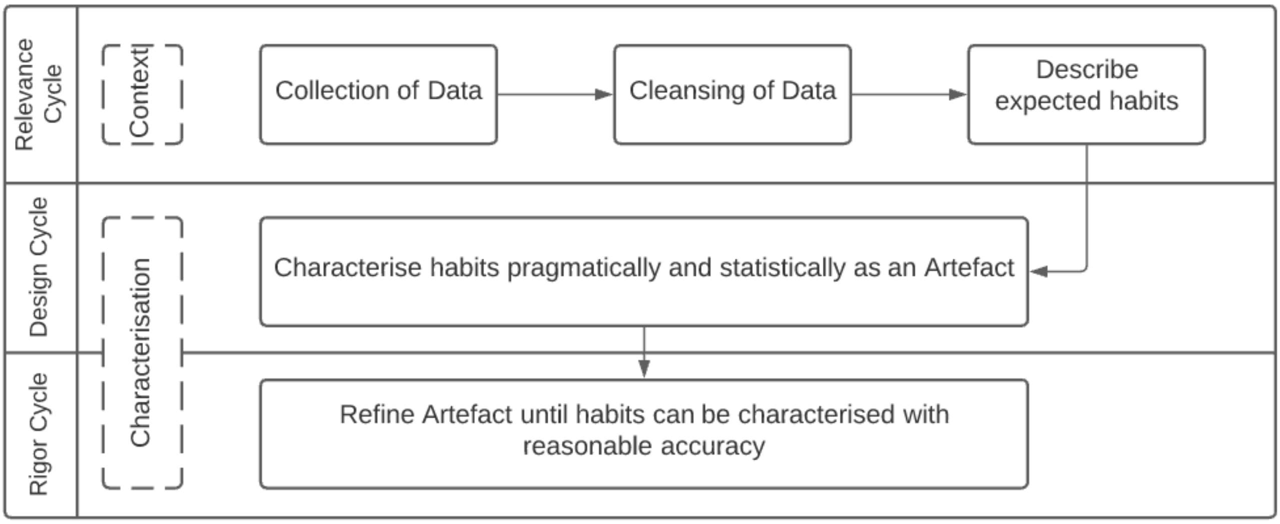
An example of a health habit may be a walk from the individual's work desk to a coffee machine in the communal kitchen area and back to their work desk again. This may be the same trip taken every day by an individual and possibly at multiple times during the day. If this trip occurs at the same time(s) every day, that would constitute a very clearly defined and distinguishable habit of movement of the individual. Typically, step counts and duration for these trips would have a small threshold defined for variation, in order for this to be identified correctly (and accurately) as a pattern of habitual behaviour. Where the identification of the pattern becomes increasingly difficult is when this habit occurs at different times or is not necessarily every day (maybe it is not every day in a week because the office worker sometimes eats out).

Greater degrees of variation to this habit can further increase the complexity of correctly identifying the habit. For instance, the individual may take a different route to the coffee machine than the usual one, whether that be a conscious decision or prompted by external factors like walking with a colleague. This can significantly affect the step counts and durations, in which case this occurrence of the trip may not be identified as a habit (or part of an existing established habit) because it either does not match the typical pattern of behaviour that has been previously exhibited, or because it varies too much from that pattern to be characterised as an instance of that pattern and is thus rejected.

1.6. Research Process

The research process followed a Design Science Research Methodology approach (Peffers, K., Tuunanen, T., Rothenberger, M.A., et al. 2007) which consists of three successive “cycles” or phases (see Figure 1). Initially in the Relevance Cycle the literature review was undertaken, followed by the consideration of data collection and data cleansing activities, and then expected health habits which were desired to be found from this type of data were described in detail. Next the Design Cycle involved the systematic approach of the design and development of an artefact for pragmatically and statistically defining the habitual behaviour. This was followed by the Rigor Cycle in which the established artefact was refined over several iterations until a desired level of accuracy for habitual behaviour characterisation and identification was achieved.

Figure 1: Research Process



1.7. Approach to Analysis

The approach to analysis in this research is a pragmatic approach following an empirical, heuristic methodology. This is achieved by adopting a systematic analytical approach, achieved through high level pragmatic decision making for defining characteristics of the dataset. Simple statistics such as mean, standard deviation, and range are then applied to the data in order to characterise the habitual envelope of an individual; this allows for the comparison of individuals irrespective of their setting or varying demographics when observing variations between them. An individual's data can then also be compared with others across different sets of data of varying characteristics. Often traditional data analysis in this area is conducted in-depth and at fine granularity, making it impractical outside of a laboratory type settings. This approach allows for wider applicability in characterising and identifying patterns in data sets while still maintaining a reasonable level of accuracy without high-precision monitoring or measurement instruments.

1.8. Key Contributions, Outcomes, and Findings

- A novel pragmatic approach for identifying health habits utilising a minimal number of attributes. Using a design artefact (later introduced as the "DHIF-PP" artefact) devised through the application of the Design Science Research methodology.
- The DHIF-PP artefact has allowed for a level of characterisation which is able to distinguish between differences and commonalities in patterns of health habits.
- It has been found from the case studies that step count data recorded at 1-minute resolution from consumer grade wearable activity monitors is sufficient for identifying and characterising health habits of individuals.
- The DHIF-PP artefact whilst focused on office type settings, it is designed to be more widely applicable across other type of settings that may be of interest to researchers looking to identify health habits of individuals.

1.9. Outline of the Thesis

In Chapter 2 the literature review explores the definition of behaviour, the definition of a health habit, behaviour change theories, properties of steps, and daily step count goals. Also discussed are the typical characteristics of health habits which have been identified as important for behaviour change research studies. Types of structured environments are defined as well as their influence on health habits, and the types of daily activities are defined.

In Chapter 3 the methodology and design science approach to the systematic creation of a template artefact is introduced and described in detail. The way in which the artefact provides for the characterisation and identification of physical activity and sedentary habitual behaviour patterns particularly in step count data sets is also explained. The final template approach to characterising health habits both in a pragmatic and statistical sense is described in detail.

In Chapters 4, 5, and 6 the three case studies are presented in detail. These comprise case study 1: Simulated Workplace Tasks; case study 2: Open-Plan Workplace Tasks; and case study 3: Working from Home Versus Office. Data collected is analysed and characteristics of a range of particular habits are computed and differentiated between individuals using the template approach.

In Chapter 7 a discussion on the scope and implications of the research contribution is provided and overall conclusions are drawn for the generality and significance of the research, and finally recommendations and future considerations are indicated.

2. LITERATURE REVIEW

2.1. Introduction

This chapter documents the literature review that was undertaken to determine the current landscape for habitual pattern characterisation in daily activity data. The overall coverage of the literature review was on the general area of health behaviour change and its theories, habitual physical activity patterns, and the nature of step count data and its analysis. As this is an interdisciplinary area of study, without an established direct body of knowledge, it was necessary to cover a number of areas of background knowledge in a broad landscape appraisal, rather than attempt to conduct a narrow systematic review. The methodological approach taken was to identify key concept areas related to the problem description, identified heuristically in consultation with members of the supervisory team, and then to identify prominent relevant papers in each concept area from which further references could be identified by snowballing. While this is not as comprehensive as a conventional systematic approach might be, it was necessary to trade off depth with breadth to ensure a fuller appreciation of the related work in all aspects of the project.

Repeated Google Scholar searches were made between the years 1990 to 2021 using the key words listed immediately below. A list of prominent and recent papers were extracted for reading based on the apparent relevance from the titles and abstracts, with other references being added from these as indicated in their texts. The discussion in the following sections is synthesized from those concepts deemed most relevant in these papers.

Concepts of interest:

- Step count / walking
- Wearable device / activity monitoring / physical activity trackers
- Reliability/Accuracy/Validity of physical activity trackers/wearable devices
- Physical activity / Daily Activity of Living / human activity recognition
- Sedentary behaviour / physical inactivity
- Habitual health behaviour / Patterns of health behaviour
- Physical activity in the workplace
- Physical activity and the effect of the environment
- Increasing physical activity / reducing sedentary behaviour
- Physical activity nudges/interventions

The ultimate purpose of this literature review was to identify practices, issues and potential gaps reported within the literature regarding health behaviour patterns and the analysis of data for identifying patterns of behaviour in movements. The three main apparent themes covering all these concepts are Health Behaviour and Behaviour Change, Human Activity and Measurement, and

Increasing Human Activity. Figure 2 shows a mapping of these themes to concepts and sub-concepts emerging from the overall literature review process.

Figure 2: Mapping for Literature Review

2.2. Health Behaviour and Behaviour Change

2.2.1. Definition of a Behaviour

Behaviour can be defined as "the way in which one acts or conducts oneself, especially towards others" (Salovey, P., Rothman, A.J., Rodin, J., 1998). In the context of health behaviour, these acts are the way in which individuals look after their own health. Behaviours generally (including health behaviours) differ from one person to another and can contribute to positive or negative personal (including health) consequences for an individual (Salovey, P., Rothman, A.J., Rodin, J., 1998), (Simon, H.A., 1992). Behaviour is further described as “an attempt on the part of an individual to bring about some state of affairs – either to effect a change from one state of affairs to another, or to maintain a currently existing one” (Ossorio, 2010).

At a high level, individuals may be seen to be more active or less active than others based on their daily total step counts, and the health behaviours of individuals and their attitude towards their own health may be closely linked to their step counts. An individual who works in an office and takes frequent walks away from their work desk is perceived as more active than an individual that works in an office and remains seated at their work desk for most of the day (Spinney, R., Smith, L., Ucci, M., et al. 2015). However, the difference in daily total step counts may be subtle between these two individuals, depending upon how many steps they achieve both inside and outside of the workplace. For instance, there may be a long walk during the lunch break for one of them, and an in situ sit-down meal for the other, while the first makes few steps during working hours and the second makes many. When the behaviours and health habits are examined at a greater resolution (e.g., 1-minute intervals) the degree of active and sedentary behaviour become substantially clearer (Nicolai, S., Benzinger, P., Skelton, D.A., et al. 2010), (Feehan, L.M., Lu, N., Xie, H., et al. 2020), reducing the level of uncertainty that comes from analysing only daily total step counts.

When authors discuss health behaviours in the context of temporal sequences of step counts, the focus is usually on the deliberate actions of movement from one location to another (Hayes, T.L., Hagler, S., Austin, D., et al., 2009). As behaviour generally encompasses mood and attitude, a step count pattern might vary between an individual in a happy mood compared to a sad or angry mood for example (Biddle, S., Fox, K.R., Boutcher, Stephen H, 2003). However, these emotional aspects have been deemed out of scope for the purposes of this research, as they are not practically directly measurable and therefore not able to be incorporated consistently in the proposed template-based characterisation approach.

2.2.2. Definition of a Habit

Verplanken and Aarts (1999) refer to habits as being “learned sequences of acts that have become automatic responses to specific cues and are functional in obtaining certain goals or end-states”. Every day an individual follows various routines that have been instilled over time, which constitute the set of habits they develop and carry out without any conscious thought. The health-related habits developed contribute to the on-going positive or negative health behaviours of an individual (Aarts, H., Paulussen, T., Schaalma, H., 1997).

A narrative review that looked at 136 empirical studies and 8 literature reviews and how they used the term "habit" and the methods in which they measured it has proposed a more modern definition. Defining a habit as "a process by which stimulus generates an impulse to act as a result of a learned stimulus-response association". Further describing, "habit-generated impulses may compete or combine with impulses and inhibitions arising from other sources, including conscious decision-making, to influence responses, and need not generate behaviour" (Gardner, B., 2015). Such stimulus may greatly vary in a constrained workplace setting, a typical habit may be to have a break for lunch or to eat with the stimuli being a pre-set alarm on an individual's mobile device, or on a digital calendar. Or may simply be triggered by feeling hungry and the lunch break happens ad hoc or organically.

2.2.3. Behaviour Change Theories and Models of Behaviour

Behaviour change theories provide the current understanding of how positive behaviour change can potentially be enacted within an individual and making lasting positive habitual health behaviour changes that are sustainable as automatic processes (Gardner, B., Lally, P., Wardle, J., 2012). Many behaviour change ideas have been theorised and published (U.S. Department of Health and Human Services, 2018). The following section describes three behaviour change theories deemed as highly relevant to the research in this thesis (Kwasnicka, D., Dombrowski, S., White, M., et al. 2016), as they are focused on behaviour change and the ways in which behaviour change is measured, and change can be enabled.

2.2.3.1. Theory of Expanded, Extended, and Enhanced Opportunities (TEO)

TEO looks at increasing physical activity through modifying existing periods of time that have been allocated to physical activity. An example in youth physical activity promotion (Beets, M.W., Okely, A., Weaver, R.G., et al. 2016) examines these three core components as follows:

- Expansion: The concept of replacing time that is already allocated for what is considered low active or sedentary activities and replacing them with more active activities.

- Extension: The concept of increasing the length of time that is already allocated for physical activity opportunities.

- Enhancement: The concept of modifying an existing physical activity opportunity and increasing the degree of activity accumulated in that period-of-time.

Table 1 below provides examples of the usage of TEO in the youth physical activity promotion study.

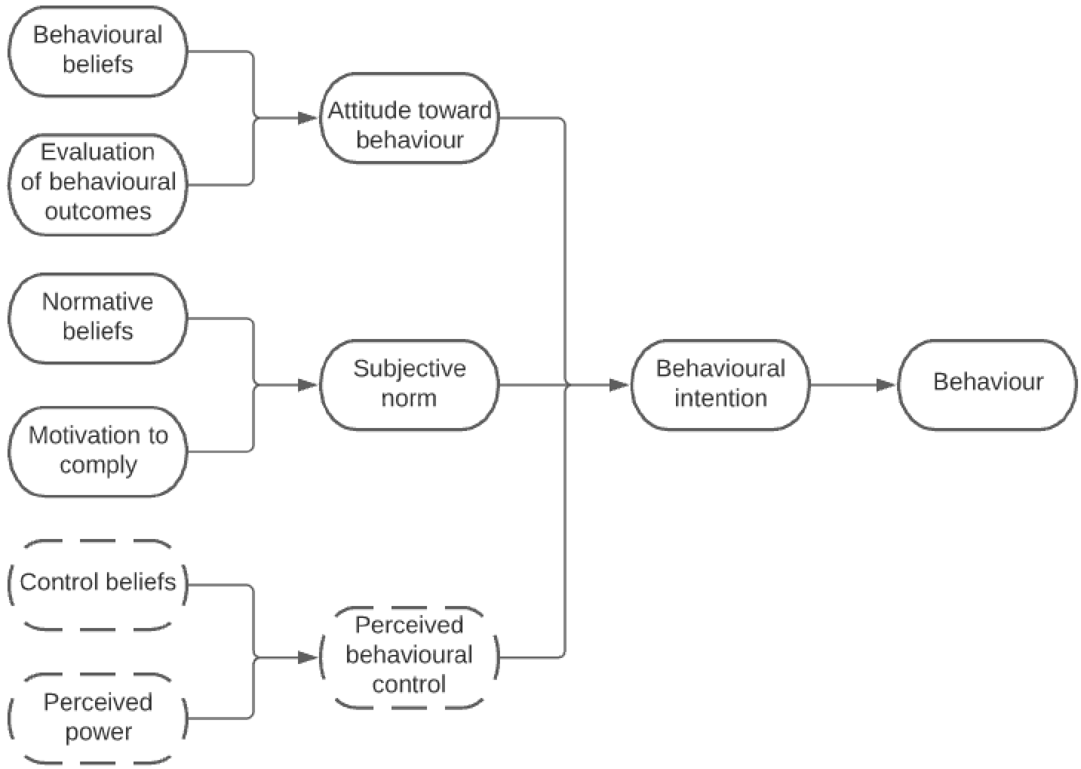
Table 1: Expanded, Extended, and Enhanced examples (Beets, M.W., Okely, A., Weaver, R.G., et al. 2016)

Theoretical Mechanism	Examples
Expansion	Substituting seat work with active learning tasks in general education classrooms. Providing a before or after school opportunity to be active, where one did not exist previously.
Extension	Providing additional physical education (PE) lessons per week, on top of what is currently provided. Lengthening or adding additional recess PE sessions per week or allocating more time for recess or PE on a given day.
Enhancement	Reducing student wait time during PE lessons to increase physical activity Increasing portable equipment options for students during recess. Providing choice among two or more activity opportunities

2.2.3.2. Theory of Reasoned Action (TRA) and Theory of Planned Behaviour (TPB)

TRA and TPB work on the assumption that the best predictor of a behaviour is the intention to do it (Glanz, K., Rimer, B.K., Viswanath, K., 2015). That intention is deemed to be determined by attitudes and perceptions which determine individual motivational factors regarding the behaviour. TRA and TPB are able to be used to explain the large portion of variance in intention and predict a number of different health behaviours and intentions. Some examples of those include smoking, alcohol consumption, breastfeeding, donating blood, and health services utilisation (Hackman, C., Knowlden, A., 2014). Figure 3 below describes the TRA and TPB model:

Figure 3: Theory of Reasoned Action and Theory of Planned Behaviour

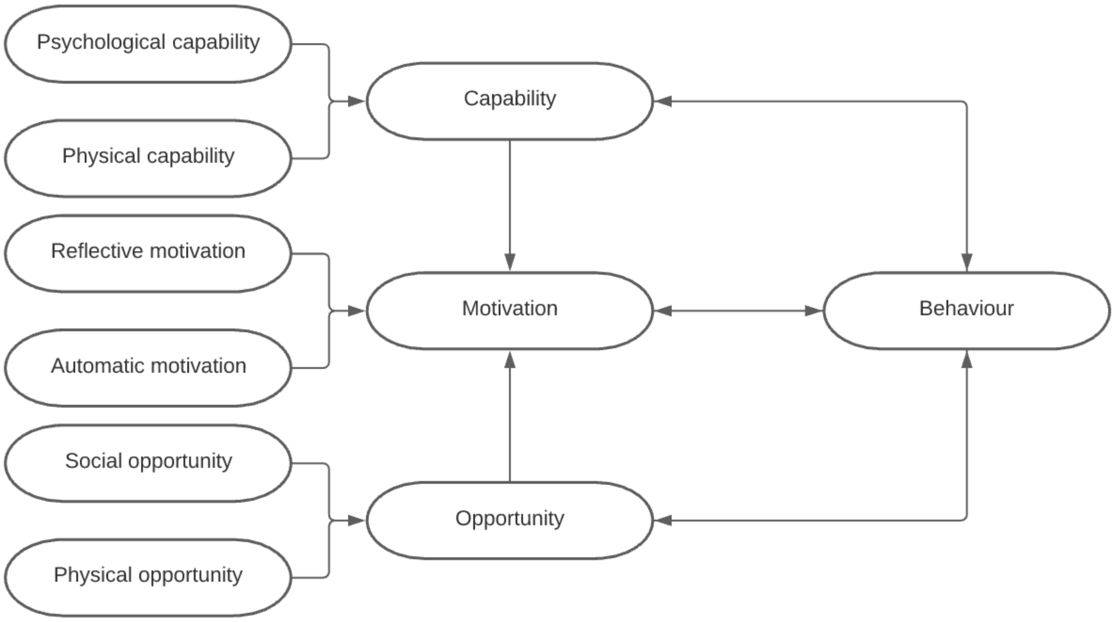


2.2.3.3. The COM-B Simple Model of Behaviour (change)

The COM-B model has four interacting parts. The first three are interrelated primary determinants for behaviour: Capability (physical/psychological), Opportunity (physical/social), and Motivation (automatic/reflective). These first three parts simultaneously affect and reflect the fourth part, a Behaviour from an individual (Michie, S., Stralen, M., West, R., 2011). Capability is whether an individual can do something physically or mentally; Opportunity is whether there is a suitable window to do something, and Motivation is whether there is perceived value or purpose for the individual that makes the 'something' worth doing.

The COM-B model has been applied in an intervention to improve hearing-aid use in adult auditory rehabilitation. It was concluded that "the use of the COM-B model has laid solid foundations for intervention development that can be linked back to psychological theory to address the problem of hearing-aid use" (Barker, F., Atkins, L., de Lusignan, S., 2016). Demonstrating a more general applicability of the COM-B model for health behaviour change.

Figure 4: COM-B Model of Behaviour



2.3. Human Activity and Measurement

2.3.1. Properties of a Step

A typical step is made up of various factors (Lacquaniti, F., Grasso, R., Zago, M., 1999), (Whittle, M.W., 2014), including predominantly stride length and walking speed (Samson, M.M., Crowe, A., de Vreede, P.L., et al. 2001), each of which define the way in which an individual takes each step. Generally, most people would have a very similar step action based on kinematics, but due to the differences in each of these factors across individuals, their steps can nevertheless be differentiated from one another.

As part of this research, we need to make some assumptions within reasonable bounds of what is an 'average' step. The factors that are to be taken into consideration are leg length (based on anthropometric measurements of leg components) and step range (the quantity of steps that are taken per minute on average). Leg length has been found to correspond to step range values of 111 steps per minute for individuals that are 5 ft tall and 85 steps per minute for individuals that are 6 ft 6 in tall (Beets, M.W., Agiovlasitis, S., Fahs, C.A., et al. 2010). While step range and leg length have a clear impact on the step counts of individuals, for the purpose of identifying patterns of habitual behaviour within step count data, step range and leg length have an insignificant impact on the accurate identification of these patterns (Chung, M.-J., Wang, M.-J.J., 2010).

2.3.2. Daily Step Count Goals

Often 10,000 steps are the recommended daily step count target to reach or maintain a healthy level of activity (McCormack, G., Giles-Corti, B., Milligan, R., 2006). The goal of the daily step count target and the number of steps individuals reach can vary according to many circumstances. It is accepted that the rate at which the average person takes steps is 100 per minute (Tudor-Locke, C., Craig, C.L., Brown, W.J., et al. 2011).

The quantity of steps per day has been classified according to active lifestyle categories by Tudor-Locke and Basset (2004) as follows in Table 1:

Table 2: Steps per day classification (Tudor-Locke, C., Craig, C.L., Brown, W.J., et al. 2011)

Steps per day	Classification
<5000	Sedentary lifestyle
5000 – 7499	Physically inactive
7500 – 9999	Moderately active
≥10,000	Physically active
≥12,500	Very active

Not only do the daily step count totals that individuals reach vary from country to country (Tudor-Locke, C., Craig, C.L., Brown, W.J., et al. 2011), but the daily step count totals are also impacted upon by the profession of an individual. e.g., office workers are more likely to achieve lower daily step count totals compared to farmers or professional athletes (Thomas, L., Williams, M., 2006), and by physical constraints such as age, disability, and cultural limitations (Hino, K., Usui, H., Hanazato, M., 2020).

In some instances, passive steps are taken in the hope of reducing time spent sedentary such as sit-stand desks in an office (Gray, C.M., 2018). This helps to facilitate movement and activity by allowing an individual to moderate the time they spend sitting or standing throughout the day. This may lead to more physical activity throughout the day compared to if they are only sitting for most of their work hours (Straker, L., Abbott, R., Heiden, M., et al. 2013).

2.3.3. Wearable Devices

Many wearable devices exist on the market today for the purposes of step counting. There are different types of step counting wearable devices that typically fall into one of six categories (Bassett, D.R., Toth, L.P., LaMunion, S.R., et al. 2017):

- waist-worn
- pocket
- thigh
- ankle

- foot
- wrist

The consumer step counting wearable device used for the purpose of this research was the Fitbit Charge HR 2 devices which was primarily measuring step counts. These devices are generally worn on the wrist (Abrams, D.B., Turner, J.R., et al. 2013) and so we have followed this convention with the individuals involved in the data collection process. These are deemed to perform within acceptable levels of validity and reliability compared with research grade wearable devices (Bassett, D.R., Toth, L.P., LaMunion, S.R., et al. 2017), (Dontje, M.L., de Groot, M., Lengton, R.R., et al. 2015), (Fuller, D., Colwell, E., Low, J., 2020). The choice of a wrist mounted device also ensures the effectiveness of the data collection exercise in a daily routine, as it assumes the wearing of the device in a natural position such as a watch or jewellery. It should be noted that as these devices are worn on the wrist, there is the possibility that steps will not be accurately recorded when the wrist is not in motion e.g., pushing a trolley but this has been found to make no significant difference to the recording of unencumbered free walking step counts (Alinia, P., Cain, C., Fallahzadeh, R., et al. 2017). The devices are not prone to substantial erroneous step counts in desk-based wrist movement tasks e.g., typing on a keyboard or using a phone. They may however erroneously record steps if an individual moves their wrist around rapidly or vigorously while stationary e.g., using hand gestures.

Prior work has been done to look at the effectiveness of wearable step counting devices and compare them against one another (Sushames, A., Edwards, A., Thompson, F., et al. 2016). While it has been found there are strong correlations between very different consumer devices (e.g. ActiGraph devices compared to Fitbit devices) there are still discrepancies such as the under-reporting of step counts, such as <100% of actual steps being counted with 11 different devices in one study (Toth, L., Park, S., Springer, C., et al. 2018), which should be noted when using these devices for kinaesthetic research purposes (Chu, A., Ng, S., Paknezhad, M., et al. 2017). There is also reported work to assess the validity of wearable devices for measuring steps across different conditions such as using a treadmill, over ground, and 24-hour free-living conditions (An, H., Jones, G., Kang, S., et al. 2017), (Toth, L., Park, S., Springer, C., et al. 2018). While there is a constant influx of new wearable devices each year, it has been found that the well-established brands are the ones most commonly used in research and the degree to which new wearable devices are thoroughly validated is quite low (Henriksen, A., Haugen Mikalsen, M., Woldaregay, A., et al. 2018). Better accuracy might be achieved if future research is able to make use of slightly higher precision consumer-grade wearable devices such as Garmin watches (El-Amrawy, F., Nounou, M.I., 2015).

2.3.4. Habits in Context

How habits of individuals are affected by their settings is not well reflected in the literature. Different frameworks of ideas have been suggested for expressing what are "habits in context" (Yerxa, E., 2002). These allow some scaffolding for characterisations and descriptors to be determined which make allowances and give insights to the many factors, idiosyncrasies, and contextual information surrounding habitual behaviour (Wood, W., Tam, L., Witt, M., 2005). Within this thesis for the purpose of this research, "habits" are assumed to be a "learned sequence of acts that achieve an intended goal or outcome" (Neal, D., Wood, W., Quinn, J., 2006) rather than subconsciously and contextually determined.

2.3.5. Types of Environments

While there are many types of environments that can be categorised, the focus of this research and the types of environments that are of the most significance to this research are structured and unstructured environments, in a constrained setting.

2.3.5.1. Structured Environments

Structured environments are the locations that a person spends most of their day during the week (Lockwood, R. N., 2003), that are made up of various rigid locations or markers. Structured environments are often buildings but are not confined to solely buildings and their interiors and because of this they can typically be described as constrained (Smith, L., Ucci, M., Marmot, A., et al. 2013). An example of a structured environment is an office space which for the most part does not change in shape, size, or layout. If the environment is altered, it is often a minor change, and the locations are likely to be unaffected and still contextually the same to the individuals that utilise the space.

2.3.5.2. Unstructured Environments

Unstructured environments are those in which an individual spends time generally between being in structured environments (Lockwood, R. N., 2003). They have the potential for change in their shape, size, or layout either frequently, or infrequently with a certain degree of uncertainty as to when or how it will change. An example of an unstructured environment is an outdoor park. An outdoor park may have usually accessible sections closed for maintenance or gardening, or tree lopping. There may be events happening which affect the attendance popularity of sections such as sporting events or public fairs. This is a type of environment which can be altered frequently or changed in significant ways over time and for various purposes.

2.3.5.3. Constrained Settings

A constrained setting can be characterised by a variety of distinguishable markers within a given environment. Constrained settings will typically have a set of locations frequented by those in which occupy the space throughout the day (Smith, L., Ucci, M., Marmot, A., et al. 2013). An office can generally be described as a constrained setting due to the desks, cubicles, walls, corridors etc. Often an office environment will have similar markers throughout and is recognisable as an office at first glance to most people. The markers are generally rows of desks or cubicles, a shared kitchen space, meeting rooms etc. However, constrained settings are not necessarily strictly indoor settings. Outdoor settings can also be constrained such as an outdoor sports stadium that will have its own set of markers that are common between most outdoor sports stadiums. Or nature reserves where there may be commonalities between them such as a car park, picnic tables, amenities etc. There will be numerous trips per individual between these locations. These repeated trips form the basis for characterising repeated habitual behaviour.

2.3.6. The Influence of Environments on Habits

The types of environments that an individual is likely to move between on a typical day can vary greatly (Lewis, S., Gambles, R., Rapoport, R., 2007). A typical day may begin at home, an environment that while it will have similar characteristics to other homes in terms of layout and function, will still be unique to each individual. For example, a typical home will have at least a bedroom, bathroom, and kitchen that all serve a particular set of purposes. However, from one home to another these rooms are not likely to be in the same location within the home and not necessarily used for the same purposes across all homes. In the case of the kitchen if an individual does not cook, their time spent in or around the kitchen area could be theorised to be lower than an individual who does cook.

This example can be extended to school, university, or the workplace (Neal, D., Wood, W., Quinn, J., 2006). Each will have different layouts, different functions in different areas, and the purpose and intention of the individual in these environments will also differ (Engelen, L., Dhillon, H.M., Chau, J.Y., et al. 2016). In the case of a high stress workplace, this may influence an individual who is a smoker to smoke more before, during, or after work as a coping mechanism for dealing with the stress of the work environment (Kouvonen, A., 2005).

Influential factors in the environment can be as simple as being seated near an irritating co-worker or student that is disrupting one's ability to work or study (Roper, K.O., Juneja, P., 2008). This could potentially lead to higher-than-average step counts from the individual who is uncomfortable, leaving their desk to minimise their time spent in proximity to the other person. The converse could also be true, if a co-worker or student gets along very well with the individual, they might not leave their desk as often as they otherwise would, leading to a lower average step count.

The office environment is one that is particularly known for sedentary habits. As of 2018, over 80% of all US jobs were deemed to be predominantly sedentary (Gremaud, A., Carr, L., Simmering, J., et al. 2018). The increased risk of health problems because of sedentary habits is a large problem for office workers not only in the US, but on a global scale (Parry, S., Straker, L., 2013). There are many common interventions targeted at decreasing sedentary behaviour (Biddle, S.J.H., Petrolini, I., Pearson, N., 2014), (Prince, S.A., Saunders, T.J., Gresty, K., et al. 2014). More recent approaches involve enhanced subject engagement methods such as gamifying wearable devices (Gremaud, A., Carr, L., Simmering, J., et al. 2018).

2.3.7. Daily Activity Types

Daily activity types are a high-level categorisation of activities of daily living which are defined as “fundamental skills that are required to independently care for oneself such as eating, bathing, and mobility” (Edemekong, P.F., Bomgaars, D.L., Sukumaran, S., et al. 2021). Two distinct types of daily activities have been recognised: “mandatory” for those that are almost always certain to happen and “optional” for those that are not certain or infrequent. These types of daily activities have their own learned associations and cues to trigger the intended goal-oriented response (Wood, W., Neal, D., 2007).

2.3.7.1. Mandatory Activities

Mandatory activities are those that the average person would almost always partake in daily. This could include but is not limited to bathroom breaks, eating lunch, walking to and from locations in structured or unstructured environments for various reasons (Mlinac, M.E., Feng, M.C., 2016). There are some exceptions for mandatory activities in specific circumstances. For example, if individuals are fasting for religious or health related reasons then meals that are typically had at certain times of the day might be skipped entirely and this could be across multiple days or weeks instead of a one-off occurrence. A one-off occurrence in this example might happen if the individual is simply too busy to eat a meal (e.g., lunch). Other factors that can impact on mandatory activities include health related reasons if an individual is ill or injured (Duclos, C., Beauregard, M.-

P., Bottari, C., et al. 2015). For the purpose of this research, it is assumed that specific mandatory activities have been observed for the duration of the case studies.

2.3.7.2. Optional Activities

Optional daily activities are those that the average person may or may not partake in daily (Frank, L.D., Engelke, P.O., Schmid, T.L., 2003). This could include a long walk on their lunch break or occasional trips to a café or coffee machine area depending on their environment (structured or unstructured). Naturally, there is a greater degree of variance in the frequency and duration of optional activities that adds a layer of noise to any step count dataset. It must be noted that while optional activities in some cases may be one off, there are still many optional activities that are repeated activities, across the same day or across multiple days or even weeks.

2.4. Increasing Human Activity

2.4.1. Point-in-time Interactions

Point-in-time interactions are the identification of moments throughout the day where an individual can be prompted or be made aware that they currently have an opportunity to increase their daily total step count and consequently their overall health benefit associated with taking more steps (Lars, K., 2020). Using the approach proposed in this thesis for characterising and identifying habitual behaviour, researchers in health behaviour change could set up interventions in which participants are encouraged or 'nudged' towards behaviour change at points-in-time throughout the day (Toner, J., Allen-Collinson, J., Jones, L., 2021) identified via the template artefact.

An example of a point-in-time interaction might be that a pattern of habitual behaviour of walking to the communal kitchen and back to their work desk has been identified as it was triggered autonomously by the individual (Neal, D., Wood, W., Labrecque, J., et al. 2012). This might be a habit that happens at the same time every day, a few times a day. The individual can be notified at or before the commencement of the activity that this is a point-in-time when more steps can be taken. The individual might then take a longer route to the kitchen area than they normally would (i.e., taking more steps by not going a more direct route to their destination) to leverage this opportunity to their benefit. If the individual is under time pressure (e.g., has a meeting directly after their lunch break) then the point-in-time interaction would be dismissed as not viable given the situation. In this way the point-in-time interactions encourage more steps to be taken rather than strictly trying to enforce that more steps are taken.

2.4.2. The benefits of point-in-time Interactions

The ability to identify points-in-time for an interaction could allow for the improvement of existing health habits. This is only a slight yet significant change to an individual's existing health habits, instead of trying to forcefully persuade an individual to develop new health habits that are shown in the literature to not be sustained long term (Tuong, W., Larsen, E.R., Armstrong, A.W., 2014). Modification of existing health habits are consequently more likely to be sustainable, beneficial changes to an individual's routine.

2.4.3. The challenges of detecting Point-In-Time interaction opportunities

There are no clear markers for determining what precisely is a point-in-time interaction opportunity. This leads to the risk of false identification (Mori, T., Shimakawa, H., Harada, F., 2021). However, the harm in a false identification may not be a severe problem in our situation as an individual would still be contributing to their step count and wellbeing (An, H.-S., Jones, G.C., Kang, S.-K., et al. 2017), even if the point-in-time detection is a false positive and so the intervention is sub-optimal. It would still be at the individual's discretion whether this identified point-in-time is a viable time for them to increase their step count based on their schedule or routine.

2.5. Conclusion

The literature review has described the landscape within which habitual health behaviours (especially those which are workplace and stepping or sedentary based) occur and how they are constituted and described. It has revealed several issues which contribute to the significant gap that there are currently no simple, low cost, non-intrusive, precise methodologies for characterising and identifying such health habits. There are also no methodologies for working with as little as two parameters in the health habit characterisation and identification process with reasonable accuracy, which affect the value that can be obtained for health behaviour change interventions in such cases. In summary, through the literature review process a gap in knowledge to be addressed in this thesis has been identified, which requires research to derive a systematic and user-friendly approach to habitual health behaviour characterisation which is also highly accessible and cost effective.

3. METHODOLOGY

3.1. A Pragmatic Approach – The Design Science Research Methodology

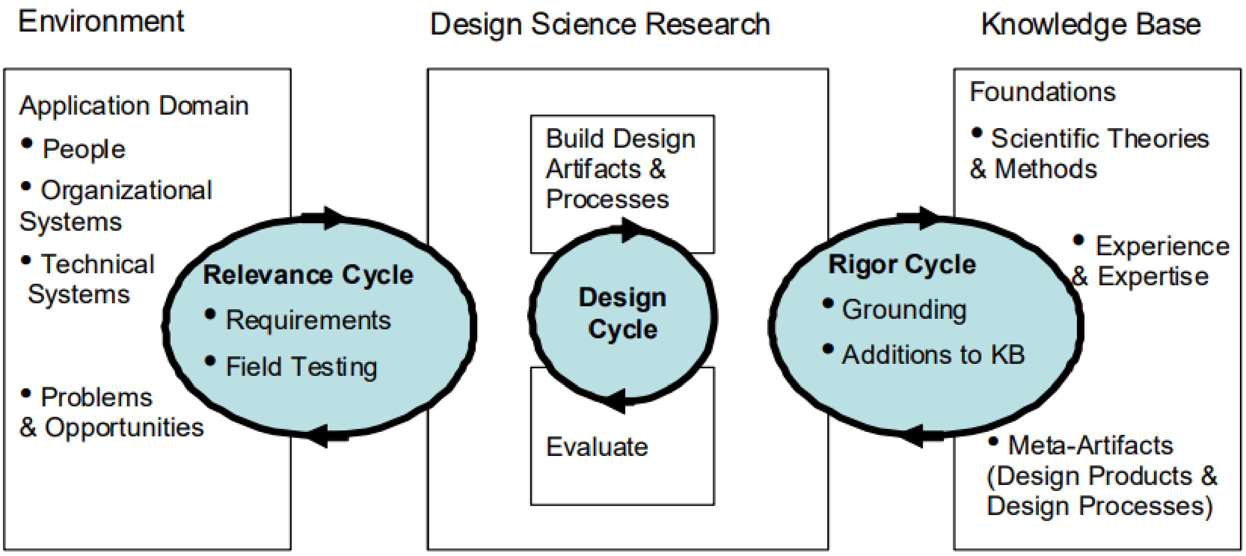
Research paradigms have been defined by Bogdan and Biklen (1997) as “a loose collection of logically related assumptions, concepts, or propositions that orient thinking and research” (p.22). There are no clear methodological approaches best suited to the current research problem. Furthermore, the type of data being analysed does not lend itself well to an artificial intelligence approach using rule based or machine learning algorithms. This is due to the nature of the data generally having a high degree of noise that requires observation and analysis to apply a level of pragmatism. This research thus required a very problem-centred approach with the focus being on the “what” and “how” of the achievement of the desired result.

The Design Science Research Methodology was identified as the most logical approach to use, with its adaptive process of designing and developing an artefact that is refined over several iterations to improve its design. The Design Science Research Methodology is defined as “knowledge and understanding of a design problem and its solution are acquired in the building and application of an artefact” (Hevner, M., Park, R. 2004). This methodology has been widely used in Information Systems research, primarily to identify the role and form of an IT artefact and has been growing in popularity over the past 15 years as it usefully provides an “interaction between research and practice” (Pascal, A., Renaud, A., 2020).

There exist three key cycles (Hevner, A.R., 2007) to the Design Science Research Methodology that describe the general approach:

- **Relevance Cycle**: determining what data of interest is contextually relevant to solving the problem which is subsequently used in informing the design of the artefact in the Design Cycle.
- **Design Cycle**: the determination of values and variability in the contextualized data, to define the scope of data that is of interest, this includes but is not limited to lower and upper bounds, contextual descriptors, and the like. The artefact is defined in the Design Cycle.
- **Rigor Cycle**: the application of the artefact and successive iterations to inform the Design Cycle again and refine the artefact for reapplication with the refinements to its design.

Figure 5: Design Science Research Methodology Cycles (Hevner, A.R., 2007)

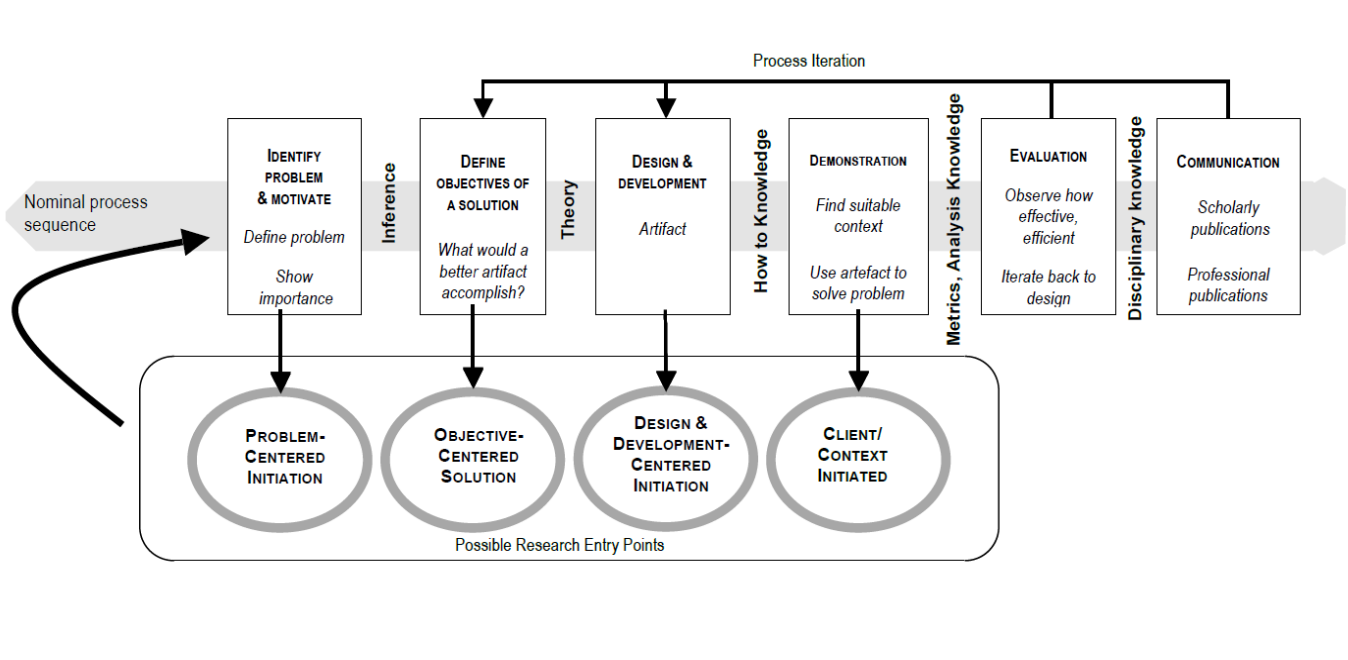


3.2. Applying the Design Science Research Methodology

The Design Science Research Methodology has been applied in this research using the six-step process as outlined by the Design Science Research Methodology process model in Figure 6: Design Science Research Methodology Process Model (Peffers, K., Tuunanen, T., Rothenberger, M.A., et al. 2007) below. This has allowed an artefact for habitual behaviour characterisation to be designed, developed, and refined, with the following specific interpretations for each step in the process model.

1. Identify Problem & Motivate
2. Define Objectives of a Solution
3. Design & Development
4. Demonstration
5. Evaluation
6. Communication

Figure 6: Design Science Research Methodology Process Model (Peffers, K., Tuunanen, T., Rothenberger, M.A., et al. 2007)



3.2.1. Identify Problem & Motivate

The motivation and importance of this research is that existing approaches are generally expensive, intrusive to participants, and the interventions are carried out in laboratory or laboratory-like settings. A cheaper, less intrusive, and free-living approach to supporting this type of intervention is the identified need.

3.2.2. Define Objectives of a Solution

A new artefact for processing data and characterising habitual behaviour would allow for greater accessibility to carry out this type of research in the health behaviour change space. This would be achieved by providing a simple hybrid process of automated analysis coupled with human definitions and guidance, following a prescribed “template” of data analysis and decision making.

3.2.3. Design & Development

Approaching the artefact design initially with a focus on ease-of-accessibility to researchers undertaking a pragmatic process using intuitive knowledge of what a health habit is then hypothesizing habitual envelopes of thresholds. This step would be revisited for refining the health habit envelope (the parameters of which the health habit consists of and is constrained by) further when applying it to real data using quantitative bounds.

3.2.4. Demonstration

Suitable contexts would be sought for the data analysis and application of the artefact. Three distinctly different data sets have had the artefact applied to them to help refine the artefact and to test whether the artefact is generic enough to suit most test cases.

3.2.5. Evaluation

With the artefact applied to the initial data set (case study 1: Simulated Tasks) a baseline reading, and understanding was achieved for expected workplace habitual behaviour. As this was a controlled behaviour sequence, the quantitative results provided a validation of the results against perfect ground truth. The artefact solution was then refined through the iterative process of the Design Science Research approach gradually from the feedback of case study 1, to reach stability. The artefact in its final form was then used as the desired instance of the flexible template to be applied in the two later case studies.

3.2.6. Communication

To communicate the artefact's design and application, conference papers were written and accepted after peer review for Global Telehealth 2018 (GT2018) (Poultney, N., Maeder, A., 2018), and IEEE Engineering in Medicine and Biology Society 2018 (EMBS) (Maeder, A.J., Poultney, N., 2018), and feedback from the peer review process was then reflected in the revision of the artefact. Conference papers of the artefact's application were also submitted to the 2021 Hawaii International Conference on System Sciences (HICSS) (Poultney, N., Maeder, Anthony., 2020) and Health Information and Knowledge Management 2021 (HIKM) (Poultney, N., Maeder, Anthony., 2021) conferences. While these conference papers were not accepted at these conferences, the feedback from the peer review process was further incorporated into the refinement of the artefact design. A further paper on the performance of the final form of the artefact was presented at the 14th PErvasive Technologies Related to Assistive Environments Conference 2021 (PETRA) (Poultney, N., Maeder, Anthony., 2021). An overall description of the project and its findings including the Design Science Research process and resulting artefact, have been submitted for review to the journal "Technologies" published by the Multidisciplinary Digital Publishing Institute (MDPI)

(Poultney, N., Maeder, Anthony., 2021), as an overarching descriptive paper detailing the whole research contribution.

3.3. Data Collection Process

The data has been collected using Fitbit wearable devices, specifically the Fitbit Charge HR 2. This was the mid-range consumer grade Fitbit device model available at the time of the data collection phase of this research and well suited to recording participant step count data. The data could then be extracted from the devices using the Fitbit APIs available through their servers at 1-minute resolution.

Similarly, cheap Bluetooth beacon devices roughly the size of a key fob were chosen for use in the second case study as several of them placed around the office space were sufficient in mapping out participant movements. This is in conjunction with the use of a mobile application that utilises Bluetooth on the participants mobile phones.

3.4. Determining Data Relevance

The data can initially be analysed quantitatively starting with the high-level classification of active or sedentary binary values for each data point. This is the initial delimiter for the periods of physical activity an individual exhibits at any given time of any day. In large data sets, earlier data cleansing using Pareto analysis will have eliminated a large quantity of sedentary data points, easing the difficulty in hypothesising initial parameter values for finding instances of health habits.

Once the active and sedentary data points have been identified the next step is to identify periods of time with consistently higher consecutive ‘active’ steps that lie between ‘sedentary’ data (step count values of zero or below an imposed minimum threshold e.g., <5 steps in a minute) points that are either singular or consecutive. This allows for peak periods of activity to be identified which will at some point drop off to no activity. This aspect of a health habit that is to be identified quantitatively as the ‘peak periods’ of activity will vary (sometimes greatly) across individuals. The step counts for these data points across a specific period of time are crucial in classifying the various types of patterns discovered to be of a similar nature.

Figure 7: Determining Data Relevance

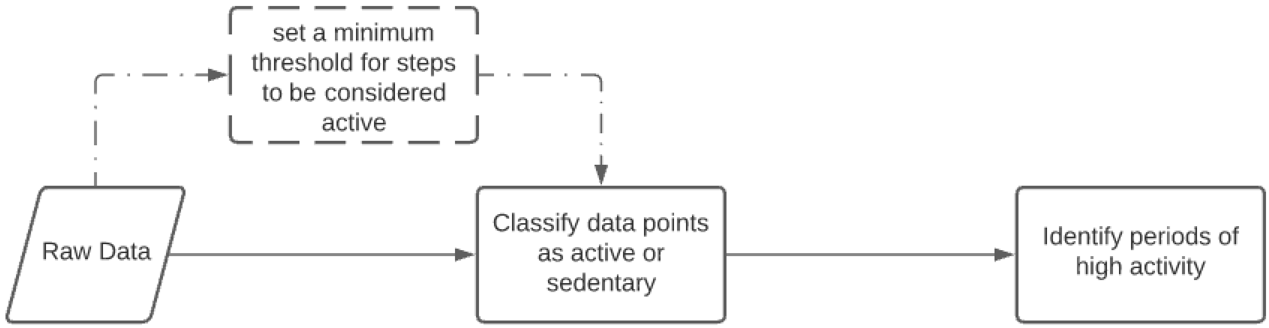


Table 3: Raw Data Example

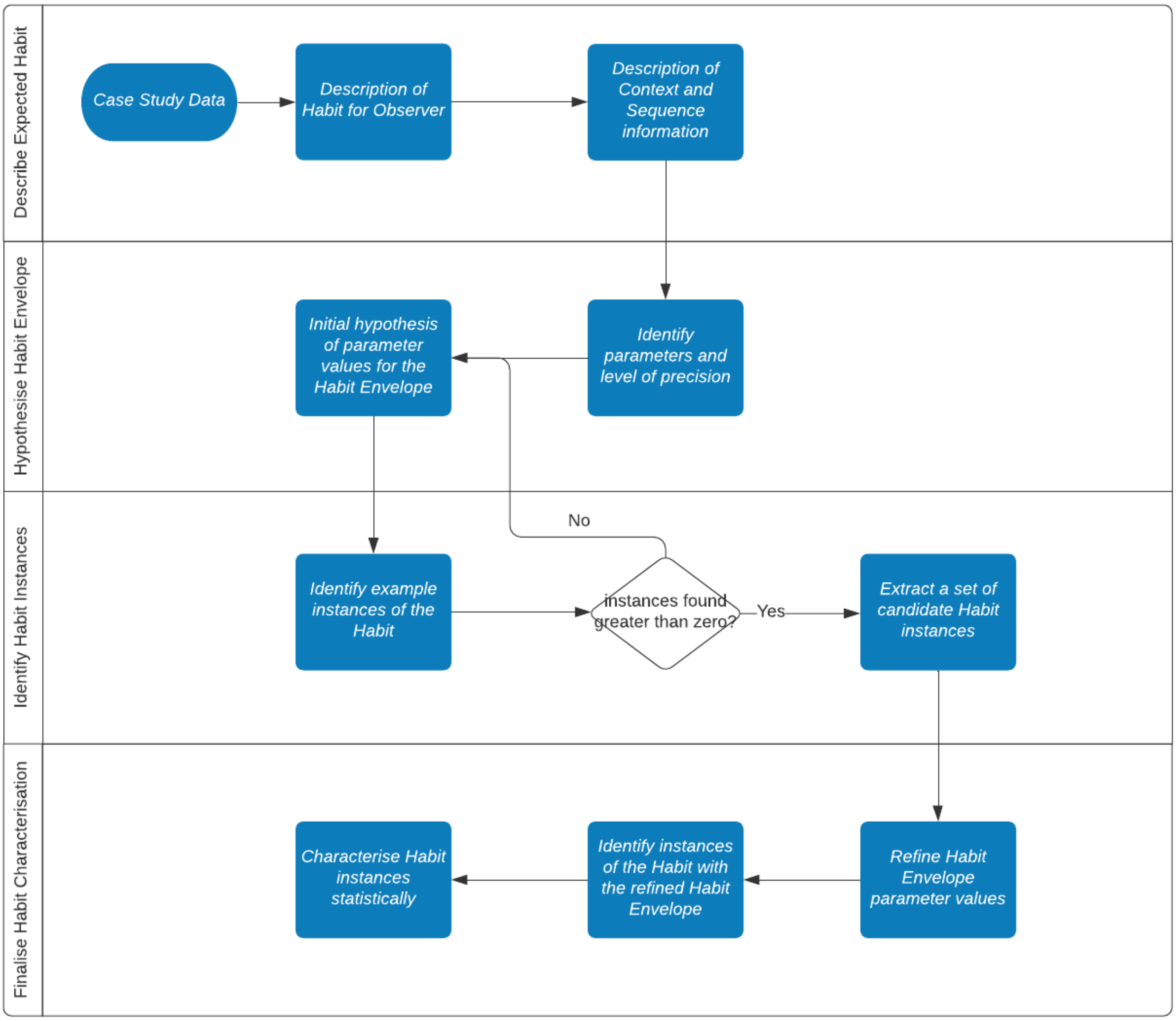
Minimum steps for a data point to be considered “active” set as 5 steps in any given minute.

Timestamp	Step Count	Active?
9:42:00 AM	26	Active
9:43:00 AM	43	Active
9:44:00 AM	37	Active
9:45:00 AM	39	Active
9:46:00 AM	77	Active
9:47:00 AM	74	Active
9:48:00 AM	0	Sedentary
9:49:00 AM	3	Sedentary
9:50:00 AM	34	Active

3.5. Processing Pipeline

Through the application of the Design Science Research Methodology, the design, development, and refinement of the solution artefact is achieved through six steps. The six steps of the Design Science Research Methodology have been distilled into four distinct phases for the practical process of creating the solution artefact which is titled the DHIF-PP artefact (Describe, Hypothesise, Identify, Finalise – Processing Pipeline). The phases and flow of steps are shown in Figure 8 below along the vertical row headings. With the steps explained in detail in the text that follows for the process of describing, hypothesising, identifying, and finalising the parameters of a health habit characterisation. A health habit being repeated pattern of healthy behaviour by an individual over a period of time.

Figure 8: The Four Phases of the Processing Pipeline



1. Describe Expected Health Habit

In the first phase the health habit is initially to be described to the observer. e.g., “a short walk to immediate workplace surroundings such as coffee area or bathroom and then returning to office desk”.

Then the observer provided with a description of the context and sequence information to delimit the health habit. e.g., “several times per day, generally between periods of sedentary behaviour and usually involving continuous walking with a short sedentary period in the middle”.

2. Hypothesise Health Habit Envelope

In the second phase identify what the parameters are and their precision that would be used or useful to collect during the health habit for characterisation purposes. e.g., step count at 1-minute resolution, timestamps at 1-minute resolution, proximity detection at origin and destination binary value at 1-minute resolution.

Then an initial hypothesis of parameter values is defined (transition or continuity constraints envelope). The thresholds or "window sizes" have typically been "vaguely characterised" with no clear consensus on window size preferences to be employed relying on the figures used in previous works (Banos, O., Galvez, J.-M., Damas, M., et al. 2014).

Step counts at 1-minute resolution and with as little data as 7 days has been found to be sufficient in detecting health habits and physical activity patterns (Nicolai, S., Benzinger, P., Skelton, D.A., et al. 2010), (Feehan, L.M., Lu, N., Xie, H., et al. 2020). In one case 72 hours of data at 1-minute resolution yielded useful results (Egerton, T., Brauer., S., 2009).

3. Identify Health Habit Instances

The third phase involves identifying some examples of instances/occurrences of the health habit with the hypothesised parameter values. If there are one or more instances of a health habit found with the hypothesised parameter values, then a set of "candidate" health habit instances are selected pragmatically. However, if no health habit instances were found then return to the second phase and hypothesise new parameter values.

4. Finalise Health Habit Characterisation

In the fourth phase the health habit envelope of parameter values (thresholds) is refined. Then an attempt is made to identify more health habit instances with the new parameter values and rejecting health habit instances that no longer fall within the new health habit envelope parameters, finishing with the characterisation of the health habit instances statistically.

3.6. Health Habit Variants

The health habits can be classified into "Health Habit Variants" based on their characteristics. These classifications have been devised to be used as a high-level description of the identified health habits. There are three different variants of health habit size defined as part of this research. Each type of health habit size variant has a differing period-of-time and thus a different understanding is involved around describing the health habits.

- Micro (extremely small/small) – The Micro health habit variant is the most difficult variant to identify due to its short transient nature. Very close pragmatic observation of a data set is required to determine if there are any micro health habit variants in a data set. An example of a Micro health habit variant may be defined as an active → inactive → active sequence of events in which the start and end time is extremely short such as 3 minutes in total duration. These types of health habit variants can be difficult to distinguish from the noise in a data set. An example of this might be a short walk from an office desk to a watercooler, then back to the office desk all within 3 minutes.

- Meso (middle/intermediate) – The Meso health habit variant is subtle to identify as it is larger than Micro but smaller than Macro. These health habits are generally more distinctive than Micro and the markers to identify them are significantly clearer than those of the Micro health habit variant. An example of a Meso health habit variant may be defined as an active → inactive → active sequence of events in which the start and end time is a moderate length, enough to perform a specific task. For example. a 10-minute total duration would make a Meso health habit variant easier to identify than a Micro health habit variant, as the tasks that make up the sequence on average will occur for a longer duration of time each and stand out more clearly from the noise in the data. An example of this might be a walk from an office desk to a cafeteria elsewhere in the building to purchase a take-away refreshment, and back to the office desk.

- Macro (large-scale/overall) – The Macro health habit variant characterises the most prolonged variant, which is the easiest to identify as it covers a significantly larger period of time than the others. Macro health habits are relatively infrequent compared with Meso and Micro, due to this lengthier nature. An example of a Macro health habit variant may be defined as an active → inactive → active sequence of events in which the start and end time is a long period of time in which either a specific task or series of tasks is undertaken. An example of this might be a walk from an office desk out to the office building precinct, and then a few laps around the office building (e.g., while having a phone conversation) and finally returning to the office desk, which might be approaching one hour in duration.

The Meso health habit variant type can also include Micro health habit variants within it. Similarly, the Macro health habit variant type can include Meso and Micro health habit variants within it.

The health habit variants are a way of classifying the characterised data for further representation and analysis. They allow for pragmatically applying some intuitive classifications across multiple data points, tying them together to form a high-level overview of the health habits they encompass.

3.7. Example Application of the DHIF-PP Artefact

The following example application of the DHIF-PP artefact describes each step that is taken when using the DHIF-PP artefact utilising the four phases of the processing pipeline.

3.7.1. Describe Expected Health Habit

A basic example of a health habit may be an office worker who routinely has a walk of a morning upon arriving at the office, that is generally of a similar distance and time duration. This walk is followed by a long period of sedentary or low-activity behaviour (whether that be them working at their desk or in a morning meeting). This could be viewed as a sequence of health habits: “start-of-day walk followed by sedentary period repeated daily weekdays”. Characterising a sequence of health habits in this way allows for insights and a more holistic view of a participant’s daily health habits and routines.

3.7.2. Hypothesize Health Habit Envelope

At this stage of the process, a hypothesis is proposed for what the health habit envelope might look like. It is hypothesized that if the participant is in the office as confirmed with data from Bluetooth beacons and a mobile application on their smart phone, that this participant will leave their office at some point to get food or a beverage at the coffee area. Then they will return to their office immediately after. In this instance, there will be Bluetooth beacons that can confirm the location of the participant throughout their movements in the building. We hypothesize that we will see repeated trips to the coffee area following the sequence of

“Office → Coffee → Office”. The time duration may differ greatly due to the intention behind the trip to and from the Coffee area. Therefore, the time component of the hypothesized health habit envelope in this case is defined as >2 minutes and <20 minutes, given the distance from the office to the coffee area it is estimated that to get from one location to the other is a 5-minute walk, then a period of up to 10 minutes in the coffee area before a 5-minute return walk back to the office. The walk itself is hypothesised to range between >2 minutes and <5 minutes with time spent at either side of the health habit in the office being a minimum of >2 minutes in duration. The period spent at the coffee area likely to have the most variance depending on the purpose of the trip to the coffee area (e.g., if the participant is at the coffee area for a one-hour lunch break compared to being at the coffee area to make a coffee). An initial identification of any “Office → Coffee → Office” sequences will allow for refinement around the expectations of the Health Habit Envelope.

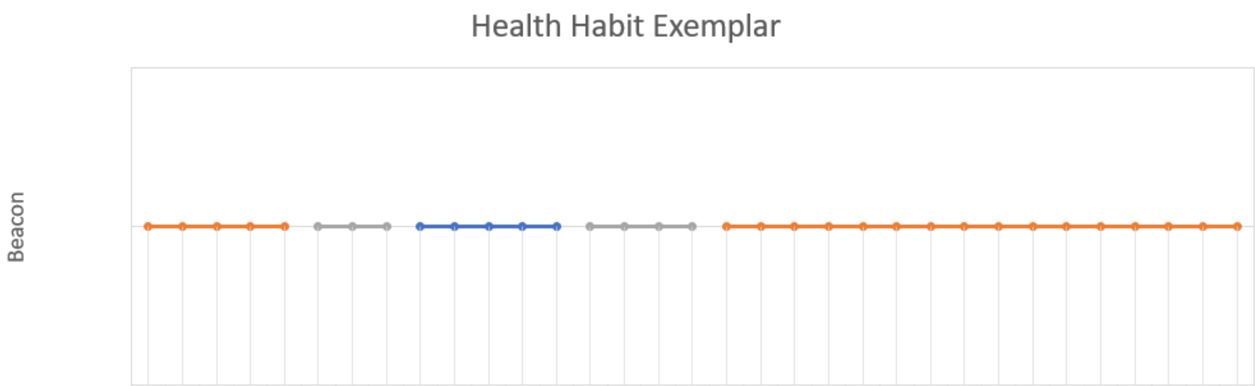
3.7.3. Identify Health Habit Instances

In Figure 9 below binary data points of 1 are used for indicating when a participant was present in a particular location within a data set and a blank entry that indicates when the opposite was true. In this example a health habit is present in which at 10:14am the participant is in the office as identified with a Bluetooth beacon in combination with a mobile application on their smart phone. The participant leaves the office space for a period of time at 10:16am and then is found to be located within the coffee area at 10:20am, followed by a return to the office at 10:29am. The hypothesized health habit of “Office → Coffee → Office” has been identified.

It is to be noted that once a location has been logged for the participant via the Bluetooth beacons and smartphone, the location is not necessarily logged continuously whilst they are within the vicinity of the Bluetooth beacon. This implies that the participant whilst initially left the office area at 10:16am the participant was most probably walking to the coffee area until the minutes leading up to 10:20am.

Further instances of the “Office → Coffee → Office” health habit would then be identified using the previously hypothesised parameters with refinement to occur in the next and step of the processing pipeline if little or no habits have been found with the parameters.

Figure 9: Health Habit Exemplar

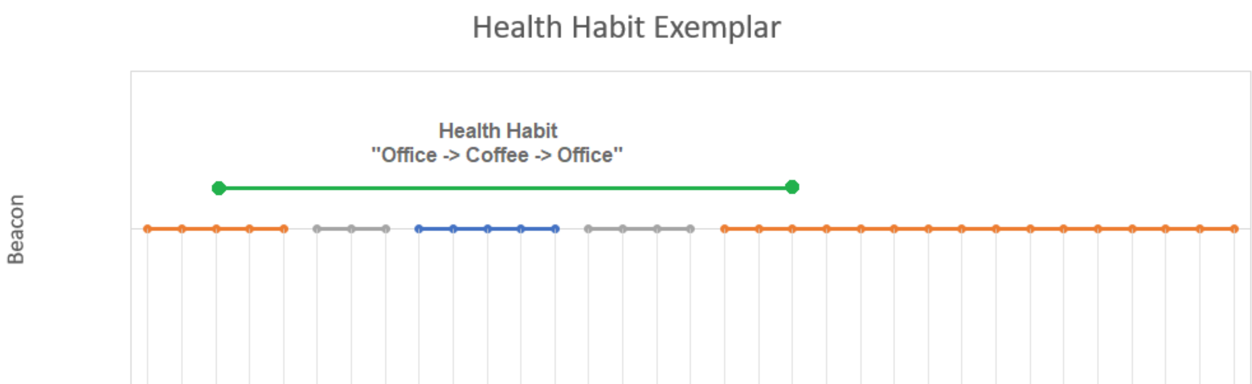


	10 AM :12	10 AM :13	10 AM :14	10 AM :15	10 AM :16	10 AM :17	10 AM :18	10 AM :19	10 AM :20	10 AM :21	10 AM :22	10 AM :23	10 AM :24	10 AM :25	10 AM :26	10 AM :27	10 AM :28	10 AM :29	10 AM :30	10 AM :31	10 AM :32	10 AM :33	10 AM :34	10 AM :35	10 AM :36	10 AM :37	10 AM :38	10 AM :39	10 AM :40	10 AM :41	10 AM :42	10 AM :43	10 AM :44
coffee									1	1	1	1	1																				
office	1	1	1	1	1													1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
unknown						1	1	1						1	1	1	1																

Timestamp

The health habit once identified and characterised can then be annotated visually using a line to distinguish the health habit within the graph, shown in Figure 10 below.

Figure 10: Health Habit Line Exemplar



	10 AM :12	10 AM :13	10 AM :14	10 AM :15	10 AM :16	10 AM :17	10 AM :18	10 AM :19	10 AM :20	10 AM :21	10 AM :22	10 AM :23	10 AM :24	10 AM :25	10 AM :26	10 AM :27	10 AM :28	10 AM :29	10 AM :30	10 AM :31	10 AM :32	10 AM :33	10 AM :34	10 AM :35	10 AM :36	10 AM :37	10 AM :38	10 AM :39	10 AM :40	10 AM :41	10 AM :42	10 AM :43	10 AM :44
coffee									1	1	1	1	1																				
office	1	1	1	1	1													1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
unknown						1	1	1						1	1	1	1																

Timestamp

At this point the primary health habit identification and characterisation is complete.

3.7.4. Finalise Health Habit Characterisation

Now the Health Habit Characterisation is refined: if there are ambiguities in the data this is the stage in which the Health Habit Envelope boundaries should be tightened such as if there does appear to be a sequence of "Office → Coffee → Office" but the travel time from the office to coffee area is on average >7 minutes and less than <10 minutes than the originally hypothesised values (>2 minutes and <5 minutes) could be altered to catch these instances.

Previously identified health habits are rejected if they no longer meet the refined criteria. If there is more data to be processed, then the latest iteration of Health Habit Envelope is applied.

In this instance the Health Habits are well defined with the combination of location data from the Bluetooth beacons and the timestamps at 1-minute resolution.

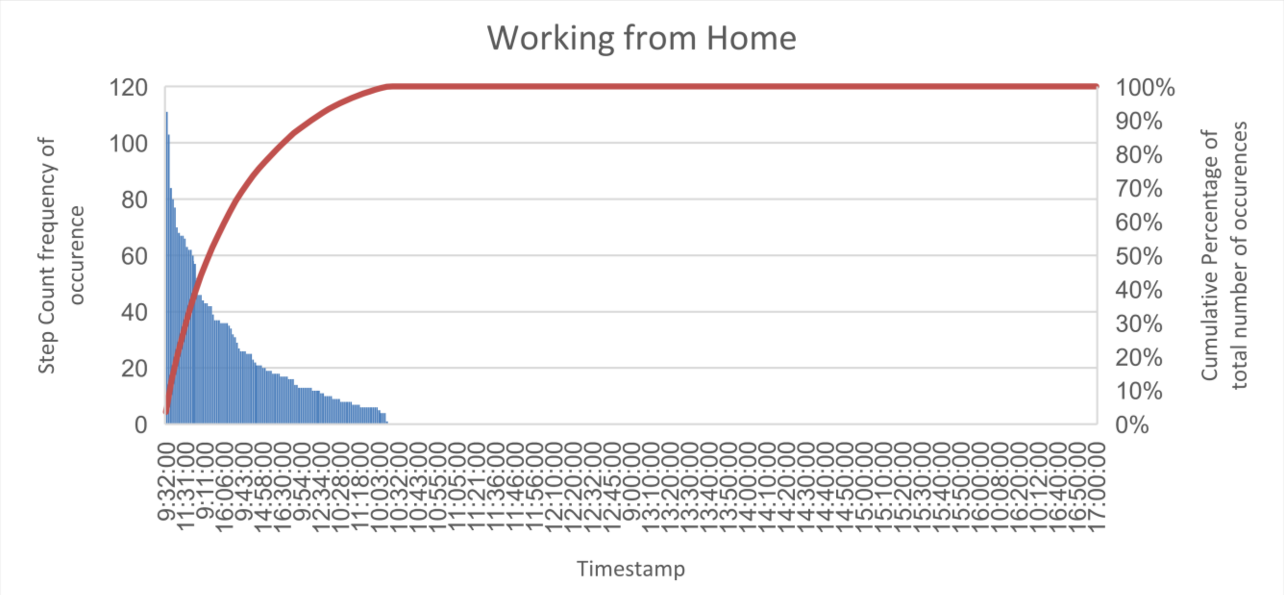
3.8. Pareto Analysis

Pareto Analysis is a technique used for identifying the top portion of causes which need to be addressed to resolve most of the problems (Montgomery, D. C., 1991). Pareto analysis is often referred to as the "80/20" (or similar proportions) rule which assumes the top portion is approximately 20% of the causes and the remaining approximately 80% are the problems. This technique is thus also commonly described as the "vital few and the trivial many". Pareto analysis is often used in areas like quality control where specific actions are associated with managing causes and problems, although it is not limited to this domain.

In the context of this research, Pareto analysis is used to identify the minority of the step count data that accounts for the dominant health habits in extremely large data sets, or data sets which after initial observation appear to be reasonably complex, so as to ascertain a sensible starting point for the analysis process. Pareto analysis can be used in this way to determine the most significant periods of time where activity is occurring for further analysis in very large data sets: this is the context in which we are working with our datasets of many thousands of step count values. The size of consecutive runs of step count entries will make it clearer that it is a large or small environment (in the instances where there is no location or contextual data to reference), as the data sets are at a fine granular 1-minute resolution across a 24-hour period, over several days (or weeks). Because of this level of resolution and the workplace environment where subjects have largely stationary jobs, there will generally be more entries of zero step count than entries of non-zero step count. This is the initial step for understanding where to begin searching for patterns in the data set.

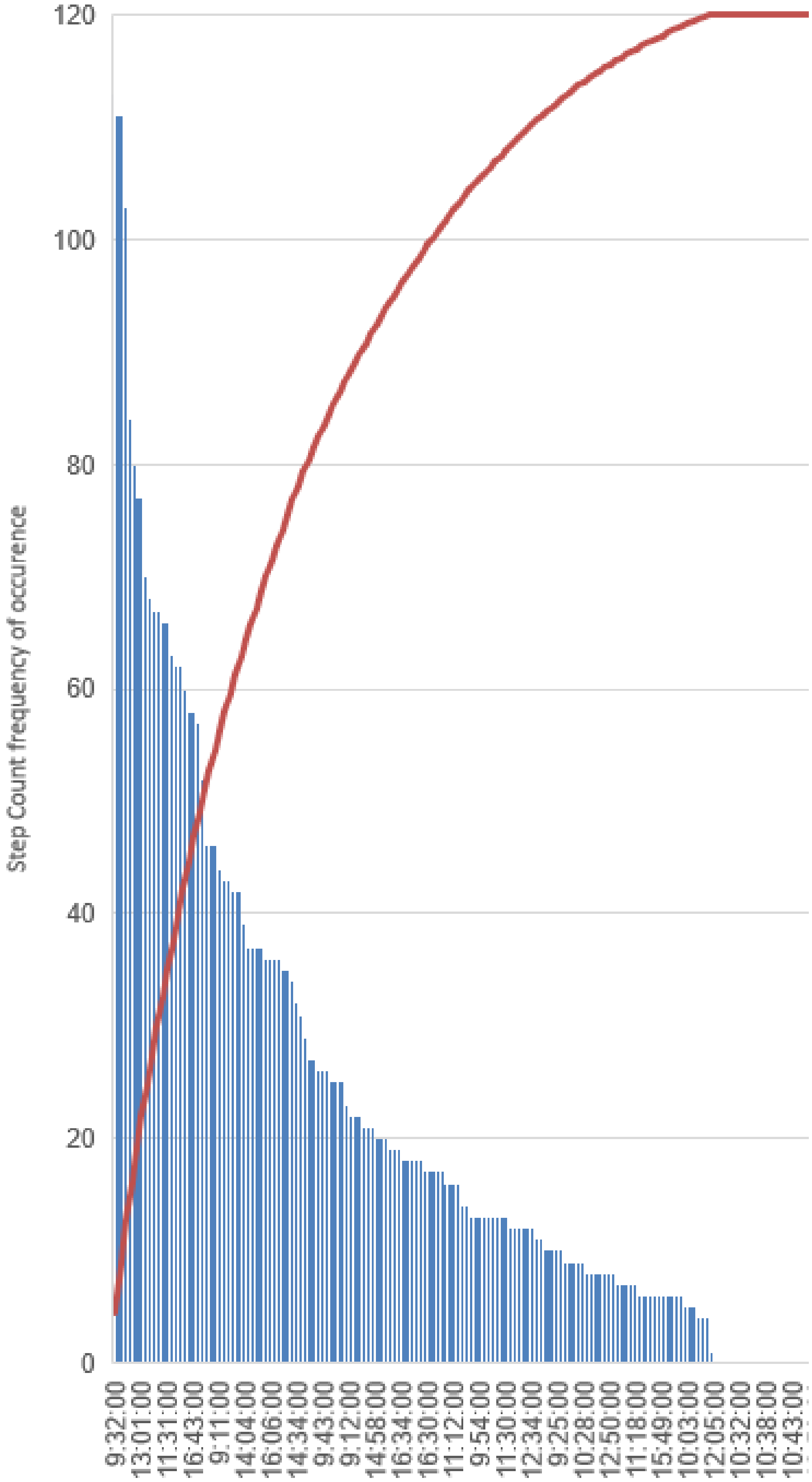
The Pareto chart in Figure 11 below was generated from a single day of working from home data of a sample participant applied to the hours from 9am through to 5pm. It can be observed from the Pareto chart that timestamps on the left of the cumulative total line are the timestamps of most interest. They are of the most interest due to the statistically higher quantity of step counts measured at those times in the 24-hour period. The Pareto chart helps to identify the starting point for applying the DHIF-PP artefact.

Figure 11: Pareto Chart Exemplar



Below in Figure 12 is a magnified version of Figure 11 for easier readability of the data and timestamps.

Figure 12: Pareto Chart Exemplar Magnified



3.9. Limitations

The scope of discussion here has been limited to the characterisation and identification of walking activities. Conversely the same form of description could be used for sedentary activities. It is beyond the scope of this research for the characterisation of vigorous exercise health habits to be examined although it may be possible to extrapolate to characterise and identify running or similar vigorous exercise outside the bounds of a constrained workplace setting. Similarly, unconstrained environments such as vast outdoor areas like farms might be of interest for future research to expand upon the DHIF-PP artefact derived from this research.

Some scenarios that may not be suitable for the application of the DHIF-PP artefact could include where there are too many variables making a feasible zone for an envelope difficult. Instances where variables are not logically connected like sitting and standing (stationary) compared to standing and walking (movement). In a data set where there is a uniform spread in values the Pareto approach would not be feasible in identifying a good starting point for the data analysis.

3.10. Conclusion

This chapter has described the conceptualisation and process of arriving at the DHIF-PP artefact for use in habit characterisation. A worked example of how it might be applied to a synthetic case has been provided. The next three chapters will present three case studies of the template-driven pragmatic approach described above applied to three different situations. Case study 1 describes the initial groundwork for trialling the approach in which some simple simulated activities were considered. Case study 2 of common office worker movement habits further demonstrated the general applicability of the approach as it introduced more complexity in the characterisation process. Case study 3 applied the approach to two longitudinal data sets of two different participants, in two different locations, thereby showing how the approach can be applied in realistically varied settings.

4. CASE STUDY 1 – SIMULATED WORKPLACE TASKS

4.1. Overview

This chapter reports on the first of three independent case studies for application of the DHIF-PP artefact. This case study was undertaken using a small cohort of volunteer participants simulating examples of typical expected workplace habitual behaviours involving tasks with either "simple" repetitive movement tasks (e.g., walking, climbing stairs), and "compound" movement tasks constructed from successive phases of these simple tasks, perhaps but not necessarily separated by inactive periods. Simulation of these tasks by the participants provided an initial baseline assessment of the DHIF-PP artefact. Prior work has used such an initial simulation of tasks successfully for establishing baseline properties of expected physical activity monitoring outputs and their analysis (Shoaib, M., Bosch, S., Scholten, H., et al. 2015).

The data collected for this case study was cumulative step counts and timestamps, each at a 1-minute resolution. The choice of these two data items was made on the basis of constructing a minimal plausible data set for these kinds of health habits. This first case study provided an initial demonstration of the DHIF-PP artefact's application, giving an indication that the approach was fit for the intended purpose, and enabling experimental calibration of the parameters for conducting the intended characterisation of health habits and analysis of results. It also assisted in shaping and refining the DHIF-PP artefact within the iterative cycle of design science research, for further applications with other case studies.

4.2. Aim

To establish the utility and robustness of the DHIF-PP artefact for a range of simulated typical habitual behaviour activities in an open plan multi-storey office environment, using trained participants to undertake a set of specified activities with deliberate repetition. Further to identify any significant limitations and/or required modifications to the DHIF-PP artefact. The research questions to be answered are as follows:

- Can a set of simulated activities establish a reasonable baseline reading for the types of activities officer workers are hypothesised to exhibit?
- What are the limitations of the simulated activities?

4.3. Methodology

The site for this case study was a large multi-storey office environment as to ascertain what typical officer worker movements would look like in the data, the Tower building at Flinders University Tonsley Campus. The overall workplace structure is of open-plan desk seating around the periphery of each floor, with a row of internal offices delineating the open-plan area from the central core space of the building. In the central core are numerous meeting rooms, personal social areas, and a central public space on each level. There are multiple connectivity options within and between levels, consisting of corridors, stairs, and elevators. This contextual information provides a scaffold for understanding the types of typical movement-based physical activities that individuals may undertake during their workday. This workplace was selected for this first case study as it was expected that characterisations of habitual behaviour would be able to be made more accurately in such a constrained environment than in an unconstrained (e.g., outdoor) setting.

Typical worker activities observed informally consisted of fetching and delivering items, attending meetings, making presentations, and using facilities such as coffee machine or bathroom. In this environment, different individuals were able to establish their own sets of health habits independently and could choose different activity patterns for the same type of task (e.g., preferring different meeting locations or taking different routes to the same destination). However, for highly repetitive activities (e.g., bathroom visits), it was noted that individuals tended to take the most direct paths. This relatively constrained and structured setting lends itself to a limited choice of paths from one location to another, especially if within close proximity. This is a workplace environment in which sedentary habitual behaviours are often the most dominant, generally for several prolonged periods throughout the working day.

The case study data set collected in this setting consisted of three different simulated tasks performed with eight repetitions and a Long Walk task which was repeated four times by three human participants, all of whom were young (20-30 years-old) adult males chosen to participate due similarities in levels of physical fitness and age, and height. The simulated tasks were designed to replicate typical office physical activity health habits which had already been noted through informal observation. These tasks were specifically:

- a simple Long Walk activity, consisting of a single concentrated period of sustained walking from one corner of the building (open-plan office space) to the opposite corner (meeting room),

- a compound Short Walk activity, with two periods of limited walking (from desk to public space or vice versa) separated by a minor period of inactivity (making a cup of coffee).

- a compound Stairs climbing activity, commencing with the participant walking up two flights of stairs, followed by a 5-minute period of inactivity, then proceeding to walk back down the stairs to the start location.

- a compound Meeting activity, commencing with the participant walking for approximately 300 steps, followed by a 5-minute period of inactivity to simulate a meeting, then proceeding to walk back to their initial location.

A 'simple' activity is referred to as a 'Type 1' activity and a 'compound' activity is referred to as a 'Type 2' activity for the purpose of this case study to clearly distinguish between the two different sequences of activity.

All participants were given a uniquely identified fully charged Fitbit to wear for the duration of the data collection exercise, which took about 2 hours in total. Fitbit devices were chosen as they are a mainstream reasonably inexpensive consumer grade monitoring device that aligns with the objectives of this research. Each activity had a predefined path of travel to observe a consistent period of travel that could be compared from one participant to another, and the start time and end time were recorded. The activities were undertaken in between multi-minute periods of "passive sedentary" inactivity typical of an office worker, and to ensure that successive repetitions of the same activity were somewhat independent to reduce the learning effect.

The average step is being characterised as having the following attributes for the purposes of this research under the assumption that individual's height is not generally measured in the context of this research:

- Step range: approximately 90 to 110 steps per minute.
- Individual's height: approximately 6 ft.

Participants have not had their height measured or step range assessed. In a laboratory-type setting with numerous monitoring instruments step range and leg length would be of greater importance where habit identification is sought after with extreme precision.

The data processing was a manual task. Future work may look to automate aspects of the process in the initial phase when dealing with the raw data and the process of cleaning the data using software e.g., a data processing automation script developed with a programming language such as Python.

4.4. Results & Analysis

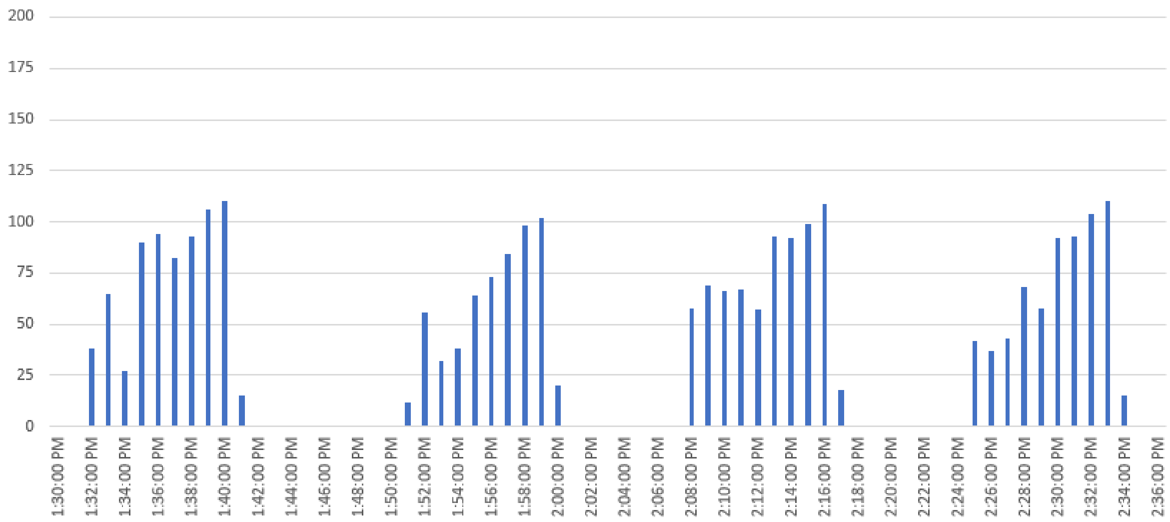
The four types of activities undertaken by the participants as mentioned above were predefined with initial estimations of their profiles as shown below in Table 4, based on prior informal observations by the author as to the typical daily activities officer workers exhibit in the office space. The activities are broken up by periods of inactivity specified by the minutes in which the participant did not record any step counts indicating the participant being in a sedentary state.

Table 4: Predefined activity descriptions

Activity	Estimated Time & Step	Activity Profile
Long Walk (single sustained – Type 1)	**Activity:** >3min >300stp	Inactive >3 min **Active Type 1** Inactive 3 min
Short Walk (two separated phases – Type 2)	**Activity:** >1min <3min >50stp <150stp **Inactivity:** <2 min	Inactive >2 min **Active Type 2** Inactive <2 min **Active Type 2** Inactive >2 min
Stairs (two separated phases – Type 2)	**Activity:** >2min <6min >180steps <250steps **Inactivity:** >4min	**Active Type 1** Inactive >4 min **Active Type 2**
Meeting (two separated phases – Type 2)	**Activity:** >6min <10min >225steps <400steps **Inactivity:** >6min <10min	**Active Type 1** Inactive <6 min **Active Type 2** Inactive <6 min

Each Activity will now be considered in more detail, showing the types of variations which may affect health habit identification using such measurements, and demonstrate application of the DHIF-PP artefact to them.

The Long Walk was a simple single-phase activity (termed a ‘Type 1’ activity) which commenced with the participant in a sedentary state, followed by walking to a distant location with a deliberately increasing pace, and then assuming a sedentary state on arrival. Typical results for all four repetitions of the Long Walk are shown for each of the three participants in Figure 13 below. In these and subsequent graphs, the X axis shows clock time in 1-minute intervals, and the Y axis shows step counts for each time interval.



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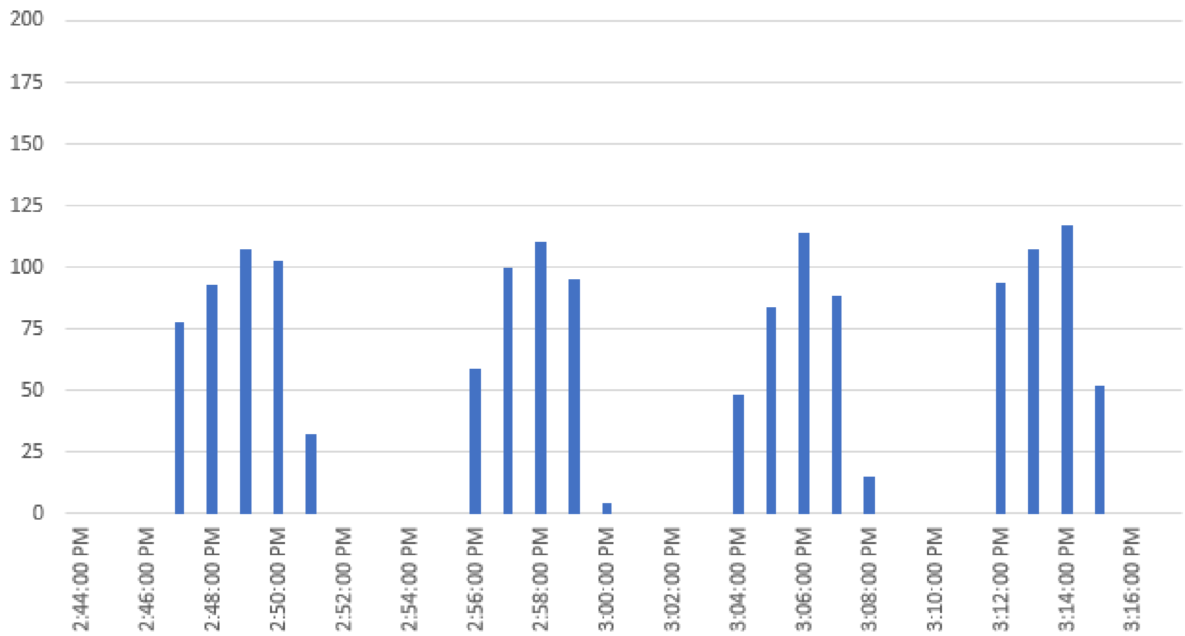

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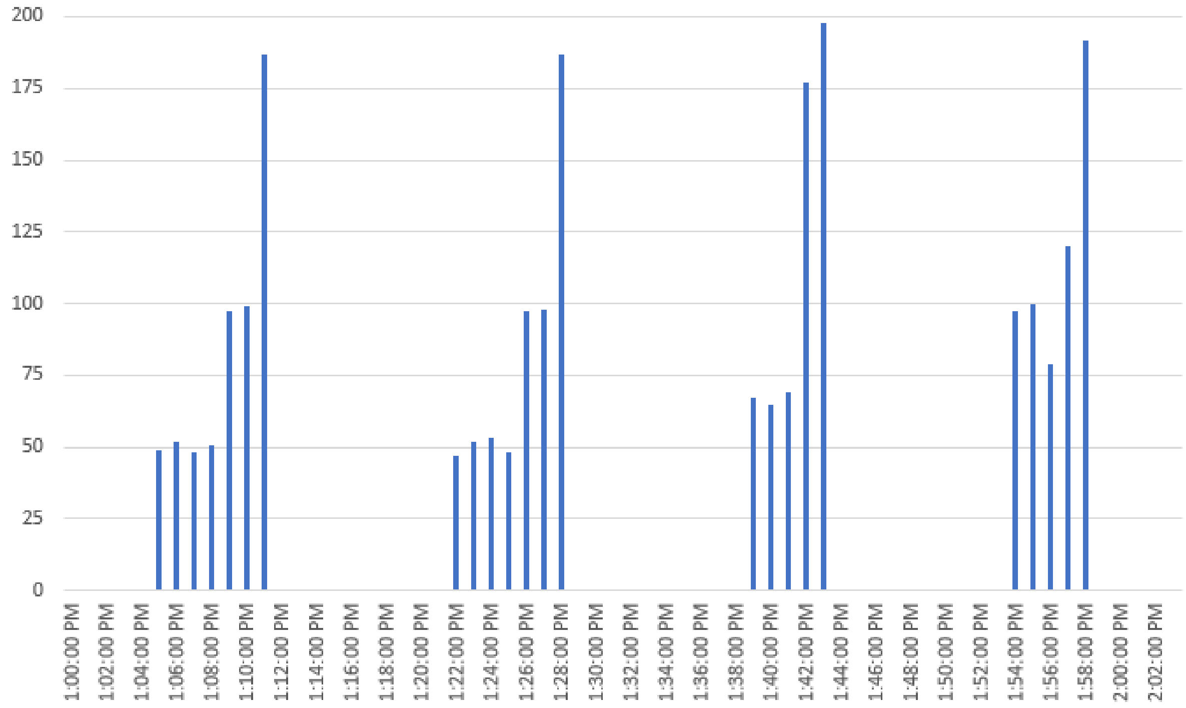


Figure 13: Step and Time data for Long Walk activity (respectively for participants A, B, C)

One might hypothesize the typical Long Walk graph profile would show a natural upward trend due to the instruction given to participants to attempt an increasing pace, with the earlier slower walking pace taking a longer duration with lower step count, compared with the later faster pace. However, this idealized form is not seen consistently across the participants. Differences in levels of fitness and body size would affect stride and gait of the participants. The variations in overall time duration and total step count between the three participants on this account are clearly visible. The high degree of consistency for each individual participant's profile is also apparent.

It is interesting that participants A and B had a similar rate of steps per minute for a large part of the Long Walk activity in comparison to participant C where there was a sudden large increase in steps per minute towards the end of the activity. Participant C perhaps felt time pressure while completing the activity and increased their speed as a result whether consciously or subconsciously.

The DHIF-PP artefact was then applied to characterize these datasets. For the first step, sequences within the data of a period of at least 3 minutes of inactivity before, and again after, a continuously active period of at least 3 minutes, were extracted based on the estimates of Table 4 above.

The next step required the time and step parameters for the activity to be refined for all instances which had been preserved by the data cleansing, from the raw data. Table 5 below shows the characterisation results for these three participants, obtained using all four repetitions each.

Table 5: Parameters for Long Walk Characterisation

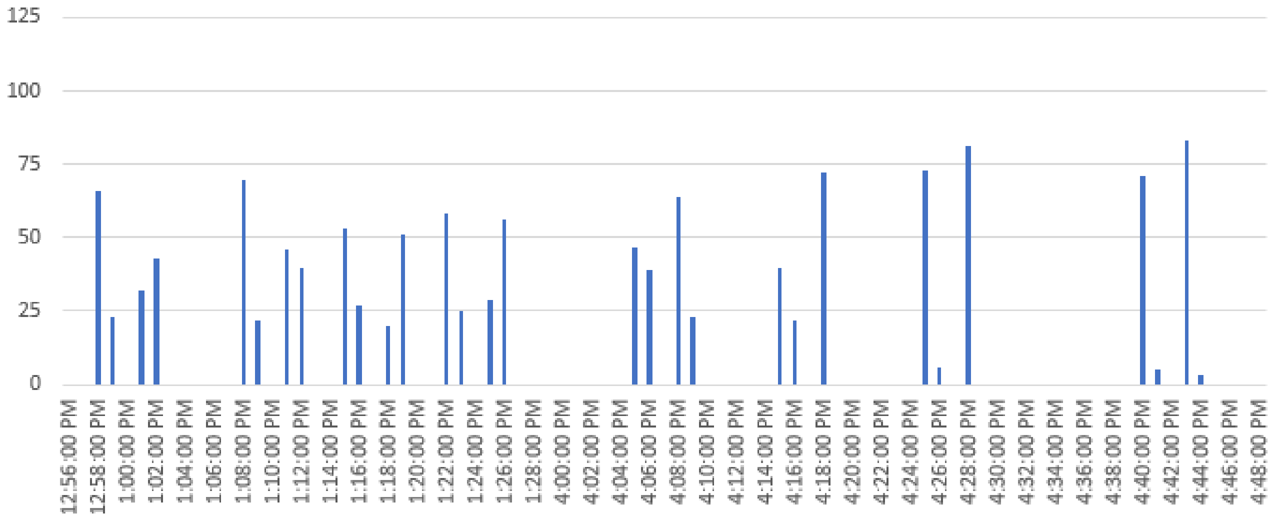
Participant	A	B	C	All
Activity Type 1 - Steps (Mean)	672.25	375.00	582.25	543.17
Activity Type 1 - Steps (Std Dev)	13.40	107.62	15.04	53.93
Activity Type 1 - Time (Mean)	10.00	4.75	6.00	6.92
Activity Type 1 - Time (Std Dev)	0.00	0.50	1.15	0.58

The next step was achieved by constructing a statistical model for the activity, using the above tabulated parameters. As this was a simple activity, using parameter mean and standard deviation was deemed to provide a suitable model to include all eight cases, for each participant.

The last step was achieved by combining the three sets of participant parameters to provide an overall inclusion envelope, shown in the column labelled ‘All’ in Table 5 above. Due to the wide dispersion of the data parameters across the three participants, two standard deviations were chosen around the overall mean to define the activity envelope. This again allowed inclusion of all twenty-four cases having Long Walk characteristics.

While this characterisation envelope construction used a basic statistical approach due to the intrinsic simplicity of the type of activity, it would be expected that more robust statistical or parametric approaches are needed for cases with more complex patterns, or more highly variable participant data. For example, the skewness in the successive minutes for an instance of this type of activity could be incorporated with an additional parameter based on a higher order statistic.

The Short Walk was a compound activity which commenced with the participant sedentary, then walking to a nearby location at a constant pace, remaining inactive there for at least 1 minute, then proceeding back to the start location and resuming a sedentary state. This ‘Type 2’ activity thus consists of a two-part walk with an intervening non-walk period i.e., three components. Typical results for all eight repetitions of the Short Walk are shown for each of the three participants in Figure 14 below.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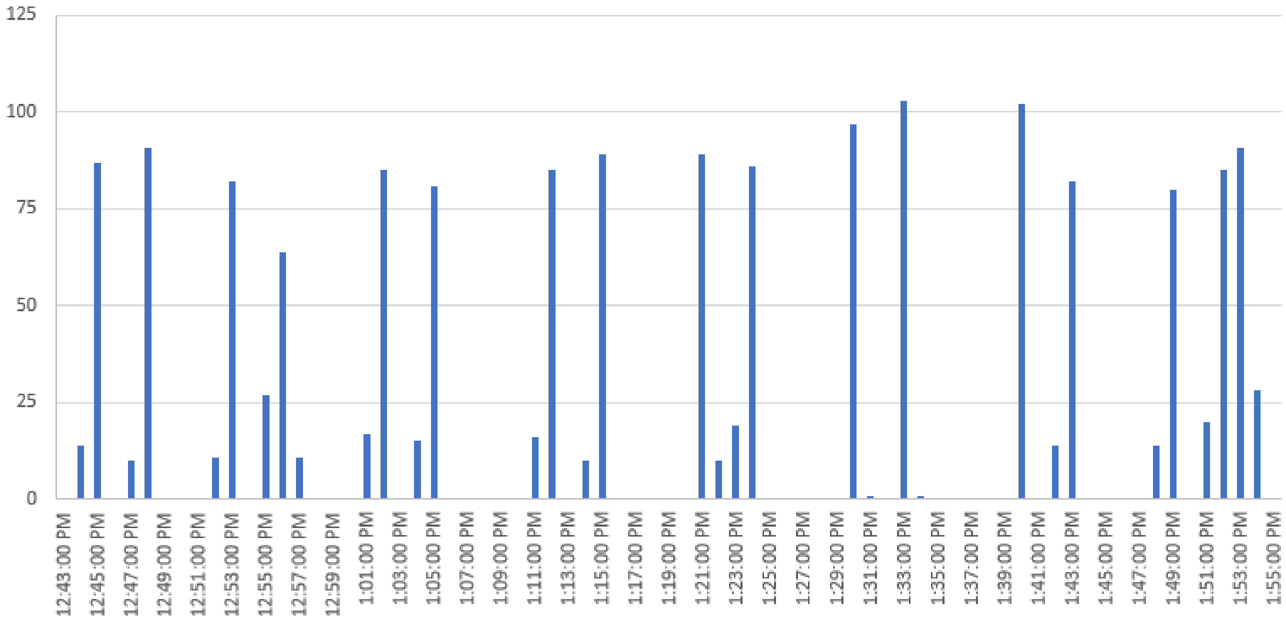
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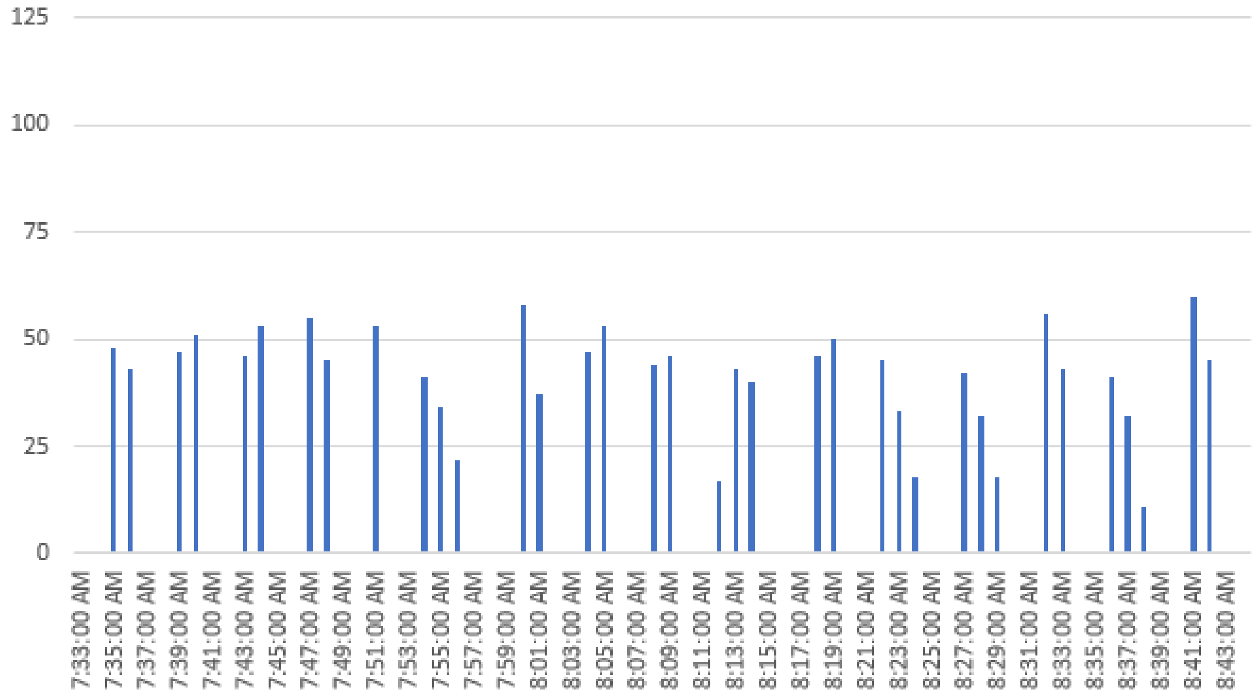


Figure 14: Step and Time data for Short Walk activity (respectively for participants A, B, C)

It can be seen in Figure 14 that the Short Walk activity appears to have less variation than the Long Walk, within and between participant data, for both the overall step counts and time durations. However, the component step counts in adjacent minutes can vary considerably because of the randomness of the exact starting time within the 1-minute sampling resolution. The short period of inactivity between pairs of walking activities can be seen to be consistent because it corresponds to a discrete action (e.g.,, making coffee).

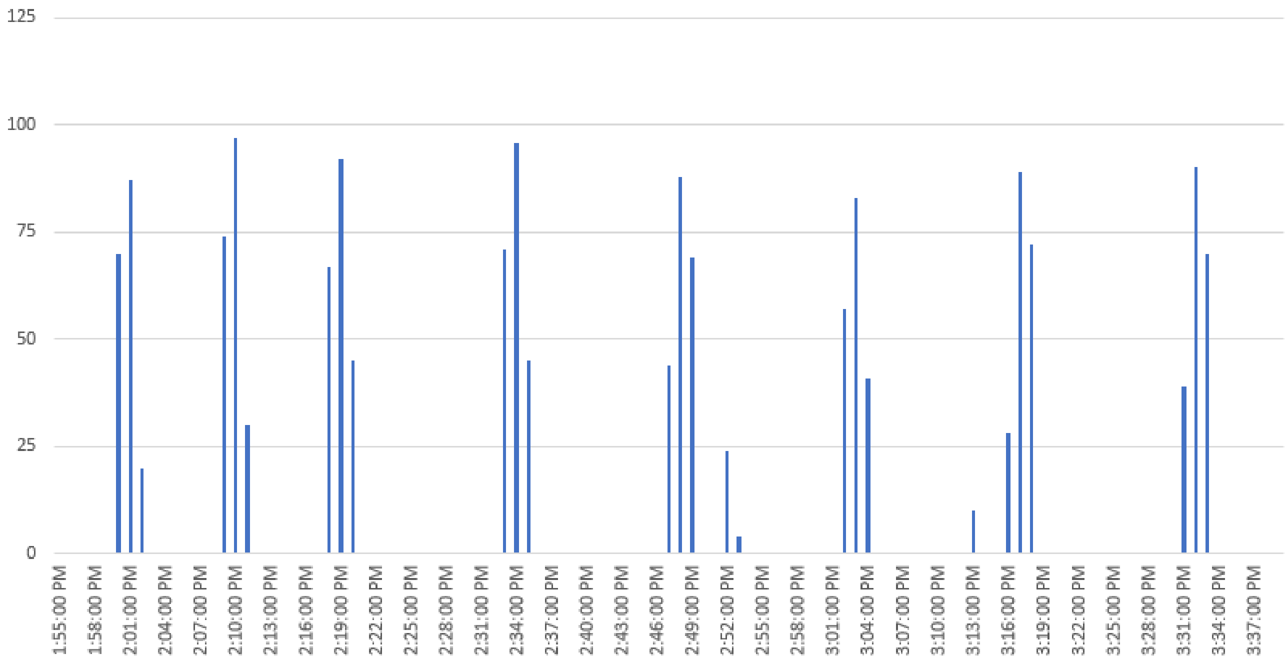
The rate of steps per minute for participant C is much more consistent across the entirety of the activity in comparison to participants A and B. Perhaps indicating differences in fitness of the participants that may not have been prominent in the Long Walk activity.

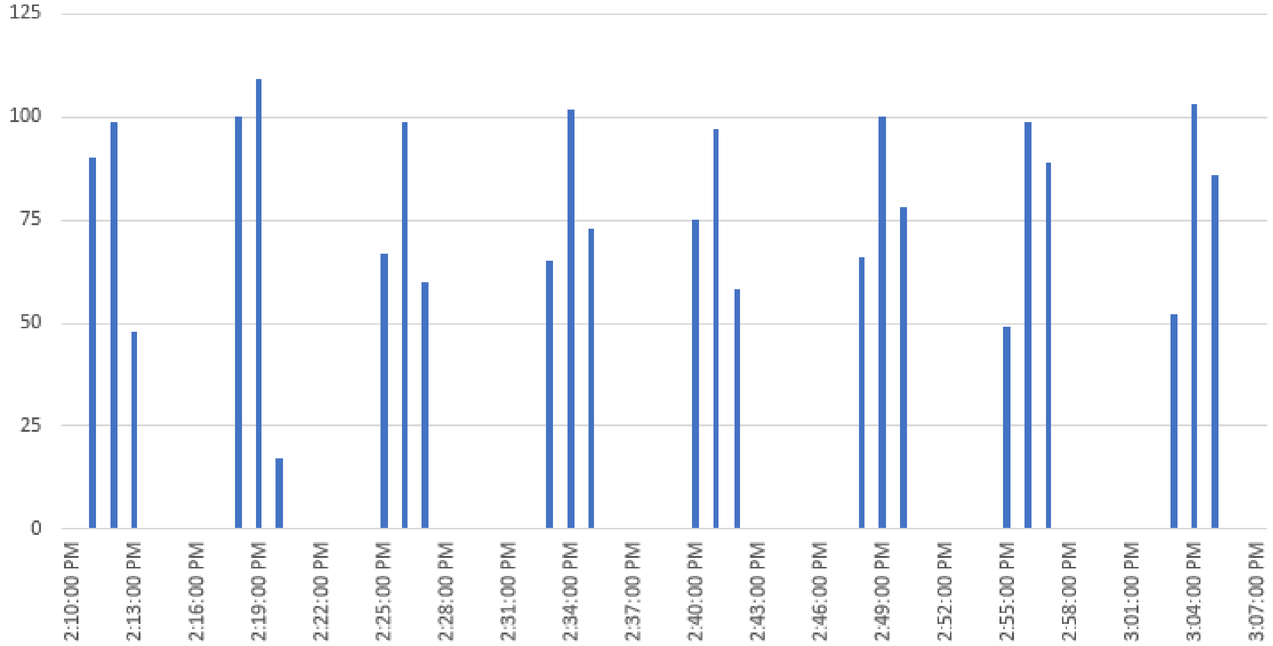
Following the DHIF-PP artefact design process using the Table 4 estimates, data cleansing consisted of identifying 2 minutes of inactivity prior and post a period of between 3- and 5-minutes containing activity with at least 1 minute of inactivity. The data analysis required the time and step parameters to be refined, from the dataset: as before mean and standard deviation were chosen. Table 5 below shows these results for these three participants. For the health habit envelope, single standard deviation values for all parameters were adopted, resulting in exclusion of four of the twenty-four individual cases.

Table 6: Parameters for Short Walk Characterisation

Participant	A	B	C	All
Activity Type 2 Phase 1 - Steps (Mean)	80.88	98.75	87.50	89.04
Activity Type 2 Phase 1 - Steps (Std Dev)	9.30	3.54	14.65	5.56
Activity Type 2 Phase 1 - Time (Mean)	2.00	1.88	2.13	2.00
Activity Type 2 Phase 1 - Time (Std Dev)	0	0.35	0.64	0.32
Internal Inactivity Time (Mean)	1.00	0.88	2.00	1.29
Internal Inactivity Time (Std Dev)	0.00	0.35	0.00	0.20
Activity Type 2 Phase 2 - Steps (Mean)	80.38	101.00	99.38	93.58
Activity Type 2 Phase 2 - Steps (Std Dev)	6.72	3.70	2.72	2.08
Activity Type 2 Phase 2 - Time (Mean)	1.75	2.13	2.38	2.08
Activity Type 2 Phase 2 - Time (Std Dev)	0.46	0.35	0.52	0.08

The same process as described above was next applied to the stairs and meeting tasks respectively:





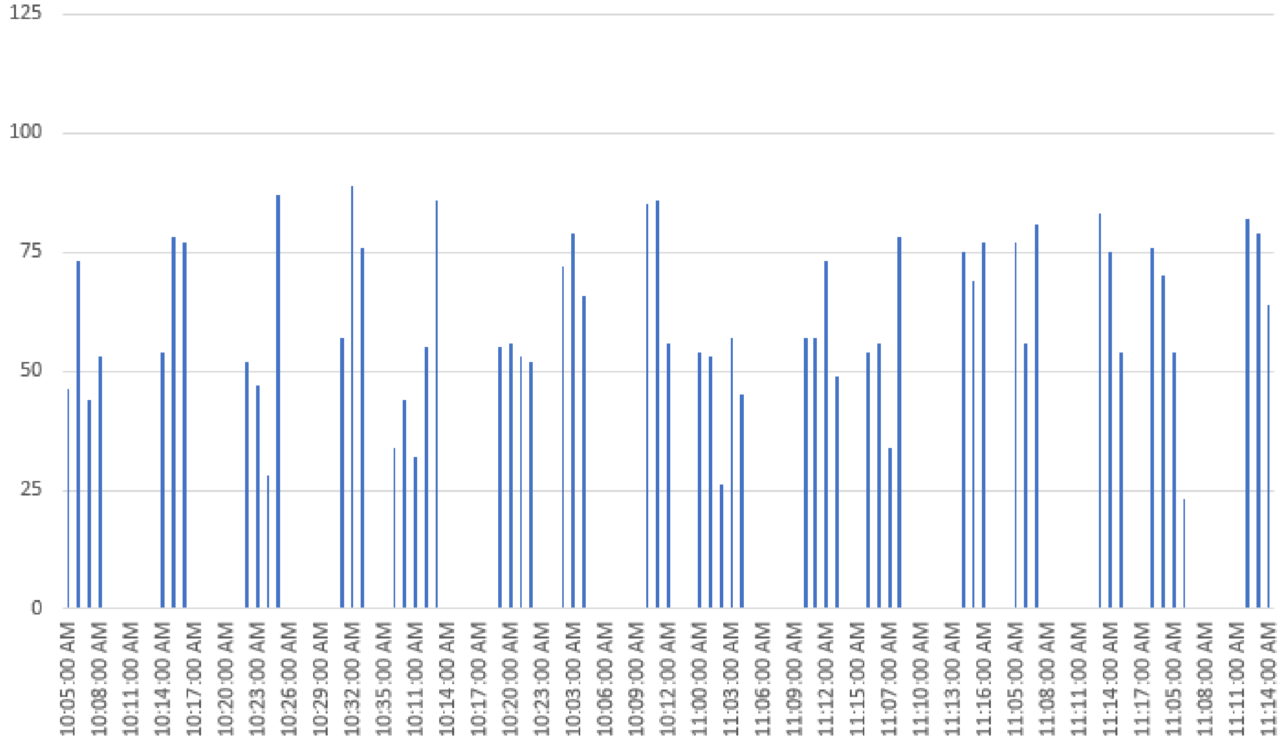


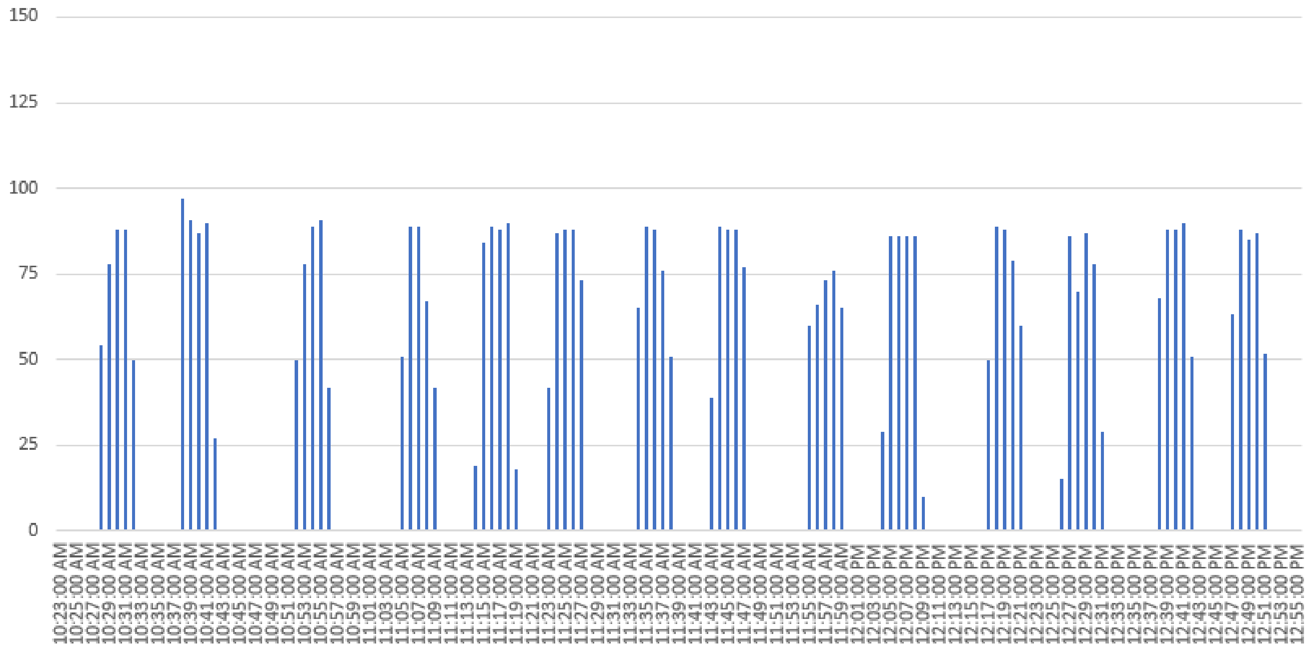
Figure 15: Step and Time data for Stair's activity (respectively for participants A, B, C)

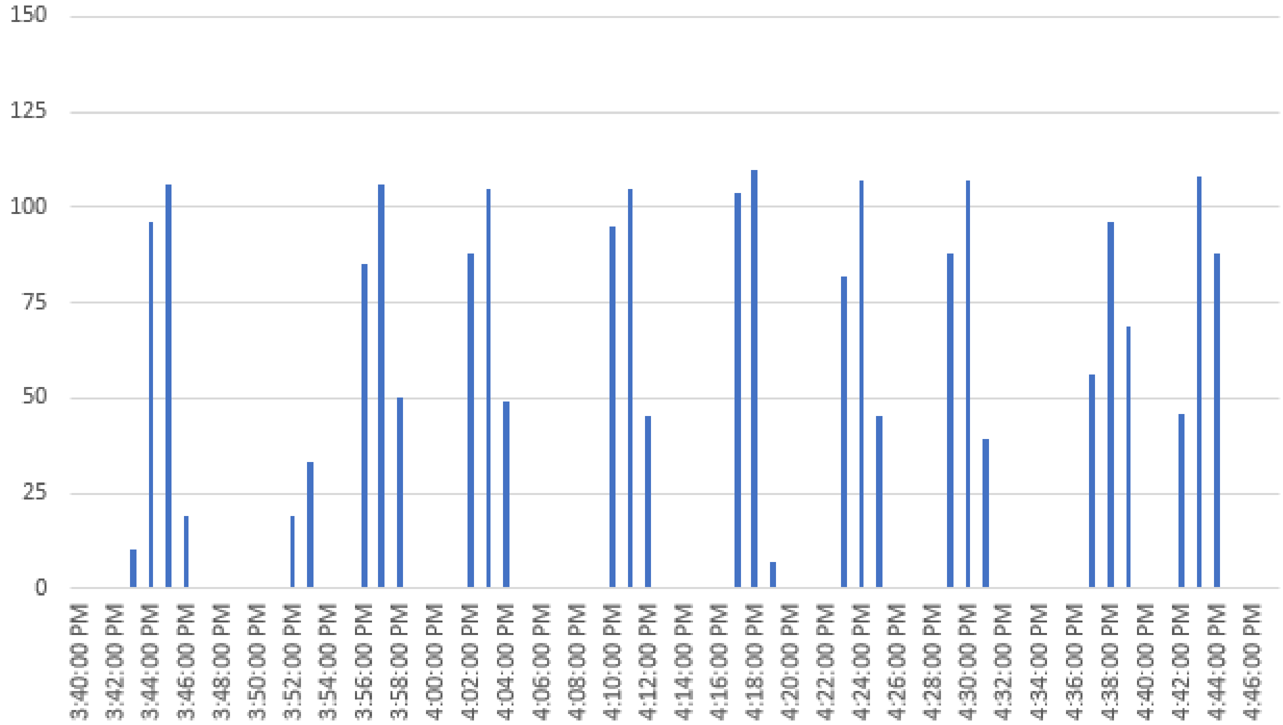
Differences between participants are clearly visible with Participant C showing significant inconsistencies in the pattern of step and time taken in the stair activity when compared to Participants A and B. This may be indicative of differences in levels of fitness between participants similar to that of the Short Walk activity results. Participants A and B however, are quite consistent in their rate of steps per minute across the Stair's activity.

Table 7: Parameters for Stairs Task Characterisation

Participant	A	B	C	All
Activity 1 Steps (Mean)	204.00	232.50	224.00	220.17
Activity 1 Steps (Std Dev)	21.21	5.45	12.92	7.88
Activity 1 Time (Mean)	3.88	3.00	4.00	3.63
Activity 1 Time (Std Dev)	1.46	0.00	0.76	0.73
Internal Inactivity Time (Mean)	10.00	4.75	5.00	6.58
Internal Inactivity Time (Std Dev)	2.20	0.50	0.00	1.16
Activity 2 Steps (Mean)	200.75	237.75	221.00	219.83
Activity 2 Steps (Std Dev)	8.97	8.02	8.68	0.49
Activity 2 Time (Mean)	3.25	3.00	3.25	3.17
Activity 2 Time (Std Dev)	0.46	0.00	0.46	0.27

Participant A took longer breaks with a larger period of inactivity during Activity 1 (upstairs climb). The stairs climb task was undertaken multiple times consecutively on the same day by Participant A for the first 4 instances. The other 4 instances consecutively on a different day. There was a noticeable increase in time duration to complete the second instance of the task for Participant A. It could be inferred that the participant was fatigued after the first instance.





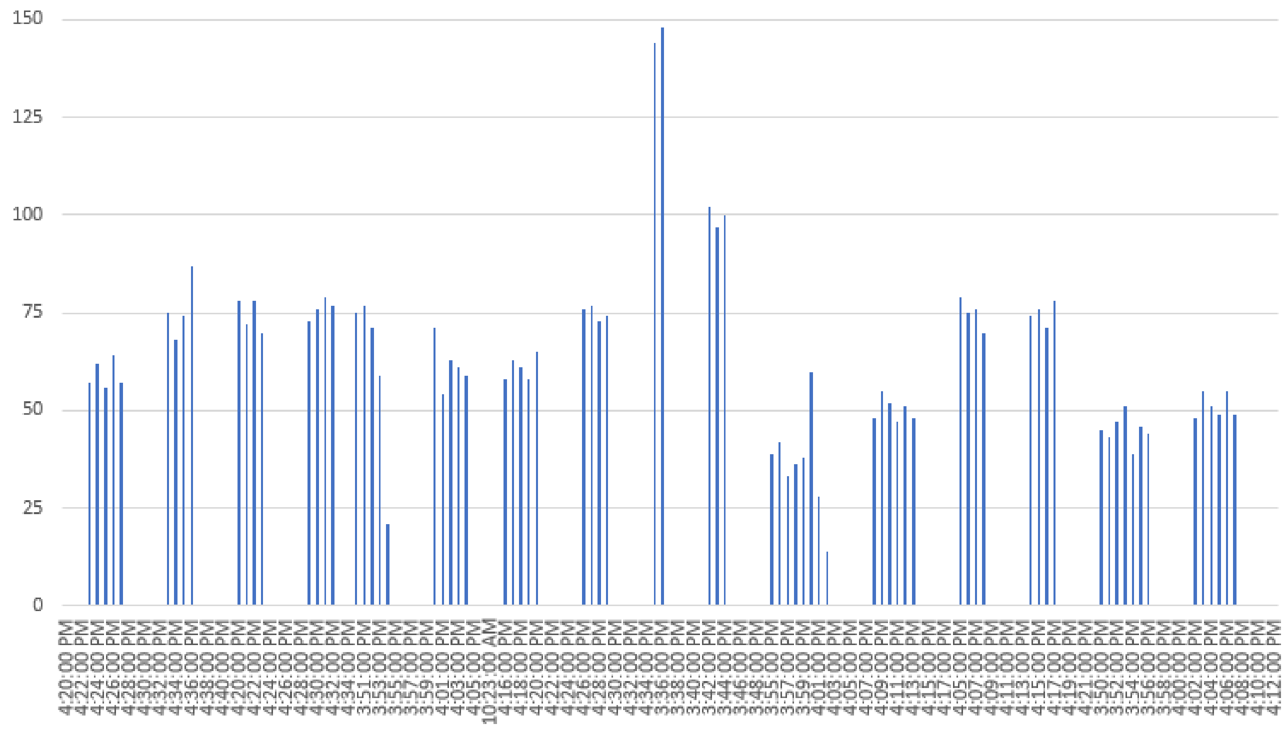


Figure 16: Step and Time data for Meeting activity (respectively for participants A, B, C)

Participant B has a consistently shorter duration of travel time compared to the other participants. This could be due to differences in fitness, stride length and gait between participants. There is generally a consistency between participants in duration and step count except for Participant C which has a few outlying activities. Particularly the activity at 15:35 while consistent with step count has a significantly shorter duration than all the other activities.

Table 8: Parameters for Meeting Task Characterisation

Participant	A	B	C	All
Activity 1 Steps (Mean)	365.14	232.00	299.88	299.01
Activity 1 Steps (Std Dev)	17.53	8.68	7.95	5.33
Activity 1 Time (Mean)	5.14	3.25	5.00	4.46
Activity 1 Time (Std Dev)	0.38	0.50	1.85	0.82
Internal Inactivity Time (Mean)	9.29	8.00	10.00	9.10
Internal Inactivity Time (Std Dev)	1.38	1.83	0	0.95
Activity 2 Steps (Mean)	373.14	235.25	302.88	303.76
Activity 2 Steps (Std Dev)	17.53	10.53	3.60	6.96
Activity 2 Time (Mean)	5.29	3.00	4.50	4.26
Activity 2 Time (Std Dev)	0.49	0	1.07	0.54

Participant A on average is taking a far greater number of steps to complete activity 1 (walking to the meeting) compared to the other participants. Participant B exhibits much less steps than the other two participants for activity 1. This is potentially a fitness factor as the variance might be too great to account for differences in gait and stride length between participants.

The baseline assessment of the simulated tasks is essential for future studies. There are endless possibilities to consider when considering how an environment influences health habits; they cannot all be possibly accounted for and are not a significant input into this research. Common sense has been applied where necessary to include or exclude subsets of data that do not appear to be consistent with already identified patterns of habitual behaviour. Noise in the data can be a significant detriment to the accurate identification of patterns of habitual behaviour. Assessing a specifically designed tasks in a controlled manner has allowed for the Design Science Research approach to be utilised in a way where noise does not interfere with the application of the DHIF-PP artefact.

4.5. Limitations

A challenge in identifying and characterising these types of small-scale habitual behaviours using step count data arises from the degree of noise in the data. This Short Walk habitual behaviour becomes increasingly difficult to identify when there is noise caused by distractions or interruptions to the individual, such as pausing when encountering a colleague in passing, which can affect the duration and sometimes also the step counts. It is also affected by the quantized time sampling rate which results in most 1-minute samples containing a mixture of some inactive and some active time.

4.6. Conclusion

This case study has described how the DHIF-PP artefact is applied for this type of typical office-based health habit characterisation, and instances of the related parameters for the health habit models have been derived. As this was based on data obtained from experimental simulation of the activities by three subjects, an indication of expected variation and anomalies was gained for some "conventional" type of subjects.

The simulated tasks serve as a "control" or baseline understanding of anticipated workplace health habits. Future studies and interventions can make comparisons to the outcomes of this baseline assessment.

This case study allowed for an initial DHIF-PP artefact design of which future case studies can use and refine to achieve a level of desirable stability in the processing of data, characterising health habits, and identifying those health habits in broader, and noisier data sets with a reasonable level of accuracy.

5. CASE STUDY 2 – OPEN-PLAN WORKPLACE TASKS

5.1. Overview

This chapter describes the second case study, to determine the feasibility of characterising sequences of similar habitual behaviours over a set of predefined health habits for a naturally occurring group of individuals in a workplace, and the feasibility of using an additional measurement variable being the location within an office building alongside step count data. The DHIF-PP artefact was applied to data collected from a heterogeneous group of office workers occupying the same open-plan physical office environment and with similar work roles and workplace movement health habits, being members of staff and students attached to a university research centre.

In this instance, location data based on proximity to Bluetooth beacons dispersed around the office building area was used, in addition to Fitbit logged step count data (as in case study one). Each participant carried a mobile device (typically their personal phone) which logged detection of beacons and provided a means for unique identification of a participant. Location data was obtained only when in a 3-5m proximity of a beacon, at approximately 30 second sampling rate. It was not possible to resolve the distance from the beacon or the strength of the beacon signal using this setup. Location data was saved on the mobile device which also provided a clock time timestamp on receipt and was later downloaded for analysis. Step count was obtained using a wrist worn Fitbit, as previously described in case study 1.

The motivation behind using Bluetooth beacons for location data is an outcome of understanding the value that location data adds to this research, despite not being a necessity. The value Bluetooth beacons add to the data analysis cannot be undervalued and should be adopted where possible to increase the overall research quality.

5.2. Aim

To provide a “real-world” demonstration of use of the DHIF-PP artefact for a range of typical habitual behaviour activities in an open plan multi-storey office environment, allowing participants to undertake their normal activities freely and subsequently identifying those which are similar and repeated. Further to investigate use of the DHIF-PP artefact with multiple parameters (via location and step count) available for characterisation of habitual activities.

5.3. Methodology

The site of the case study was the tower building at the Flinders University Tonsley Campus, the same as described for Case Study 1, where a detailed description of the physical layout and environment was provided. There were 7 participants (n=7) collecting data from 4 to 8 days depending on regular work-in-office/work outside of office routine situation (see Table 8). The participants consisted of 5 male and 2 female volunteers, ranging in age from 22 years old to 62 years old and all within the second or third quartile of height/weight distribution for their age groups. The participants were working in the same office area of the building and were of the same profession so there was anticipated there would be less deviation from typical office activities based on the group doing similar work throughout a typical workday. Participants were required to have their Bluetooth facility enabled on their mobile device and carry the device on their person at all times, to log the locations which they passed throughout the day.

The Flinders University Tonsley Campus office space in which the case study took place is being an open plan office setting is rather representative of 21st century office settings.

Typical office activities expected in this setting consisted of visiting co-worker locations to talk or fetch items, attending group office business meetings, using facilities such as printer or coffee machine, making trips to the bathroom, and socialising in public areas. A total of eleven Bluetooth beacons were installed at key locations throughout the office space on the second floor of the building where the participants worked, including in the proximity of participant open plan office desks (Desk 1 to Desk 4), doors that must be passed to enter or leave the office space where the desks are sited (Doorway 1 and Doorway 2), coffee/lunchroom (Room), in the vicinity of the entrance/exit door to the bathrooms (Bathroom, 2 beacons), and at the entry to the staircases leading up and down from the second floor of the building where these locations reside (Stair 1 and Stair 2). The office building layout with Bluetooth beacon locations is shown in Figure 17 below:

Figure 17: Office building layout with Bluetooth beacons (Flinders University, Tonsley Campus Map with Bluetooth beacon markings, 2019)

Table 9: Participant data collection days

Participant ID	14th (Tue)	15th (Wed)	16th (Thu)	17th (Fri)	Weekend	20th (Mon)	21st (Tue)	22nd (Wed)	23rd (Thu)	24th (Fri)
A	.	Y	Y	Y		Y	Y	.	Y	Y
B	Y	Y	Y	.		Y	.	Y	Y	.
C	Y	Y	Y	Y		Y	Y	.	.	.
D	Y	Y	Y	Y		Y	Y	Y	Y	.
E	.	.	.	.		Y	Y	Y	Y	.
F	Y	Y	Y	Y		.	.	.	.	.
G	Y	Y	Y	Y		.	.	.	.	.

5.4. Results & Analysis

The data analysis and activity identification were carried out as a manual process. Future research may look to automate aspects of this process where possible although due to the small volume of data as mentioned previously it is not suitable for common machine learning techniques to process the data automatically. The data collected from the participants was collected independently from Fitibit devices for the step counts with timestamps and from Bluetooth devices with timestamps, meaning the data from the two sources has to be synchronised using their timestamps before any data analysis could be conducted.

Two short compound activities were selected from observed behaviours of the workplace population, as being daily health habits with multiple repetitions across all participants. The combination of location data from the Bluetooth beacons and the step counts and durations signify the type of activities observed in the data. Only data points that were deemed without a reasonable doubt that they are in fact an activity, qualified for inclusion. These health habits were hypothesised below in Table 10 and Table 11, serving as the design of the DHIF-PP artefact for identifying and characterising instances of the health habits within the case study data set.

Table 10: Office -> Coffee Area -> Office Health Habit

Activity 1	Activity Profile
Phase 1 (Office)	Office beacon is pinged with a period of step activity prior to the event indicating the participant having arrived at the Office location. Followed by a period of low activity at the Office location.
Phase 2 (Coffee Area)	Step activity immediately after the low activity period followed immediately by the Coffee Area beacon being pinged. Followed by a period of low activity at (or around) the Coffee Area.
Phase 3 (Office)	Step activity followed by the Office beacon being pinged indicating the return of the participant back to the original Office location.

Table 11: Office -> Bathroom -> Office Health Habit

Activity 2	Activity Profile
Phase 1 (Office)	Office beacon is pinged with a period of step activity prior to the event indicating the participant having arrived at the Office location. Followed by a period of low activity at the Office location.
Phase 2 (Bathroom)	Step activity immediately after the low activity period followed immediately by the Bathroom beacon being pinged. Followed by a period of low activity at the Bathroom location.
Phase 3 (Office)	Step activity followed by the Office beacon being pinged indicating the return of the participant back to the original Office location.

5.4.1. Participant Health Habits Overview

From the data collection period across all 7 participants there were 9 instances of well-defined health habit exemplars for both described health habits.

Table 12: Instances of health habits found across all participants, over the observation period

Instances of Health Habits	#
(A) Office -> Coffee -> Office	5
(B) Office -> Bathroom -> Office	4

Quality of the data was reduced due to Bluetooth beacons sometimes not picking up a participant's mobile device when in the vicinity of the Bluetooth beacons. This made for some erroneous data where a participant had appeared to teleport from one location to another, despite having passed a Bluetooth beacon in between the locations but this was not recorded by the mobile device. This had a significant impact on identifying more well-defined health habits. Table 13 to Table 19 below show the acceptance and rejection rate of health habits across all participants as deemed acceptable or not. This is based on whether they fall within the activity profiles described above with significant levels of noise in the data:

Table 13: Participant A health habits

Habit Type	Accepted (%)	Rejected (%)	Total (%)
(C) Office -> Coffee -> Office	3 (75%)	1 (25%)	4 (100%)
(D) Office -> Bathroom -> Office	0 (0%)	1 (100%)	1 (100%)

Table 14: Participant B health habits

Habit Type	Accepted (%)	Rejected (%)	Total (%)
(A) Office -> Coffee -> Office	0 (0%)	0 (0%)	0 (0%)
(B) Office -> Bathroom -> Office	0 (0%)	0 (0%)	0 (0%)

Table 15: Participant C health habits

Habit Type	Accepted (%)	Rejected (%)	Total (%)
(A) Office -> Coffee -> Office	0 (0%)	1 (100%)	1 (100%)
(B) Office -> Bathroom -> Office	1 (100%)	0 (0%)	1 (100%)

Table 16: Participant D health habits

Habit Type	Accepted (%)	Rejected (%)	Total (%)
(A) Office -> Coffee -> Office	1 (100%)	0 (0%)	1 (100%)
(B) Office -> Bathroom -> Office	0 (0%)	1 (100%)	1 (100%)

Table 17: Participant E health habits

Habit Type	Accepted (%)	Rejected (%)	Total (%)
(A) Office -> Coffee -> Office	0 (0%)	0 (0%)	0 (0%)
(B) Office -> Bathroom -> Office	0 (0%)	0 (0%)	0 (0%)

Note: There were no health habits of either type identified for participant E.

Table 18: Participant F health habits

Habit Type	Accepted (%)	Rejected (%)	Total (%)
(A) Office -> Coffee -> Office	0 (0%)	1 (100%)	1 (100%)
(B) Office -> Bathroom -> Office	0 (0%)	1 (100%)	1 (100%)

Table 19: Participant G health habits

Habit Type	Accepted (%)	Rejected (%)	Total (%)
(A) Office -> Coffee -> Office	1 (20%)	4 (80%)	5 (100%)
(B) Office -> Bathroom -> Office	3 (42.86%)	4 (57.14%)	7 (100%)

In the coffee health habit and bathroom health habit instance figures below, the health habit line is distinguishable by the green horizontal line on each of the figures.

5.4.2. Coffee Health Habit

The following section details the instances of the Coffee Health Habit that have been characterised and identified across all participants in the case study, over the course of the study.

Table 20: Parameters for Coffee Area trip characterisation

Participant	A	A	A	D	G	-	-
Instance	**Inst 1**	**Inst 2**	**Inst 3**	**Inst 4**	**Inst 5**	**Mean**	**Std. Dev**
Activity 1 Steps	24	77	54	60	37	50.40	20.55
Activity 1 Time	1	1	1	1	2	1.20	0.45
Internal Low Activity 1 Time	38	29	208	0	51	65.20	82.00
Activity 2 Steps	19	114	35	77	33	55.60	39.19
Activity 2 Time	1	2	1	1	1	1.20	0.45
Internal Low Activity 2 Time	13	0	0	2	1	3.20	5.54
Activity 3 Steps	73	61	82	47	36	59.80	18.70
Activity 3 Time	1	1	1	1	1	1.00	0.00

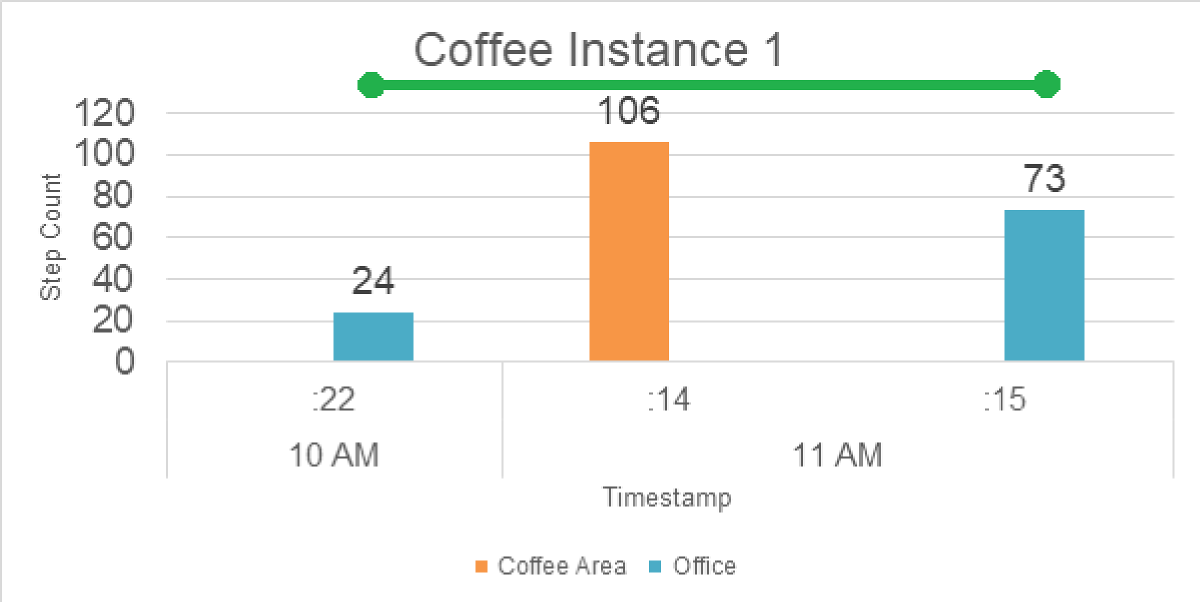


Figure 18: Coffee Health Habit Instance 1

This participant was observed to have walked around the immediate coffee area as the return trip was less than the steps taken in the coffee area.

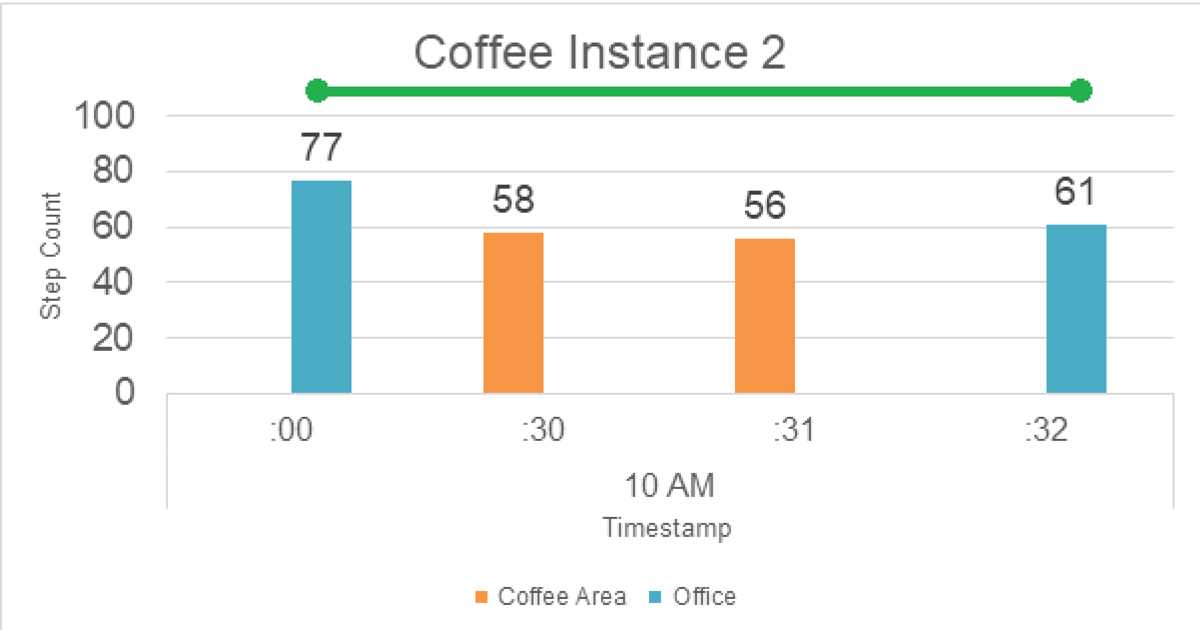


Figure 19: Coffee Health Habit Instance 2

This participant completed the return trip to the coffee area within four minutes indicating this was a purposeful trip to the coffee area with no time for distractions and was likely not interrupted by external factors like a co-worker stopping them to chat.

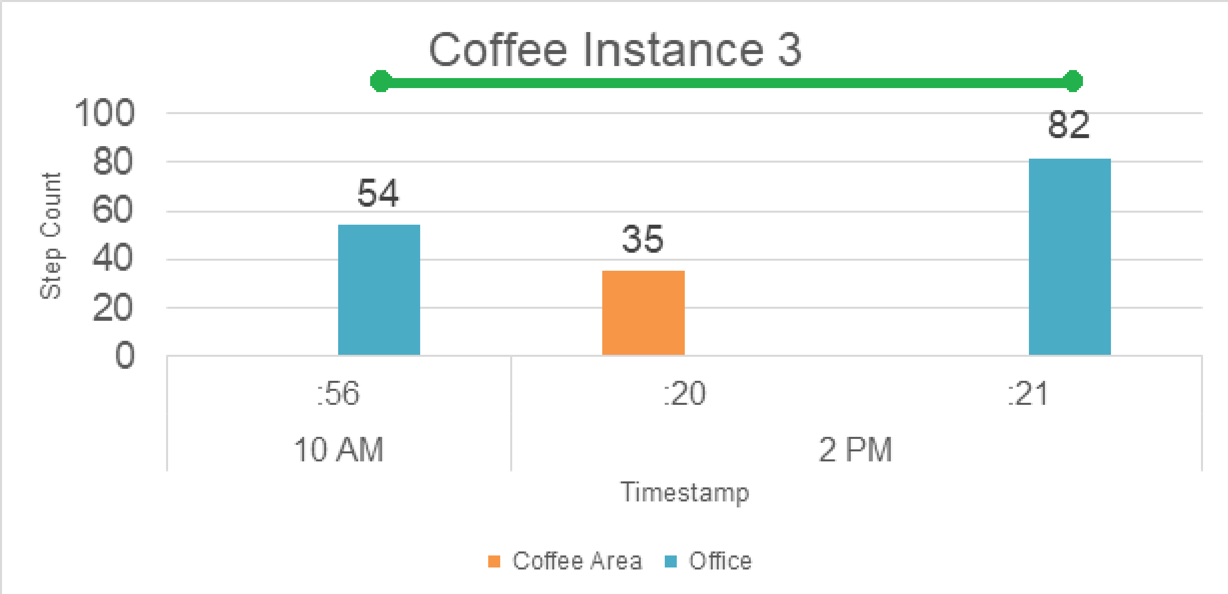


Figure 20: Coffee Health Habit Instance 3

This participant appears to have made a purposeful trip to the coffee area as there are a clear number of steps taken to get to the coffee area then only a few steps observed towards the end of a lengthy sedentary period followed by a brief walk back to the office. This indicates almost three hours of time spend in the coffee area. This participant most likely took a longer journey back to the office as indicated by the large step count of the return trip.

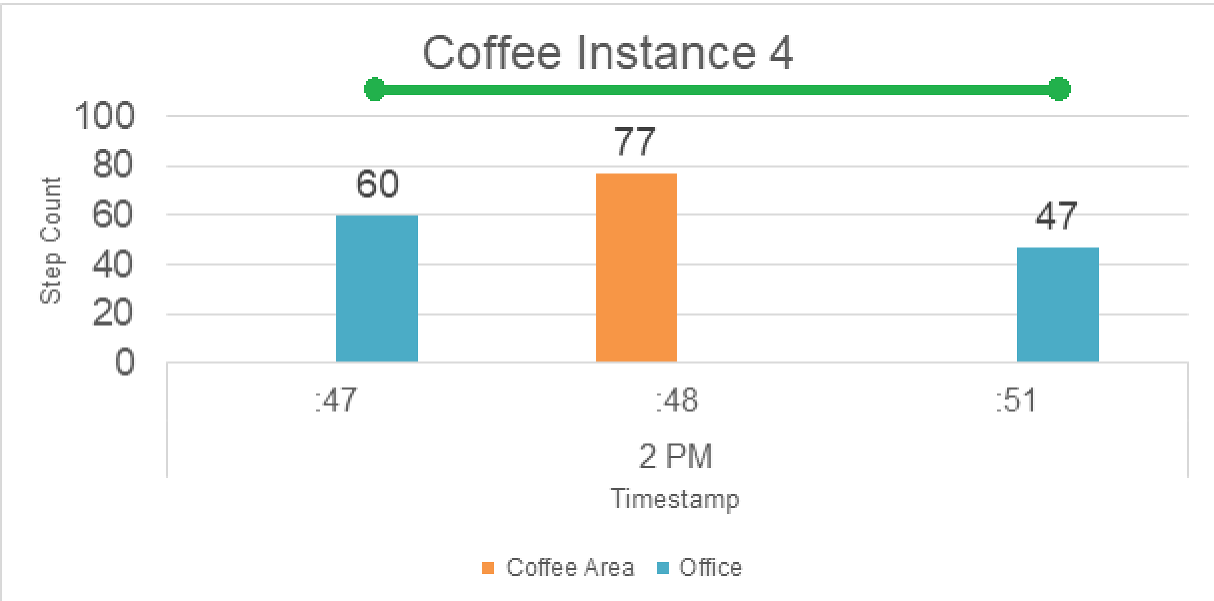


Figure 21: Coffee Health Habit Instance 4

This participant has been observed to have made a purposeful trip to the coffee area as indicated by the locations recorded and the duration of the trip. The participant then spent approximately three to four minutes in the coffee area before returning to the office.

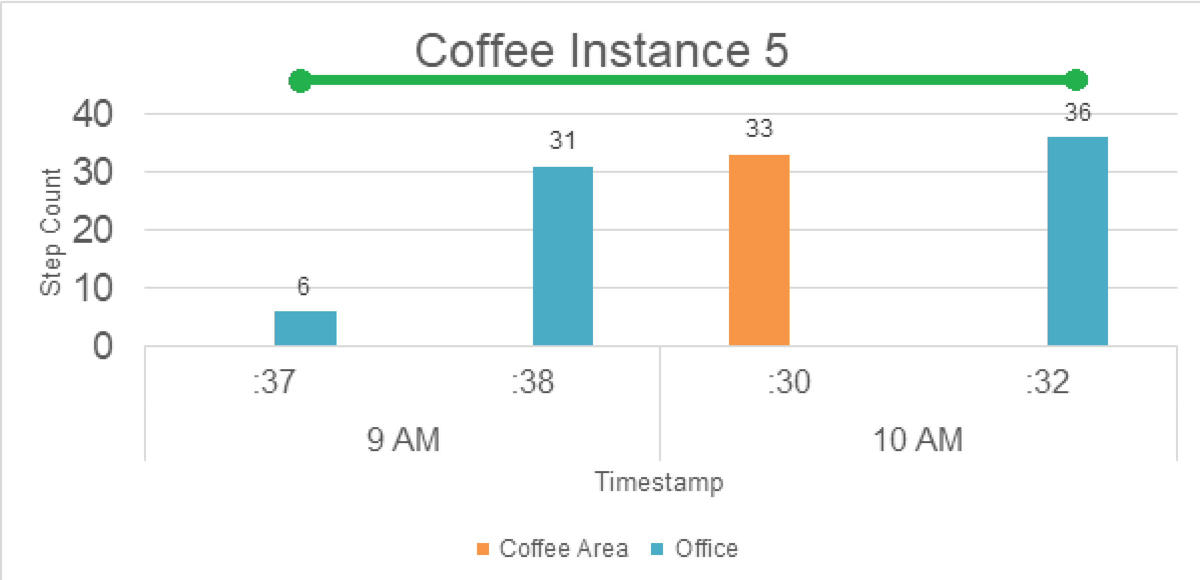


Figure 22: Coffee Health Habit Instance 5

This participant shows a similar consistency to Coffee instance 2 and 4 where the participant made a purposeful short duration trip to the coffee area and back to the office.

5.4.3. Bathroom Health Habit

The following section details the instances of the Bathroom Health Habit that have been characterised and identified across all participants in the case study.

Table 21: Parameters for Bathroom trip characterisation

Participant	C	G	G	G	-	-
Instance	**Inst 1**	**Inst 2**	**Inst 3**	**Inst 4**	**Mean**	**Std. Dev**
Activity 1 Steps	25	59	70	98	63.00	30.19
Activity 1 Time	1	1	1	7	2.50	3.00
Internal Low Activity 1 Time	65	36	52	33	46.50	14.89
Activity 2 Steps	38	49	77	58	55.50	16.50
Activity 2 Time	1	1	2	1	1.25	0.50
Internal Low Activity 2 Time	8	1	7	0	4.00	4.08
Activity 3 Steps	18	70	11	70	42.25	32.17
Activity 3 Time	1	1	1	1	1.00	0.00

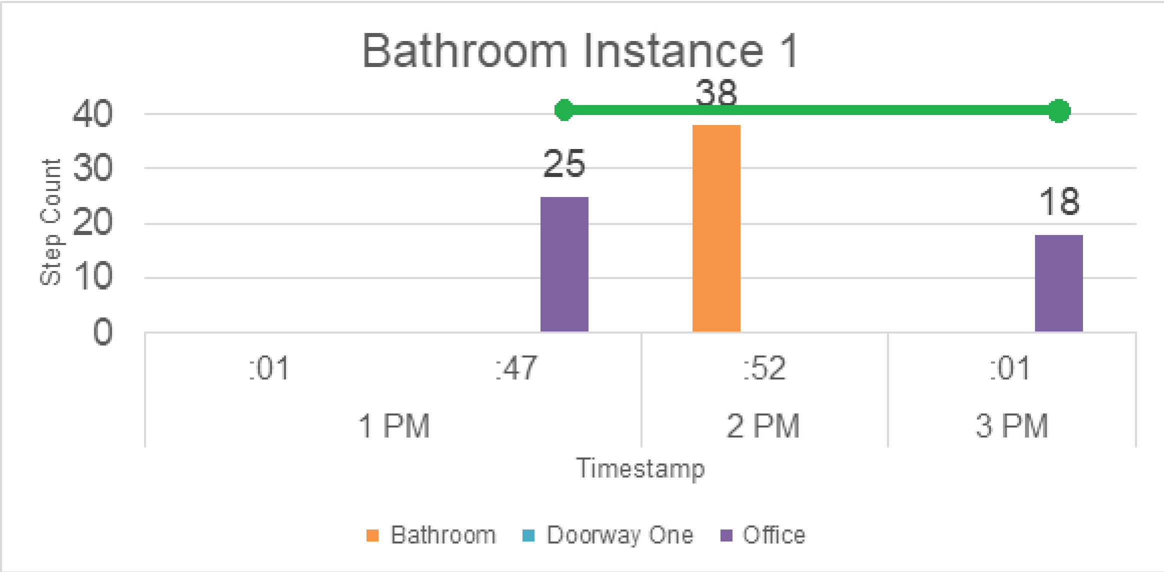


Figure 23: Bathroom Health Habit Instance 1

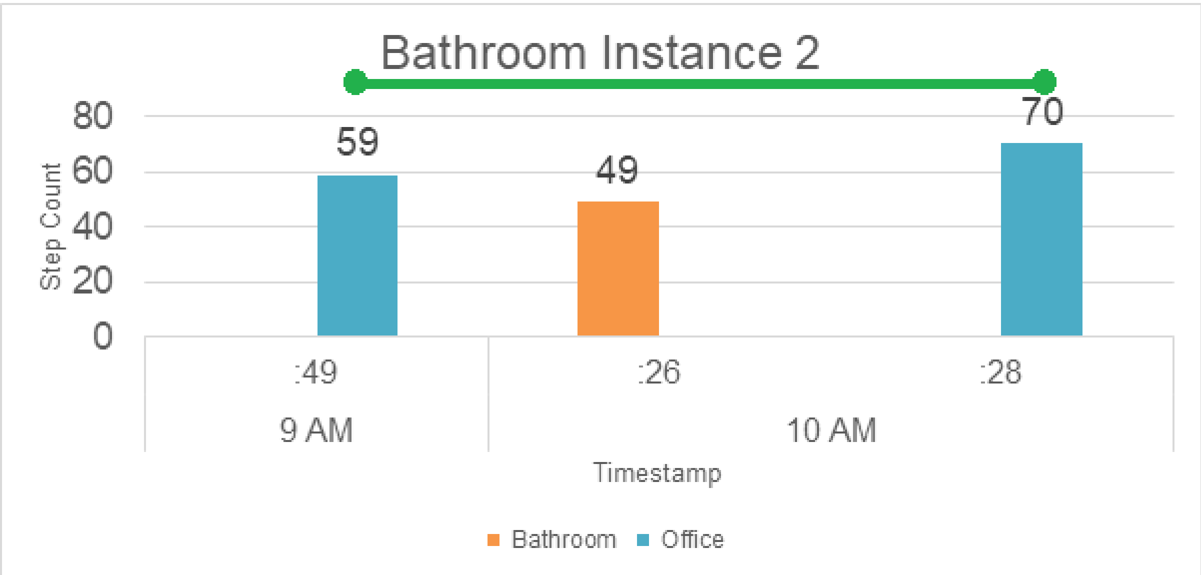


Figure 24: Bathroom Health Habit Instance 2

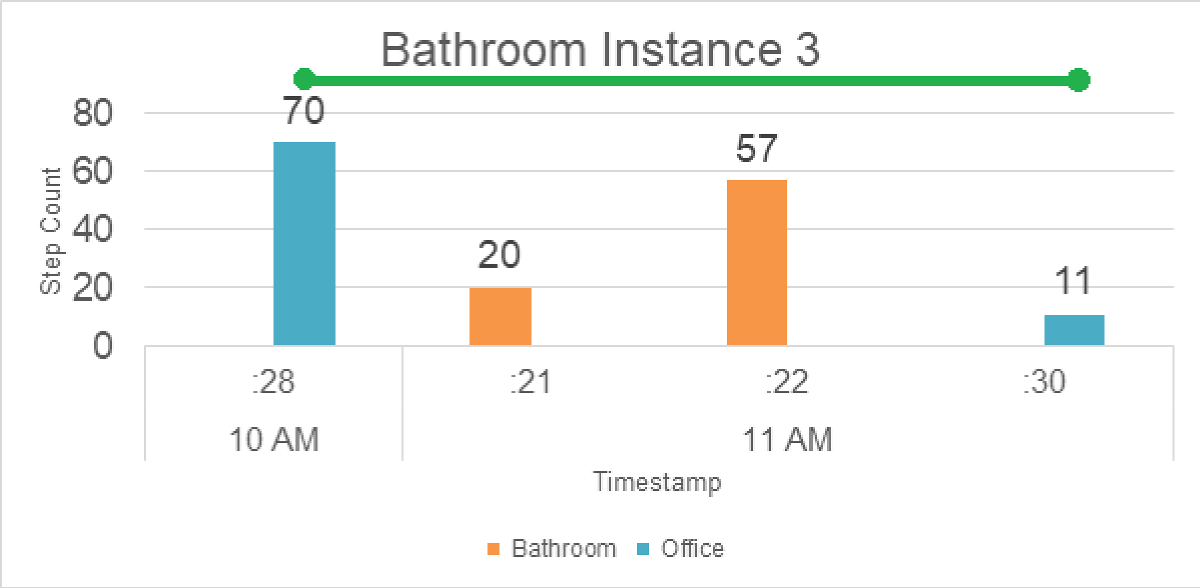


Figure 25: Bathroom Health Habit Instance 3

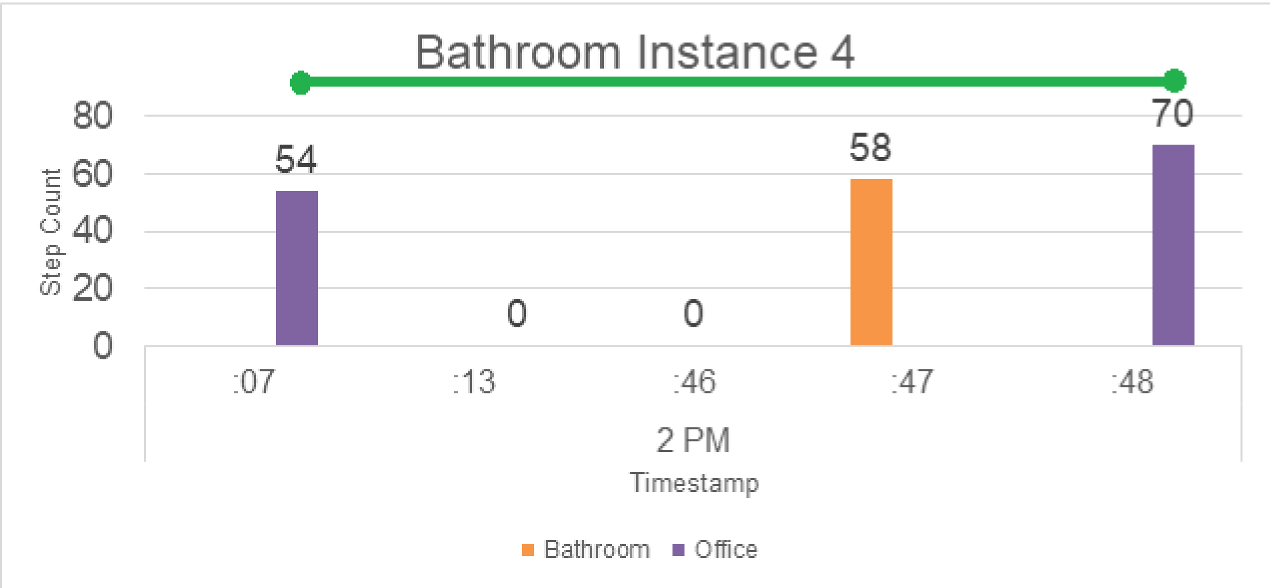


Figure 26: Bathroom Health Habit Instance 4

The above graphs show a very consistent pattern of behaviour where the participants generally go directly to the bathroom and then return to their office and spend a short duration at the bathroom, following the same or very similar path to that which they took outbound, based on the step counts observed. It should be noted that the participants in Bathroom Instances 1 and 3, have the closest positioned desks to the entrance of the office space and therefore, have the shortest possible distance to reach the bathroom.

5.5. Limitations

More activities could be considered for future studies. Activities such as using the printer at a glance may appear to look like a trip to the bathroom for example with a short pause in the hallway. This type of activity could also be interrupted by a conversation between colleagues in the hallway.

There were rare instances in which the Bluetooth beacons would not register a participant as having been in the vicinity of them despite being within acceptable range. This may be a shortcoming of the particular mobile device and it's Bluetooth receiver or the Bluetooth beacons themselves. Future studies might standardise the use of a wearable Bluetooth device or Bluetooth enabled smartphone to record the occurrence of a participant being within the vicinity of a Bluetooth beacon with greater reliability.

5.6. Conclusion

It has been found in this case study that location data, as an additional measurement, allows the identification of activities based on an individual's movements from one location to another within the constrained setting. Secondly, the characterisation of health habits of individual movements that denote repeated habitual activities in a constrained setting has been shown to be possible across a group having a typically varied demographic. Thirdly, the viability of using unobtrusive, small and inexpensive fixed measurement instrumentation (instead of highly sophisticated and expensive laboratory grade measurement instrumentation), in addition to wearable devices, for experiments in a real-world setting has been demonstrated.

Future studies would benefit from the collection of finer granularity step count data in synchronization with location data, due to the short duration and distance of components in the activities considered here. This would likely improve the accuracy of characterising such small-scale habitual behaviour but would introduce analysis complexity through the need to reconcile conflicting indications from the several complementary measurements. For example, while the step count and location data show consistent trips to and from the coffee area, there can be significant time differences in the duration of the trips. This can be due to interactions that are disruptive to a purposeful trip, flexibility in making the trip (e.g., in company vs alone; undistracted or using mobile phone in conversation), or whether the trip is ad hoc or for a planned work break (e.g., in company or alone; for morning tea or with a visitor). Richer data such as a greater number of beacons and proximity of other persons would help to explain some but not necessarily all of these variations.

6. CASE STUDY 3 – WORKING FROM HOME VERSUS OFFICE

6.1. Overview

The third case study demonstrated the methodology applied to a data set that was recorded by two participants in two different workplace locations. At the time of the study participant A was a PhD student and a programmer at Western Sydney University, and participant B was a senior academic at Flinders University. Contextually the roles of both participants involved periods of focused work as well as more sporadic work health habits (e.g., to accommodate workplace meetings both in-person and online; intensive periods of troubleshooting), The case study was based on one month of data collected from each when working from home, and another month of data collected from each when working from the office. Both data sets were collected during the year 2020 as a longitudinal study although only consisting of two participants, it was a good opportunity to collect a substantial amount of data from those participants as the opportunity presented itself through the covid lockdowns in New South Wales and South Australia, the states in which the participants resided in. This was a rare opportunity given the work from home mode was relatively uncommon prior to the global pandemic.

The primary contribution of this case study was the collection and analyse of a large longitudinal data set enabling characterisation of habitual behaviours over a relatively long duration. This case study was desired to have a data set collected in two significantly different locations and participants, which could then be compared to see any differences between expected health habitual behaviours.

6.2. Aim

To make use of the DHIF-PP artefact for a situation of individual sedentary habitual behaviour characterisation and comparison, in different environments (office and home) and for participants with different work roles and at different locations. Further to investigate the utility of applying the DHIF-PP artefact to a large longitudinal data set.

6.3. Methodology

As in case study 1 the office environment for participant B was a large multi-storey office environment, the Tower building at Flinders University Tonsley Campus. The overall workplace structure is of open-plan desk seating around the periphery of each floor, with a row of internal offices delineating the open-plan area from the central core space of the building. In the central core are numerous meeting rooms, personal social areas, and a central public space on each level. There are multiple connectivity options within and between levels, consisting of corridors, stairs, and elevators. The office environment for participant A was very similar with the main difference being the open-plan desk seating was the central part of the floor, internal offices lined this area much like in participant B's building. This contextual information provides a scaffold for understanding the types of typical movement-based physical activities that individuals may undertake during their workday.

The home environments were structured as modest three-bedroom Australian houses comprising of a kitchen area, bathrooms, living room, and a study room where the majority of the work was carried out during the working from home period.

Step counts were logged using a Fitbit Charge HR 2 device per participant. The devices were worn at a minimum between the hours of 9am to 5pm weekdays for the duration of the study both when working in the office and working from home.

The approach taken was to characterise periods of sedentary habitual behaviour by applying the DHIF-PP artefact. This provides a demonstration of the methodology to sedentary behaviour in contrast to case study 1 and case study 2. The following table defines the type of sedentary health habits that were to be identified within the data set, as they are applicable to both a working from home and working from office situation.

6.3.1. Acceptance/Rejection Criteria

Health habit instances were accepted if they were within one of the pre-defined timeframes shown in Table 22 below. Provided that any of the 1-minute step count data points within that duration was 0 with a leniency of 5 or less steps as long it there were no consecutive step counts of 1 – 5 before or after that same data point. Such data points were attributed to noise in the data, 5 steps or less in a minute being possible erroneous step counting from wrist movements while working at a desk rather than actual walking.

Consecutive data points of 5 or more step counts led to the rejection of possible candidate sedentary health habit instances as this was considered a high enough level of physical activity that it's much less likely to be noise but instead actual activity.

Table 22: Sedentary Health Habit Types

Short Duration Sedentary (short spontaneous period of work either intentionally ended or unintentionally ended from external distractions e.g., replying to emails, or working on a larger task but interrupted by a colleague)	5min to 20min

Medium Duration Sedentary (moderate length period of focused uninterrupted work e.g., focusing on a specific task such as typing a document, or a meeting with colleagues)	21min to 45min
Long Duration Sedentary (long period of focused uninterrupted work on one or many tasks, or a large duration meeting with colleagues)	46min to 3 hours

6.4. Results & Analysis

The longitudinal nature of the data collection because of having a combination of working from office data and working from home data as a direct result of SARS-CoV-2 lockdowns in Australia, provides a unique opportunity to apply the DHIF-PP artefact to sedentary patterns of habitual behaviour. The results and analysis compare the two work environment situations to see if there are any differences in the sedentary habitual behaviour between the two environments and of the two participants.

It should be noted that the data was collected in two sets, one for each scenario of working from home and working in the office. For participant A, data was collected for 4 weeks in full for both scenarios. For participant B, data was collected for 3 weeks with the first week consisting of data only for Thursday and Friday for the working from home scenario, and 4 weeks in full for the working in office scenario.

Rejected instances were instances of which they had a level of activity beyond the threshold to be considered a sedentary period of time for the participant(s).

An overall summary of the identified health habits is provided below over a series of tables, and diagrams.

Table 23: Overall Sedentary Health Habit Instances

Instances of Health Habits (overall)	Participant A	Participant B	**Total**
Short Duration Sedentary	341	248	589
Medium Duration Sedentary	136	76	212
Long Duration Sedentary	49	44	93
			894

Table 24: Working from Home Sedentary Health Habit Instances

Instances of Health Habits (working from home)	Participant A	Participant B	**Total**
Short Duration Sedentary	111	80	191
Medium Duration Sedentary	69	29	98

Long Duration Sedentary	28	15	43
			332

Table 25: Working from Office Sedentary Health Habit Instances

Instances of Health Habits (working from office)	Participant A	Participant B	**Total**
Short Duration Sedentary	230	168	398
Medium Duration Sedentary	67	47	114
Long Duration Sedentary	21	29	50
			562

With 894 sedentary health habit instances characterised and identified of all the data of both participants 562 of those instances were identified when working in the office, compared to 332 instances when working from home. Suggesting that the sedentary habitual behaviour is reduced when in a work from home situation in the case of the two participants of this study.

6.4.1. Health Habit Instances for Participant A

Participant A was working full time as a programmer and studying part-time. This meant that a significant portion of a typical weekday was consumed almost entirely by desk work between the hours of 9am to 5pm with the occasional meeting, impromptu interruptions from co-workers and generally a lunch break around the middle of the day.

Table 26: Task Instances participant A, week 1 work from home

Task Type	**Mon**	**Tue**	**Wed**	**Thu**	**Fri**	**Totals**
Short Duration Sedentary Instances	9 accepted 0 rejected	8 accepted 0 rejected	3 accepted 0 rejected	2 accepted 0 rejected	2 accepted 1 rejected	24 accepted 1 rejected
Medium Duration Sedentary Instances	4 accepted 0 rejected	1 accepted 0 rejected	6 accepted 1 rejected	5 accepted 0 rejected	2 accepted 0 rejected	18 accepted 1 rejected
Long Duration Sedentary Instances	1 accepted 0 rejected	3 accepted 0 rejected	1 accepted 0 rejected	2 accepted 0 rejected	1 accepted 0 rejected	8 accepted 0 rejected

Table 27: Task Instances Parameter Characterisation, participant A, week 1 work from home

Task Type	**Mean**	**Std. Dev**
Short Duration Sedentary Instances (minutes)	13.63	4.94
Medium Duration Sedentary Instances (minutes)	31.06	8.24
Long Duration Sedentary Instances (minutes)	78.00	27.86

Table 28: Task Instances participant A, week 2 work from home

Task Type	Mon	Tue	Wed	Thu	Fri	Totals
Short Duration Sedentary Instances	7 accepted 0 rejected	6 accepted 0 rejected	9 accepted 0 rejected	4 accepted 0 rejected	7 accepted 1 rejected	33 accepted 1 rejected
Medium Duration Sedentary Instances	2 accepted 1 rejected	3 accepted 0 rejected	6 accepted 0 rejected	2 accepted 0 rejected	3 accepted 0 rejected	16 accepted 1 rejected
Long Duration Sedentary Instances	2 accepted 0 rejected	2 accepted 1 rejected	1 accepted 0 rejected	0 accepted 1 rejected	1 accepted 0 rejected	6 accepted 2 rejected

Table 29: Task Instances Parameter Characterisation, participant A, week 2 work from home

Task Type	Mean	Std. Dev
Short Duration Sedentary Instances (minutes)	11.94	7.31
Medium Duration Sedentary Instances (minutes)	29.44	7.25
Long Duration Sedentary Instances (minutes)	68.00	31.65

Table 30: Task Instances participant A, week 3 work from home

Task Type	Mon	Tue	Wed	Thu	Fri	Totals
Short Duration Sedentary Instances	3 accepted 0 rejected	5 accepted 2 rejected	6 accepted 0 rejected	6 accepted 0 rejected	1 accepted 0 rejected	21 accepted 2 rejected
Medium Duration Sedentary Instances	5 accepted 0 rejected	1 accepted 0 rejected	6 accepted 0 rejected	2 accepted 0 rejected	0 accepted 0 rejected	14 accepted 0 rejected
Long Duration Sedentary Instances	2 accepted 0 rejected	2 accepted 1 rejected	1 accepted 1 rejected	3 accepted 0 rejected	0 accepted 1 rejected	8 accepted 3 rejected

Table 31: Task Instances Parameter Characterisation, participant A, week 3 work from home

Task Type	Mean	Std. Dev
Short Duration Sedentary Instances (minutes)	10.00	5.12
Medium Duration Sedentary Instances (minutes)	28.93	7.61
Long Duration Sedentary Instances (minutes)	72.38	17.57

Table 32: Task Instances participant A, week 4 work from home

Task Type	Mon	Tue	Wed	Thu	Fri	Totals
Short Duration Sedentary Instances	6 accepted 1 rejected	12 accepted 0 rejected	2 accepted 1 rejected	11 accepted 1 rejected	2 accepted 0 rejected	33 accepted 3 rejected
Medium Duration Sedentary Instances	7 accepted 0 rejected	4 accepted 0 rejected	2 accepted 0 rejected	3 accepted 0 rejected	5 accepted 1 rejected	21 accepted 1 rejected
Long Duration Sedentary Instances	0 accepted 1 rejected	0 accepted 1 rejected	3 accepted 0 rejected	2 accepted 0 rejected	1 accepted 1 rejected	6 accepted 3 rejected

Table 33: Task Instances Parameter Characterisation, participant A, week 4 work from home

Task Type	Mean	Std. Dev
Short Duration Sedentary Instances (minutes)	10.73	4.59
Medium Duration Sedentary Instances (minutes)	29.52	6.48
Long Duration Sedentary Instances (minutes)	69.83	19.28

Table 34: Task Instances participant A, week 1 work from office

Task Type	Mon	Tue	Wed	Thu	Fri	Totals
Short Duration Sedentary Instances	12 accepted 1 rejected	14 accepted 2 rejected	10 accepted 2 rejected	9 accepted 1 rejected	18 accepted 1 rejected	63 accepted 7 rejected
Medium Duration Sedentary Instances	5 accepted 1 rejected	1 accepted 0 rejected	3 accepted 1 rejected	2 accepted 1 rejected	1 accepted 0 rejected	12 accepted 3 rejected
Long Duration Sedentary Instances	0 accepted 0 rejected	1 accepted 1 rejected	1 accepted 0 rejected	2 accepted 0 rejected	2 accepted 0 rejected	6 accepted 1 rejected

Table 35: Task Instances Parameter Characterisation, participant A, week 1 work from office

Task Type	Mean	Std. Dev
Short Duration Sedentary Instances (minutes)	9.65	4.56
Medium Duration Sedentary Instances (minutes)	29.33	5.58
Long Duration Sedentary Instances (minutes)	63.67	18.60

Table 36: Task Instances participant A, week 2 work from office

Task Type	Mon	Tue	Wed	Thu	Fri	Totals
Short Duration Sedentary Instances	11 accepted 2 rejected	20 accepted 2 rejected	14 accepted 3 rejected	13 accepted 3 rejected	7 accepted 1 rejected	65 accepted 11 rejected
Medium Duration Sedentary Instances	3 accepted 0 rejected	3 accepted 1 rejected	4 accepted 1 rejected	4 accepted 0 rejected	5 accepted 0 rejected	19 accepted 2 rejected
Long Duration Sedentary Instances	1 accepted 1 rejected	1 accepted 0 rejected	0 accepted 0 rejected	0 accepted 0 rejected	1 accepted 1 rejected	3 accepted 2 rejected

Table 37: Task Instances Parameter Characterisation, participant A, week 2 work from office

Task Type	Mean	Std. Dev
Short Duration Sedentary Instances (minutes)	9.85	4.64
Medium Duration Sedentary Instances (minutes)	27.42	3.83
Long Duration Sedentary Instances (minutes)	56.00	8.54

Table 38: Task Instances participant A, week 3 work from office

Task Type	Mon	Tue	Wed	Thu	Fri	Totals
Short Duration Sedentary Instances	9 accepted 2 rejected	6 accepted 1 rejected	11 accepted 2 rejected	9 accepted 1 rejected	16 accepted 2 rejected	51 accepted 8 rejected
Medium Duration Sedentary Instances	6 accepted 0 rejected	2 accepted 1 rejected	4 accepted 1 rejected	2 accepted 0 rejected	5 accepted 1 rejected	19 accepted 3 rejected
Long Duration Sedentary Instances	1 accepted 0 rejected	3 accepted 0 rejected	1 accepted 0 rejected	2 accepted 0 rejected	0 accepted 0 rejected	7 accepted 0 rejected

Table 39: Task Instances Parameter Characterisation, participant A, week 3 work from office

Task Type	Mean	Std. Dev
Short Duration Sedentary Instances (minutes)	10.14	4.46
Medium Duration Sedentary Instances (minutes)	30.16	8.23
Long Duration Sedentary Instances (minutes)	65.43	16.99

Table 40: Task Instances participant A, week 4 work from office

Task Type	Mon	Tue	Wed	Thu	Fri	Totals
Short Duration Sedentary Instances	7 accepted 0 rejected	11 accepted 0 rejected	11 accepted 1 rejected	15 accepted 0 rejected	7 accepted rejected	51 accepted 1 rejected
Medium Duration Sedentary Instances	3 accepted 0 rejected	5 accepted 1 rejected	2 accepted 0 rejected	3 accepted 2 rejected	4 accepted 1 rejected	17 accepted 4 rejected
Long Duration Sedentary Instances	1 accepted 1 rejected	1 accepted 0 rejected	1 accepted 2 rejected	0 accepted 0 rejected	2 accepted rejected	5 accepted 3 rejected

Table 41: Task Instances Parameter Characterisation, participant A, week 4 work from office

Task Type	Mean	Std. Dev
Short Duration Sedentary Instances (minutes)	10.98	4.51
Medium Duration Sedentary Instances (minutes)	29.53	6.89
Long Duration Sedentary Instances (minutes)	62.40	11.93

6.4.2. Health Habit Instances for Participant B

Participant B was working full time as a senior academic and researcher. Like participant A this meant that a significant portion of a typical weekday was consumed by desk work between the hours of 9am to 5pm with the more frequent and scheduled meetings than participant A, as well impromptu interruptions from co-workers and short coffee breaks throughout the day as time constraints made lunch breaks difficult to fit into the schedule.

Table 42: Task Instances participant B, week 1 work from home

Task Type	Mon	Tue	Wed	Thu	Fri	Totals
Short Duration Sedentary Instances	N/A	N/A	N/A	8 accepted 4 rejected	11 accepted 0 rejected	19 accepted 4 rejected
Medium Duration Sedentary Instances	N/A	N/A	N/A	2 accepted 1 rejected	1 accepted 1 rejected	3 accepted 2 rejected
Long Duration Sedentary Instances	N/A	N/A	N/A	1 accepted 0 rejected	2 accepted 0 rejected	3 accepted 0 rejected

Table 43: Task Instances Parameter Characterisation, participant B, week 1 work from home

Task Type	Mean	Std. Dev
Short Duration Sedentary Instances (minutes)	11.74	5.45
Medium Duration Sedentary Instances (minutes)	29.33	2.89
Long Duration Sedentary Instances (minutes)	70.67	14.19

Table 44: Task Instances participant B, week 2 work from home

Task Type	Mon	Tue	Wed	Thu	Fri	Totals
Short Duration Sedentary Instances	15 accepted 0 rejected	4 accepted 0 rejected	6 accepted 1 rejected	9 accepted 1 rejected	9 accepted 0 rejected	43 accepted 2 rejected
Medium Duration Sedentary Instances	3 accepted 2 rejected	5 accepted 0 rejected	5 accepted 0 rejected	2 accepted 1 rejected	3 accepted 0 rejected	18 accepted 3 rejected
Long Duration Sedentary Instances	0 accepted 0 rejected	1 accepted 0 rejected	2 accepted 0 rejected	1 accepted 0 rejected	1 accepted 0 rejected	5 accepted 0 rejected

Table 45: Task Instances Parameter Characterisation, participant B, week 2 work from home

Task Type	Mean	Std. Dev
Short Duration Sedentary Instances (minutes)	11.02	4.80
Medium Duration Sedentary Instances (minutes)	35.17	7.69
Long Duration Sedentary Instances (minutes)	73.80	22.66

Table 46: Task Instances participant B, week 3 work from home

Task Type	Mon	Tue	Wed	Thu	Fri	Totals
Short Duration Sedentary Instances	3 accepted 0 rejected	2 accepted 0 rejected	8 accepted 0 rejected	5 accepted 1 rejected	N/A	18 accepted 1 rejected
Medium Duration Sedentary Instances	0 accepted 0 rejected	3 accepted 0 rejected	3 accepted 0 rejected	2 accepted 2 rejected	N/A	8 accepted 2 rejected
Long Duration Sedentary Instances	1 accepted 1 rejected	2 accepted 0 rejected	2 accepted 0 rejected	2 accepted 0 rejected	N/A	7 accepted 1 rejected

Table 47: Task Instances Parameter Characterisation, participant B, week 3 work from home

Task Type	Mean	Std. Dev
Short Duration Sedentary Instances (minutes)	12.72	5.79
Medium Duration Sedentary Instances (minutes)	31.50	8.05
Long Duration Sedentary Instances (minutes)	75.29	34.51

Note there was no data collected for a fourth week of participant B working from home as work from the office had resumed at this point.

Table 48: Task Instances participant B, week 1 work from office

Task Type	Mon	Tue	Wed	Thu	Fri	Totals
Short Duration Sedentary Instances	7 accepted 0 rejected	3 accepted 1 rejected	7 accepted 1 rejected	15 accepted 2 rejected	14 accepted 1 rejected	46 accepted 5 rejected
Medium Duration Sedentary Instances	4 accepted 0 rejected	3 accepted 0 rejected	1 accepted 0 rejected	1 accepted 0 rejected	3 accepted 0 rejected	12 accepted 0 rejected
Long Duration Sedentary Instances	2 accepted 1 rejected	3 accepted 0 rejected	3 accepted 0 rejected	1 accepted 0 rejected	1 accepted 0 rejected	10 accepted 1 rejected

Table 49: Task Instances Parameter Characterisation, participant B, week 1 work from office

Task Type	Mean	Std. Dev
Short Duration Sedentary Instances (minutes)	8.83	3.56
Medium Duration Sedentary Instances (minutes)	36.67	6.67
Long Duration Sedentary Instances (minutes)	69.80	19.41

Table 50: Task Instances participant B, week 2 work from office

Task Type	Mon	Tue	Wed	Thu	Fri	Totals
Short Duration Sedentary Instances	2 accepted 0 rejected	7 accepted 0 rejected	2 accepted 0 rejected	10 accepted 1 rejected	9 accepted 1 rejected	30 accepted 2 rejected
Medium Duration Sedentary Instances	3 accepted 1 rejected	2 accepted 0 rejected	1 accepted 0 rejected	2 accepted 0 rejected	4 accepted 1 rejected	12 accepted 2 rejected
Long Duration Sedentary Instances	1 accepted 2 rejected	3 accepted 1 rejected	2 accepted 1 rejected	1 accepted 0 rejected	1 accepted 0 rejected	8 accepted 4 rejected

Table 51: Task Instances Parameter Characterisation, participant B, week 2 work from office

Task Type	Mean	Std. Dev
Short Duration Sedentary Instances (minutes)	11.20	4.69
Medium Duration Sedentary Instances (minutes)	32.08	6.68
Long Duration Sedentary Instances (minutes)	68.88	10.33

Table 52: Task Instances participant B, week 3 work from office

Task Type	Mon	Tue	Wed	Thu	Fri	Totals
Short Duration Sedentary Instances	6 accepted 0 rejected	6 accepted 2 rejected	4 accepted 0 rejected	10 accepted 0 rejected	9 accepted 2 rejected	35 accepted 4 rejected
Medium Duration Sedentary Instances	3 accepted 0 rejected	2 accepted 0 rejected	2 accepted 0 rejected	4 accepted 0 rejected	4 accepted 0 rejected	15 accepted 0 rejected
Long Duration Sedentary Instances	2 accepted 0 rejected	2 accepted 2 rejected	0 accepted 0 rejected	1 accepted 0 rejected	1 accepted 0 rejected	6 accepted 2 rejected

Table 53: Task Instances Parameter Characterisation, participant B, week 3 work from office

Task Type	Mean	Std. Dev
Short Duration Sedentary Instances (minutes)	10.40	5.36
Medium Duration Sedentary Instances (minutes)	28.20	5.02
Long Duration Sedentary Instances (minutes)	61.33	15.76

Table 54: Task Instances participant B, week 4 work from office

Task Type	Mon	Tue	Wed	Thu	Fri	Totals
Short Duration Sedentary Instances	17 accepted 2 rejected	6 accepted 0 rejected	13 accepted 1 rejected	13 accepted 1 rejected	8 accepted 2 rejected	57 accepted 6 rejected
Medium Duration Sedentary Instances	1 accepted 1 rejected	2 accepted 0 rejected	3 accepted 0 rejected	1 accepted 1 rejected	1 accepted 1 rejected	8 accepted 3 rejected
Long Duration Sedentary Instances	2 accepted 0 rejected	3 accepted 0 rejected	0 accepted 0 rejected	0 accepted 2 rejected	0 accepted 1 rejected	5 accepted 3 rejected

Table 55: Task Instances Parameter Characterisation, participant B, week 4 work from office

Task Type	Mean	Std. Dev
Short Duration Sedentary Instances (minutes)	8.84	4.07
Medium Duration Sedentary Instances (minutes)	27.88	3.64
Long Duration Sedentary Instances (minutes)	63.60	19.92

6.4.3. Health Habit Comparison Participant A to Participant B

The following section compares different weeks of observed data and work situations between the two participants to understand the differences in sedentary habitual behaviour over a period of time.

A limitation of the data collection of participant B is that only week 2 of the 3 weeks of data collected is a full work week at home. Therefore, for the most accurate comparison possible between the two participants for working from home the week 2 data is being used for both participants.

6.4.3.1. Week 2 – Working from Home Comparison

Table 56 below shows the mean and standard deviation for the duration across all three types of sedentary task types for participant A and participant B. Also included are the total accepted and rejected instances of these sedentary task types.

Table 56: Week 2 - Work from Home Comparison

Week 2 – Work from Home Comparison				
Participant	**Task Type**	**Mean**	**Std. Dev**	**Total Instances (% accepted)**
A	Short Duration Sedentary Instances (minutes)	11.94	7.31	33 accepted (97.06%) 1 rejected
A	Medium Duration Sedentary Instances (minutes)	29.44	7.25	16 accepted (94.12%) 1 rejected
A	Long Duration Sedentary Instances (minutes)	68.00	31.65	6 accepted (75.00%) 2 rejected
B	Short Duration Sedentary Instances (minutes)	11.02	4.80	43 accepted (95.56%) 2 rejected
B	Medium Duration Sedentary Instances (minutes)	35.17	7.69	18 accepted (85.71%) 3 rejected
B	Long Duration Sedentary Instances (minutes)	73.80	22.66	5 accepted (100.00%) 0 rejected

It can be seen across week 2 that both participants have a similar amount of sedentary task type instances accepted for almost all task types except the short duration sedentary task type. Participant B has 10 more instances of the short duration sedentary task type indicating possibly either a higher degree of interruptions from external factors when working from home compared to that experienced by participant A or participant B has less opportunities for longer periods of focused work due to meeting schedules, phone calls, or similar work-based interruptions.

Both participants were able to find large blocks of time for focused work throughout the week with participant A and participant B having 6 and 5 long duration sedentary instance type instances across the one work week while working from home. There is also a higher degree of medium duration sedentary task type instances which appears to be consistent across both participants. However, on average the duration of the sedentary task type instances were approximately 5 minutes longer for participant B compared to participant A which could be attributed to task type (i.e. completing the task sooner) or external interruptions.

6.4.3.2. Week 2 – Working from Office Comparison

Table 57 below shows the mean and standard deviation for the duration across all three types of sedentary task types for participant A and participant B. Also included are the total accepted and rejected instances of these sedentary task types.

Table 57: Week 2 - Work from Office Comparison

Week 2 – Work from Office Comparison				
Participant	**Task Type**	**Mean**	**Std. Dev**	**Total Instances (% accepted)**
A	Short Duration Sedentary Instances (minutes)	9.85	4.64	65 accepted (85.53%) 11 rejected
A	Medium Duration Sedentary Instances (minutes)	27.42	3.83	19 accepted (90.48%) 2 rejected
A	Long Duration Sedentary Instances (minutes)	56.00	8.54	3 accepted (60.00%) 2 rejected
B	Short Duration Sedentary Instances (minutes)	11.20	4.69	30 accepted (93.75%) 2 rejected
B	Medium Duration Sedentary Instances (minutes)	32.08	6.68	12 accepted (14.29%) 2 rejected
B	Long Duration Sedentary Instances (minutes)	68.88	10.33	8 accepted (66.67%) 4 rejected

Across the week 2 working from office results there are some significant differences between the total instances of all task types between the participants. As this is the working from office results there are quite likely a higher degree of differences between the way interactions occur in the two different office settings. Although both offices are of a similar open-plan layout on average the sedentary instances mean duration for participant B are longer than that of participant A. Participant A appears to have more frequent interruptions, or shorter intense periods of focused work as indicated by the 65 accepted instances of the short duration sedentary task type compared to the 30 accepted instances of the short duration sedentary task type of participant B which are slightly longer in duration on average.

It is also clear that participant B was able to have much longer periods of focused work over the course of the week with 8 accepted long duration sedentary task type instances compared to participant A's 3 accepted long duration sedentary task type instances. Participant B having more than double than that of participant A. Participant A's long duration sedentary task type instances were also shorter on average.

There are more instances throughout the week where participant A did have more instances of the medium duration sedentary task type where perhaps time had been blocked out or scheduled to work on specific tasks and this may account for more instances of the medium duration sedentary task type compared to participant B.

The variations between individuals (inter subject variability) are larger than the variations within an individual (intra) which allows for the possibility of precision customisation to individuals rather than a "one size" fits all intervention. The quantity of successful heath habit instance identification can differ disproportionally between some individuals if the health habits are not so well defined.

6.5. Limitations

Future studies would benefit from the addition of more participants for better comparisons to be drawn between the participants, across multiple locations. Whether a more uniform home or office setting would yield better results for comparison is unclear, as to the impact home and office layouts have on sedentary behaviour. This may be a consideration of future studies as well.

Another limitation is that one of the participants was not able to record work from home data for the full four-week duration. The Covid lockdown in that part of Australia was lifted and working from the office was enforced again for the participant.

6.6. Conclusion

There has been a large quantity of health habits successfully identified in case study 3, particularly in comparison to case study 2. Demonstrating that a longitudinal data set as expected allows for a higher amount of well-defined health habits accepted with the characterised health habit criteria.

It has been shown that the DHIF-PP artefact is successfully able to characterise and identify sedentary health habits much-like active health habits as in case study 1 and 2. Future applications of the DHIF-PP artefact on sedentary health habits might target periods of rest such as taking a nap as another type of sedentary health habit as opposed to periods of focused work.

As a similar amount of accepted sedentary health habits were identified across both participants, in both environments, the DHIF-PP artefact is shown to be a generalisable approach for characterising and identifying sedentary health habits for varying office-type desk work whether that is from an office building or a work from home situation.

Case study 3 has also shown that there are only small differences in sedentary health habits when working from home compared to when working from the office with interruptions or short bursts of focused work (short duration sedentary instances) to be more common when working from the office. Suggesting that working from home is more conducive to longer periods of focused work.

7. DISCUSSION & CONCLUSION

7.1. Summary

The main aim of this thesis was to outline an easily accessible, cost-effective, and reasonably accurate approach to identifying and characterising health habits of individuals, with a focus on active and sedentary behaviours. The first key research question this thesis addressed was a review of the current landscape of approaches to identifying and characterising patterns of habitual movement and their limitations and implications. It was found that the existing approaches have an emphasis on expensive, high-precision laboratory-based contexts. The limitation being a lack of general accessibility with barriers in costs, equipment, and restricted contexts. Which the primary contribution of this research attempts to address. The second key research question this thesis addressed was to assess the fundamental characteristics of patterns for typical movement related health habits. Through a review of existing approaches to characterising patterns for typical movement related health habits it was found that there is a heavy reliance on strong statistical analysis of data recorded with expensive scientific instruments. This doesn't allow for a generally applicable approach to characterising patterns of typical movement related health habits due to the cost barrier, and prerequisite knowledge of advanced statistical concepts. The third key research question this thesis addressed was how can an information model for health habit patterns be framed in a way which is simple while still yielding useful results for informing future interventions? At the core of the proposed approach in this thesis the one-minute resolution of the collected data per participant is vital in yielding useful results whilst following an accessible approach to analysis.

The major contribution from this research is a novel information model following a pragmatic approach to identify health habits using a limited number of attributes that have been measured as part of typical natural-setting activity monitoring research such as step counts. This novel pragmatic approach was developed using the Design Science Research methodology and resulted in an DHIF-PP artefact which defines a procedural approach for the analysis of simple human activity and sedentary data.

While this DHIF-PP artefact is an initial and imperfect methodology, it has proven through its application to the three case studies its ability and functionality as a tool in characterising and identifying health behaviours. Though new, the DHIF-PP artefact may prove instrumental in the field of health behaviour analysis, and modification as a foundational tool. This is further discussed under the section "Future Considerations" as to the relevance it may have in several other fields of research.

It has been demonstrated using the defined DHIF-PP artefact approach that health habits can be identified through a pragmatic data extraction and health habit characterisation and identification approach, which leads to simple quantitative analysis of step count data and other parameters where available. This has been argued on the basis of three independent case studies to be a generic approach that is usable across various data sets associated with different constrained environments and participant demographics. The first case study and initial DHIF-PP artefact design was shaped by the simulation of tasks to get a baseline reading to iterate and refine the DHIF-PP artefact with (Poultney, N., Maeder, A., 2018). Then applying the refined DHIF-PP artefact in case studies 2 and 3. It has also been demonstrated that it has utility and robustness for identifying and characterising several different types of patterns of activity health habits and sedentary health habits of individuals, some of which are common among the individuals and some distinct to individuals.

The level of characterisation that has been feasible for distinguishing both differences and commonalities in patterns of health habits has been shown to be sufficient for typical practical purposes within windows based on step count data at a 1-minute resolution obtained from wearable activity monitors. This implies that it is possible to measure step count data outside of a laboratory environment with which to characterise habitual activities with a reasonable degree of accuracy, without sophisticated measuring devices and complex analytical tools.

This approach offers potential for the identification and characterisation of health habits from step count and temporal parameters with a pragmatic approach to the problem. This would enable low effort intervention tailoring for individuals based on their health habits. The paradigm use case for this approach would be to discover periods during a day where opportunities exist to increase steps taken and deliver the appropriate intervention cue. This could provide more satisfactory outcomes for non-contextual decision logic than typical contemporary consumer style solutions, such as a fixed time interval or fixed activity initiation-based approaches.

The approach has shown to be generally applicable to characterising and identifying both active health habits and sedentary health habits in tightly controlled simulated tasks akin to laboratory type settings. As well as applicable to general office worker environments with and without location data, and applicable to office-type work undertaken in a home environment.

7.2. Limitations

There have been limitations with this research in regards to the accuracy of consumer wearable devices and Bluetooth beacons. While Fitbit devices are widely considered to be a mainstream consumer wearable device the middle and low-tier models have been found to under report step counts. When it comes to using the Bluetooth beacon’s signal for location recording of an individual, they may have issues with mobile device’s Bluetooth not picking up the Bluetooth beacon signal in passing. It is difficult to determine whether this is because of interference, some kind of barrier, or the speed at which an individual passes the Bluetooth beacon.

The number of participants has also been a limiting factor. Future research would benefit from a greater quantity of participants, and the wealth of data points that would be available as a result of a larger sample size. While the focus of this research has been on a work-office setting. Applying the DHIF-PP artefact approach to other locations such as industrial workers, delivery services etc may also be suitably applicable to this approach.

There are difficulties to be had with working with 1-minute resolution data. In some cases, it is unclear where physical activity has started and ended, as a 60-second interval introduces various degrees of noise. For interventions in typical free-living scenarios that are not concerned with extreme precision the DHIF-PP artefact approach has been found to be useful.

Another limitation found is that there is no form of built-in gait analysis, or similar means of determining if an individual’s pace is different to normal, and as a result there is no way of knowing if an individual is carrying items while they are walking, or if they are pushing/pulling an object such as a trolley.

The DHIF-PP artefact produced through the use of the Design Science Research methodology is imperfect, further refinement with varying and larger data sets following the iterative process of the Design Science Research methodology is likely to yield better health habit detection rates. This would likely also simultaneously reduce the volume of false positives and false negatives. Aspects of the Design Science Research methodology that are lacking may be easier to surface and strengthen in future research work that adopts the Design Science Research methodology.

7.3. Recommendations

It is recommended that when analysing step count data, if possible, location data should be recorded in synchronisation with the step count data. This was an initial hurdle with case study 2 where these two separate data sets had to be synchronised together after the data collection period. This allows for a more accurate application of the methodology and less time spent filtering the data set and having to run manual or semi-automatic data processing techniques to synchronise the different data sets. The location data also allows easier identification, and with great accuracy, of the various types of health habits within a data set that may not otherwise be distinguished through recording of step counts and timestamps alone.

With consumer wearable devices in studies or interventions where a higher level of precision is required a 30 second data resolution would be desirable. This may however require top-tier consumer wearable devices which may not be as user-friendly, or as cost effective as general consumer grade wearable devices such as Fitbit devices.

Another recommendation is when using indoors location signal recording such as Bluetooth beacons, a higher density and quantity of Bluetooth beacons or similar devices would likely mean greater accuracy of location data of participants. Although, the placement of such devices when in greater volume would need to have a reasonable minimal difference between them to prevent noise in the data where there are overlapping signals recorded e.g., two different locations are recording that a participant is at both of them simultaneously.

If the DHIF-PP artefact were to be applied to a larger data set heuristic decisions would need to be made. The application of the DHIF-PP artefact in the three case studies described in this thesis was intended as an initial template approach to see if it was possible to characterise and identify health habits with so few parameters. Future research may expand on the DHIF-PP artefact approach through successive iterations of the DHIF-PP artefact on much larger complex data sets to improve the effectiveness and accuracy.

7.4. Future Considerations

Future applications of the DHIF-PP artefact have the capability of being adapted to many fields following further refinements to the methodology, through the use of larger and more varied data sets and using data beyond step count data, such as heart rate monitoring, blood oximeters, and other increasingly common technologies added to consumer-grade wearable devices.

Heart rate and other physiological data which is easy to capture with non-intrusive wearable devices may also be included to assist in accurate health habit identification e.g., differentiating between higher energy activities such as stair climbing compared with flat walking. Such data could also help to refine and confirm the nature of sedentary time periods, such as whether they are quiescent (like reading or talking) or involve sustained physical activity not associated with mobility (like keyboard or equipment usage).

The analysis of sleep data as a type of activity with habitual components may also be considered for analysis using this approach. Sleep related data in several types of wearable devices is also currently recorded at a 1-minute resolution so can be substituted in place of step count in the application of the DHIF-PP artefact. A sleep variant applied in conjunction with the step count variant presented here, may also provide a means to analyse the effect that sleep has on daily step count activity and health habits.

The DHIF-PP artefact approach could be expanded for the analysis of unconstrained, outdoor environments. Depending on the geography and space of the environment such as farmland, location data may be easier to capture through mobile device or consumer wearable device GPS tracking. This would likely be more difficult to track in small outdoor environments where GPS accuracy suffers if the individuals' movements are confined to a distance inside of the level of accuracy of the GPS technology available.

There are various domains in which this research could be used to better inform systems or interventions beyond the health behaviour change, quantified self, or citizen science domains. For example, consider the following:

- Online content delivery systems
  - e.g., GPS on mobile phone detecting the regularly walked path and suggesting alternative paths to maintain long term interest in the walking activity.
- Intelligent recommendation services
  - e.g., wearable, or mobile device detecting a running or cycling activity and recommending local running or cycling clubs.
- Automated delivery of entertainment media
  - e.g., upbeat music started automatically by a wearable device having detected a running activity has begun.
- Health Insurance
  - e.g., reduction in health insurance costs to the individual based on how physically active they are as measured by their wearable device (Purtill, J., 2018).
- Military application
  - e.g., identifying strengths and weaknesses in military personnel fitness assessments as measurable from wearable device step recordings.
- Entertainment media consumption activity reminder system
  - e.g., a notification or nudge when an individual has spent a prolonged period of time in one sitting consuming media such as television, video gaming, web surfing etc.
- Reminder and recommendation systems for the infirm, elderly, and/or disabled
  - e.g., a notification or nudge when an individual has been exhibiting sedentary behaviour for prolonged periods of time.

8. APPENDIX

A. "Habitual Personal Movement Patterns in a Structured Environment", Nathan Poultney and Anthony Maeder. Transforming Healthcare through Innovation in Digital Health. Global Telehealth (GT2018) Conference, Colombo, Sri Lanka, 2018.

Habitual Personal Movement Patterns in a Structured Environment

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Abstract

This paper presents an approach for describing personal movement patterns for typical daily activities undertaken by subjects within free living structured environments (e.g. home or office). Conventionally this requires specialized technology for personal movement monitoring involving measurement of location and motion, and results in the collection of large datasets in order to provide sufficient descriptive power. Here we advocate the preferential observation of sentinel activities based on the expectation of routine and repetitive personal movement episodes, which can be considered as 'habits'. These identified habitual patterns provide a useful context for understanding the dominant characteristics of typical daily activities, enabling purposeful design of behaviour change interventions to improve healthy living. This approach has been applied here to office stepcount data from consumer wearables.

Keywords:

Personal movement monitoring, health behaviour change, consumer wearables, daily activities, stepcount.

Introduction

Humans living in organised settings exhibit typical characteristic daily activities, determined by a number of factors including their personal circumstances and intentions [1] as well as the structural layout of their living environments [2]. In this work, we are concerned with those activities which require sustained bodily movement by the subject in free living circumstances, such as walking, climbing stairs or exercising. At home, typical daily activities of this type include moving between rooms, food preparation, hygiene, and gardening, while in the office they include attending meetings, collegial discussions, taking breaks, and hosting visitors. Daily activities can provide useful indicators for assessment and management of health situations such as ageing [3] or rehabilitation [4].

Within the range of daily activities, some are frequently repeated and form habitual patterns which can potentially be more readily observed and interpreted. The existence and analysis of established habits can be exploited for prediction [5] and thus can also act as an outcome measure for a health behaviour change intervention related to these habits. Furthermore, the mechanisms for the establishment of habits, and factors contributing to their reinforcement, can be harnessed to inform the design of such interventions [6]. Detection and measurement of these habits can therefore prompt the need for highly representative activity datasets for further analysis, and can enable understanding of the broader context for those preferred activities [7].

Personal movement information concerned with daily activities is commonly detected through the processing of high resolution data, gathered in large volumes within a particular setting [8]. This type of data can be extremely specific and personal to the individuals monitored, allowing for in-depth analysis of bodily movements, physical actions, and even vital signs. We have focussed on personal movement activities as the health benefits of these have been well established e.g. [9]. These activities offer a promising prospect for automated observation rather than reliance on self-report. A fundamental source of relevant data is from sensors incorporating traiaxial accelerometers, from which multiple movement-related parameters can be extracted [10]. Identifying particular spatial locations which are visited by subjects during their movement activities requires a different data source, such as wireless network points or Bluetooth beacons which allow active proximity sensing [11].

The ideal types of environments for remote collection of such data are specifically constructed and controlled spaces, often termed 'smart spaces' [12], provided with insitu sensor and instrumentation infrastructure. These environments allow for the setup of various monitoring devices and underlying controls, and thus enable much more convenient data collection on individuals by providing the ability to cover a wide range of potential parameters. The use of smart spaces for human personal movement monitoring has been widely reported in the literature, for both home and office settings. For example, multi-sensor systems have been established for monitoring movement related to health status and risk management in aged residential homes [13] as a form of telehealth, and ambient aware environments have been described for tracking human activities in broader living and working application spaces [14].

However, the complexity and overhead of operating and maintaining such purpose-built smart space environments precludes them from being generally useful in monitoring free living situations. Instead, we argue that a very simple equipment configuration can provide adequate data for detecting habitual personal movement activities and thus for characterizing an overall envelope of the most significant daily activities related to personal movement. These activities may be considered as 'sentinel' in that they are highly indicative of the majority of time spent and actions taken as a proportion of the overall set of daily personal movement activities. By observing a large fraction of the total non-trivial occurrences of physical activity during a day, it should be easier to interevene to improve the nature of the activities because of their familarity. It should also be more effective to achieve change based on this knowledge, as it will entail only a modification to an existing well-established behaviour pattern, rather than adoption of a new behaviour. Our investigation of this approach was in the office setting to enable self-experiment.

Methods

Here we will consider the implications of using a highly simplified smart space, constructed using consumer wearable device (Fitbit) and low power location beacons (Bluetooth). This presumes that future 'health-smart' infrastructure will rely more on cheap, reconfigurable, mass-produced sensors such as RFID tags and miniaturised IoT devices, rather than on custom-designed, programmable, multifunction sensor units such as Raspberry Pi or Arduino devices. This decision has the effect of constraining the potential resolution and quality of the data collected, while at the same time providing an inherently flexible and scaleable data collection environment.

We also need to consider how to identify and represent recurring habitual personal movement behaviours or 'habits'. Habitual physical activity behaviour is typified by three properties [15]:

- learned sequences of actions which have become automatic reponses;
- linked satisfactory experiences enhance a tendency to repeat the actions;
- a behaviourist response is activated by implied goal-directed cognitive drivers.

For our purposes, a habit in the domain of personal movement consists of three observable elements:

- the start and end points of the related set of actions can be established unambiguously and with useful accuracy to enable comparison of instances;
- the set of actions within the duration of a habit instance follow a well-defined sequence and intensity;
- actions associated with a habit instance are independent of actions undertaken during adjacent periods of non-habit behaviour.

The setting for our observational study was our own workplace office environment, consisting of half a floor of a modern university building with contiguous areas of open plan workstations, small offices and meeting rooms, and a shared central public space with social and eating areas. The space was highly structured and fixed in its physical layout, and allowed us the opportunity for self-experiment by the authors to collect data (therefore without need for ethics). It was acknowledged that human behaviour in the office setting tends to be strongly regular and disciplined in nature, implying that fewer and more tightly bounded habits may be expected than say in the home.

We collected daily activity data using Fitbit logs managed by the vendor online and available through their application software, and Bluetooth beacon location logs maintained via an inhouse app installed on the subjects' personal smartphones. Data was accumulated for the 2 subjects continuously during working hours (nominally 09:00-17:00) over 1 week (5 working days). This information characterized the walking habits associated with the chosen sentinel activities, within the overall space defined by the 5 key locations demarcated with low-energy Bluetooth beacons. The locations chosen for these were:

- office entrance doorway;
- office printing area;
- bathroom doorway;
- communal refreshment area bench;
- midway point between bathroom and refrehment area.

Results

As collection of high resolution data was not feasible within our chosen observational environment, we focussed on capturing enough information from simple consumer wearables on sentinel activities of personal movement to provide an opportunity for insights into the types of habitual behaviour patterns we were seeking to study. We thus needed to establish a set of candidate sentinel activities for which ground truth could be established, in order to assure the utility of the data collected. We elected to identify these sentinel activities on the basis that they were part of normal workplace intrinsic human functions, they usually occurred several times (2 or more) across all subjects through the typical working day, and were normally planned and initiated by the individual who was undertaking them rather than occurring randomly. The two characteristics chosen to distinguish sentinel activities were:

- single vs multiple locations as the activity destination;
- short vs sustained elapsed time as the activity duration.

The parameters measured were stepcounts accumulated at 1 min intervals and proximity (< 5 m) to an identified beacon with 30 sec detection intervals. The variability of stepcounts and duration of the activity were assessed for various walking activities within the study space, which included trips to the printing area, meeting rooms, bathrooms and communal refreshments area. Trips made as individuals differ from those for interacting in social groups or when hosting visitors. The starting and ending location for each trip was the office desk where the subject was normally seated. Stepcount data provided an indication of whether single or multiple destinations were visited, and location data provided ground truth for single or multiple destinations according to the sequence and timing of locations being passed by the subject.

Following data conventions described elsewhere [16], we adopted the definition of activity lasting < 30 min as a short duration, such as coffee and toilet breaks, and > 30 min as sustained duration, which aligns with local expectations of multi-party meetings and collegial conferring visits. As a pratical limit we considered only activities of a maximum 1 hr 30 mins duration, as it was observed that longer instances were infrequent. The data was summarised using simple range (i.e. sample maximum and minimum), mean and standard deviation (S.D.) statistics for the two subjects.

From the full dataset, 26 clear instances of trips aligned with these activities were extracted (see Table 1), for cases where a sequence of one or more locations could be unambiguously identified. From these instances, three categories of trips associated with sentinel activities were defined:

- single location short duration (e.g. direct return trips to the printer or bathroom);
- single location sustained duration (e.g. prolonged return trips to obtain refreshments or attend meetings);
- multiple location sustained duration (e.g. moving between several location to socialise or convey visitors).

Statistics for the stepcount and duration components of the three sentinel categories are shown in Table 2. Single location trip stepcount range was 104-213 steps and multiple location range was 245-501 steps, with the cutpoint determined by interval analysis. Short duration trip time range was 1:53-24:38 and long duration range was 28:00-1:29:27 with the cutpoint determined by the first occurrence of a validated multiple destination activity in the duration-ordered sequence.

Table 1: Data for individual activity instances

Subject	Duration (hh:mm:ss)	Stepcount (steps)	Activity
A	1:53	121	Short single
B	2:56	146	Short single
B	3:52	132	Short single
B	3:53	198	Short single
A	2:00	151	Short single
A	7:41	147	Short single
A	8:42	167	Short single
B	13:30	104	Short single
B	17:29	110	Short single
A	20:38	146	Short single
A	24:38	194	Short single
A	34:54	161	Sustained single
A	38:18	131	Sustained single
A	53:52	213	Sustained single
A	54:50	179	Sustained single
B	1:01:52	159	Sustained single
A	1:14:09	144	Sustained single
B	1:23:56	145	Sustained single
B	1:29:27	159	Sustained single
B	28:00	383	Sustained multi
B	31:19	288	Sustained multi
A	38:05	342	Sustained multi

B	59:57	324	Sustained multi
B	1:04:19	245	Sustained multi
A	1:10:48	315	Sustained multi
B	1:16:33	393	Sustained multi
B	1:23:59	501	Sustained multi

It can be seen that the mean stepcount values for single destination trips are comparable, with the sustained single trips being slightly greater than short single trips, while the S.D. values suggest a tighter distribution of stepcounts for sustained single trips than for short single trips. Sustained multiple destination trips have a substantially higher mean and S.D. confirming their different characteristic from single trips. The duration statistics show comparable mean and S.D. values for sustained single and sustained multiple trips, while short single trips are substantially shorter in mean time and with lower S.D.

Table 2: Overall sentinel activity characterisation

Activity	Stepcount (steps)	Duration (hh:mms:ss)
Short single N=11	Range = 104-198 Mean = 146 S.D. = 32	Range = 1:53-24:38 Mean = 10:31 S.D. = 8:06
Sustained single N=8	Range = 131-213 Mean = 161 S.D. = 25	Range = 34:54-1:29:27 Mean = 1:01:29 S.D. = 20:46
Sustained multi N=8	Range = 245-501 Mean = 349 S.D. = 78	Range = 28:00-1:23:59 Mean = 56:20 S.D. = 20:55

We next considered inter-subject variability and investigated whether we might be able to obtain reliable separation between the measured values for the same habit being exercised by different subjects. It was determined that there was insufficient data for this analysis to be representative for the sustained single and sustained multiple activity results, due to the skewed number of results between the two subjects being 5:3 and 2:6 respectively for sustained cases. Table 3 therefore shows the activity statistics for the only short single sentinel activities, for the two subjects.

Table 3: Short single duration sentinel activity characterisation

Activity	Stepcount	Duration
Subject A N=5	Range = 121-194 Mean = 155 S.D. = 27	Range = 1:53-24:38 Mean = 13:16 S.D. = 10:05
Subject B N=5	Range = 104-198 Mean = 138 S.D. = 38	Range = 2:56-17:29 Mean = 10:12 S.D. = 8:21

It can be seen from the above table that Subject A has higher mean stepcount and duration, and lower stepcount S.D. but higher duration S.D., than Subject B. Despite the small N values, these two statistics appear to offer a discrimination criterion as the mean values differ by 10% for stepcount and 30% for duration, and the S.D. values differ by 30% for stepcount and 20% for duration. This suggests it is necessary to consider both statistics together for the sentinel activity characterization.

Conclusion

The purpose of this work was to investigate by means of an observational study, whether use of consumer grade personal wearable activity tracking devices such as Fitbits combined with carrying smartphones on-the-person, would provide sufficient data for statistical characterization to typify often-repeated daily activities, for individual subjects. The approach we have proposed uses a simple mechanism for collecting stepcounts, validated by means of Bluetooth beacons placed at key locations associated with the sentinel activities.

We have shown experimentally that collection of a relatively small quantity of coarse scale raw data in an environment not specifically set up for daily activity habits monitoring can provide useful information on typical habits. The results reported indicated that habits could be clearly characterized with only the two simple parameters measured, and that there was good prospect for inter-subject separation if sufficient data was available. Further work will involve characterizing the amount of data needed to establish an envelope of pre-specified accuracy for the analysis, and to differentiate between different subjects.

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B. "Detecting Personal Movement Patterns in a Structured Environment", Anthony Maeder and Nathan Poultney. IEEE Engineering in Medicine and Biology Conference (EMBC), Honolulu, USA, 2018.

Detecting Personal Movement Patterns in a Structured Environment

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***Abstract*— This paper describes an approach for observation of daily activity habits in formally laid out constructed environments (e.g. in smart homes or workplaces). This process typically relies on use of specialized location and tracking technology and collection of large volumes of data, to assure desired levels of accuracy. If detection of only "sentinel" activities is sought, the granularity of data needed may be coarser. This contribution proposes use of simpler consumer level technology tracking movement and location of subjects, to detect main repetitive activity patterns.**

Introduction

Observation of habitually repeated patterns of human activity of daily living can provide highly representative datasets for further analysis [1]. Daily activity habits are commonly detected through the analysis of high resolution data, gathered in large volumes within a particular setting [2]. This type of data can be extremely specific and personal to the individuals monitored, allowing for in-depth, detailed analysis of movements, actions, and even body vitals. The ideal environment for such data collection are laboratories of smart spaces, which allow for the setup of various monitoring tools and devices and thus much easier data collection on individuals covering a wide range of potential parameters [3]. Such daily activity habits data collection systems are not as readily available in other constructed human living environments like public spaces or workplaces.

Methods

Where collection of high resolution data is not feasible within a daily activity habit observational environment, focusing on sentinel activities can provide an opportunity for capturing enough information to give insights into the types of patterns we seek. The purpose of this work is to investigate whether use of commercial grade personal wearable activity tracking devices such as Fitbits combined with carrying smartphones on-the-person, would provide sufficient data for statistical characterization to typify often-repeated repeated daily activities, for individual subjects. The solution uses dual data collection mechanisms, for detecting movement of subjects within the study space and for collecting their cumulative stepcounts. This approach helps to overcome the coarse granularity of data provided by the Fitbit stepcount application software, and integrates data from a smartphone application with the ability to detect Bluetooth beacons placed at key locations associated with the sentinel activities.

Results

Data collected for 2 subjects over 1 week during working hours was analyzed to find walking habits associated with 5 key locations around the study space, demarcated with low-energy Bluetooth beacons. The parameters measured were

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stepcounts accumulated at 1 min intervals and proximity (< 5 m) to an identified beacon with 30 sec detection intervals. The variability of stepcounts and duration of the activity were assessed for various walking activities within the study space, which included trips to the printing area, meeting rooms, bathrooms and communal refreshments area. Trips made as individuals differ from those in social groups or when hosting visitors. The starting and ending location for each trip was the office desk where the subject was normally seated. Stepcount data provided an indication of whether single or multiple locations were visited, and location data provided ground truth for single or multiple locations being passed by the subject. Sentinel activities chosen for analysis were:

- single vs multiple locations;
- short vs long time duration.

From the full dataset, 30 trips aligned with these activities were extracted, where a sequence of one or more locations could be unambiguously identified. Three categories of trips associated with sentinel activities were analyzed:

- single location short trips (e.g. printer, bathroom);
- single location long trips (e.g. refreshments, meetings);
- multiple location long trips (e.g. social, visitors).

Single location trip stepcount range was 104-213 steps and multiple location range was 245-501 steps. Statistics for the two subjects individually showed insufficient inter-subject variability for reliable separation.

Discussion

We have shown experimentally that collection of a relatively small quantity of coarse scale raw data in an environment not specifically set up for daily activity habits monitoring can provide useful information on typical habits. Further work will involve characterizing the amount of data needed to establish an envelope of pre-specified accuracy for the analysis, and to differentiate between different subjects.

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C. “Design of a Flexible Template Approach for Characterising Health Activity Habits Using Step Count Data”, Nathan Poultney and Anthony Maeder. The PErvasive Technologies Related to Assistive Environments (PETRA) Conference, Corfu, Greece, 2021.

Design of a Flexible Template Approach for Characterising Health Activity Habits Using Step Count Data

Design of a Flexible Template Approach

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This paper describes a template-driven pragmatic approach to characterising habitual ambulatory movements in constrained physical settings, using step count data from consumer wearable devices. A generic design process was undertaken using design science principles to establish the main structural elements of the template. The template was then applied to data collection and analysis for a case study in a typical office building environment. The associated activity habit characterisation results for three participants across two different simulated activities are presented.

CCS CONCEPTS • CCS - Information systems - Information systems applications - Data mining • CCS - Applied computing - Life and medical sciences- Consumer health

Additional Keywords and Phrases: human activity monitoring, step count, habit characterization, design science

ACM Reference Format:

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Introduction

The current widespread accessibility and affordability of consumer-grade wearable devices to monitor human activities opens new opportunities for behavioural characterisation using step count data. A commonly held belief in this domain is that a daily target of reaching 10,000 steps [1] can lower non-communicable disease risk factors and is of great benefit to an individual’s health and wellbeing [2]. Given any typical day which is constrained by workplace or lifestyle activity practices, this goal is not always realistic and often difficult to achieve [3]. Consequently there is a widespread need to adopt health behaviour change interventions or health behaviour maintenance, to improve preventive health practices and lower the level of risk [4].

To achieve behaviour change effectively, one family of approaches is to identify target points for leverage or “nudging”, and thereby encourage small changes to existing entrenched, repetitive, habitual behaviours [5]. This approach relies on small-scale health behaviour modifications that are more likely to be maintained long term, which can be assisted by ecological momentary context-driven interventions. This is in contrast to introducing new specific behaviours which are not easily retained beyond the initial period of intervention [6]. It also relies on the established strong association of habit with physical activity patterns [7] and behaviour change [8]. However, the determination of habits through observation or measurement is a challenge easily confounded by human subjective perception [9].

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Generally quantitatively identifying and characterising habitual behaviour specifically relating to physical activity in individuals, relies on collection of data from multiple high-precision laboratory grade measurement instruments, followed by application of sophisticated algorithms based on artificial intelligence and signal processing techniques [10]. This approach is typically expensive in time and effort for the researchers and intrusive to the participants. Additionally, physical activity habitual behaviour is seldom able to be assessed from isolated specific data sequences ready for direct analysis, but needs to be recognized and extracted from within a longitudinal series of complex situations. For this to be achieved and for the habits to be properly understood and explained, the habitual components in a dataset must be contextualized [11].

This paper proposes a more generally applicable and accessible approach than the above to identifying and characterising habitual activity behaviour from step count data, with minimal additional parameters required. Data of this type is easily collected in real-world settings, using consumer-grade wearable devices e.g. Fitbit. This approach is likely to be more appealing to participants than the stringent requirements of a laboratory setting, and thus contribute to achieving larger sample sizes and longer data collection periods for such studies.

The next section describes our methodology for establishing the design of a flexible template for identifying habitual activity behaviours. A design science approach [12] has been adopted to define a problem-centred pragmatic process, considering that this is a suitable contemporary model for addressing the research problem identified above. The design science approach allows for an iterative process of refinement, which will be beneficial for approximating and subsequently refining the characterisation of habitual activity behaviours.

Thereafter we apply the template to conduct data analysis and habit characterisation for a case study in a typical office building environment. We describe the details of the case study setting and data collection process, for three student participants of similar age and fitness and the same gender, across two different simulated activities. Then we provide associated activity habit characterisation results, to demonstrate the utility of this approach.

Methodology

The design science approach to research has been growing in popularity over the past 15 years and continues to do so as it usefully provides an "interaction between research and practice" [13]. This approach has allowed a habitual behaviour characterisation mechanism to be as defined as an action design artifact [14], with the objective of identifying and describing habitual behaviour profiles for typical office workplace routines of individuals. This involved the evolution of the solution artifact through the design science research iterative process, by which the approach was gradually refined through successive feedback to the point where stability was reached. The final version of this artifact was adopted as the instance of the desired flexible template, for subsequent application.

The successive iterations were conducted within the three design science research cycles [15] as follows:

- Relevance: the contextual settings of the known habits of interest, associated with high level structural features present in the data;
- Design: the determination of values and variability in the contextualized data, to provide categorisation of the known habits;
- Rigor: the establishment of thresholds and boundary values for defining the final habit inclusion and characterisation envelopes.

The Relevance Cycle commences with the cleansing of irrelevant data points that are deemed out of scope. All the data points outside of known or typical workhours can be culled; additionally all periods of inactivity within the workhours can be reduced to a single value recording the duration of the inactivity time period. The remaining data is regarded as ready for specification of its context, based on a set of heuristic rules that can be derived from subjective observations of the behaviours.

In the case of the office environment chosen for this study, this remaining data contains periods of sustained activity (e.g., walking [16]) interspersed with periods of inactivity, in an overall set of many such daily sequences, to form the dominant repeated high level pattern of "inactive-active-inactive". In the office setting, this may be interpreted as a simple task like walking to fetch a required item, or walking to a destination point at which a work task is to occur. More complex patterns containing structured patterns of activity and inactivity, such as "inactive-active-inactive-active-inactive", or "inactive-active#1-active#2-inactive" can also be conjectured. If additional parameters were considered, such as time of day, or location data for the person, these patterns could be more exclusively identified and further cleansing exclusion of data from consideration could be achieved.

In the Design Cycle, analysis of the contextualized data is performed next. This commences with the summarisation of step count data, in this case at the Fitbit provided 1-minute time point resolution, within each contextual occasion which was detected in the cleaned data. Some activity is continuous and some is interrupted by short periods, of less duration than would be deemed as pure inactivity. Other activity is continuous and uninterrupted, but occurs at different rates of step count for successive time points. If a wide variety of such variable summarised values occurs, applying a Pareto analysis to the 1-minute resolution data-values can help to provide a rapid indication of say 20% of data values that are likely to establish say 80% of the habitual behaviours.

Next the categorisation of the summarised data is undertaken. Each occurrence of one of the patterns determined above is parameterised with its summary values obtained in the data analysis stage, and the range of these parameters is established. Now a rationalization of the categorisation results must be conducted, by excluding outlier or anomaly cases. Again, a wide spread of possible values might be resolved with the use of the Pareto method.

Now entering the Rigor Cycle, for each category determined above, a related performance envelope can now be obtained. This envelope can be more accurately defined, the more parameters that are available, and the more distinctive the separate activities of interest. Where only step count data is available, a looser envelope might be anticipated; if additional parameters such as heart rate or vertical motion were available, this could assist in the tightening of the envelope definition. There can be a significant amount of noise affecting envelope determination, increasing the difficulty and reducing the accuracy of identifying and characterising habitual behaviours.

The final version of the design artifact which has been adopted as central to the flexible template approach, can be visualized as in Figure 1 below. The Relevance cycle corresponds to Context and Data Cleansing functions; the Design Cycle to Context and Data Analysis, plus Characterisation and Habit Categories; the Rigor Cycle to Characterisation and Habit Envelopes.

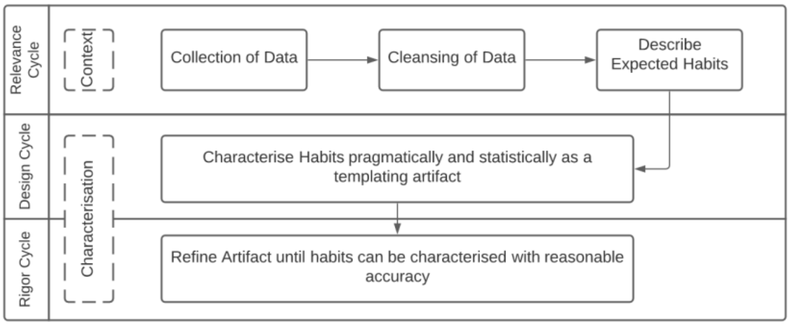

Figure 1: Template for Context to Characterisation process.

Case Study

The scenario for our case study is a large multi-story office environment. The overall structure is of open-plan desk seating around the periphery of each floor, with a row of internal officed delimiting these from the central core space of the building. In the central core are numerous meeting rooms, personal social areas, and a central public space on each level. There are multiple connectivity options within and between levels, consisting of corridors, stairs and elevators. Typical office activities consist of fetching and delivering items, attending meetings, making presentations, using facilities such as coffee machine or bathroom. This contextual information aids in understanding the types of typical movement based physical activities that individuals may undertake in their workday.

In this environment, different individuals may establish their own sets of habits independently, and may choose different activity patterns for the same type of task (e.g. preferring different meeting locations, or taking different routes to the same destination). However, for highly repetitive activities (e.g. bathroom visits), it was noted that individuals tended to take the most direct paths. This relatively constrained and structured setting lends itself to a limited choice of paths from one location to another, especially if within close proximity. Consequently, it is expected that characterisations of habitual behaviour will be more accurate than in an unconstrained or outdoor setting. This is a constrained environment in which sedentary habitual behaviours are often the most dominant, generally for several prolonged periods throughout the working day. It is therefore a good demonstration of the benefit of adoption the three stage design science research approach, as only a small percent of daily data relates to actual habits.

The case study data set collected in this setting consisted of two simulated tasks performed with eight repetitions, by three male human subjects. The simulated tasks were designed to replicate typical office physical activity habits. These were specifically a simple Long Walk activity, consisting of a single concentrated period of sustained walking from one corner of the building (office space) to the opposite corner (meeting room), and a compound Short Walk activity, with two periods of limited walking (from desk to public space or vice versa) separated by a minor period of inactivity (making a cup of coffee).

All participants were given a uniquely identified fully charged Fitbit to wear for the duration of the data collection exercise, which took about 2 hours in total. Each activity had a predefined path of travel, and the start time and end time were recorded. The activities were undertaken in between multi-minute periods of “passive sedentary” inactivity typical of an office worker, and to ensure that successive repetitions of the same activity were somewhat independent to reduce the learning effect.

Results

The two types of activities undertaken by the participants as mentioned above were predefined with initial estimations of their profiles as shown below in Table 1, based on an observational study.

Table 1: Predefined activity descriptions.

Number	Activity	Estimated Time & Step	Activity Profile
1	Long Walk (single sustained phase)	Activity: >3min >300stp	Inactive >3 min Active Type 1 Inactive >3 min
2	Short Walk (two separated phases)	Activity: >1min <3min >50stp <150stp Inactivity: <2 min	Inactive >2 min Active Type 2 Inactive <2 min Active Type 2 Inactive >2 min

Each Activity will now be considered in more detail, showing the types of variations which may affect habit identification using such measurements, and demonstrate application of the template to them.

Long Walk Activity

The Long Walk was a simple single phase activity (termed a ‘Type 1’ activity) which commenced with the participant sedentary, then walking to a distant location with a deliberately increasing pace, and then resuming a sedentary state there. Typical results for four repetitions of the Long Walk are shown for each of the three participants in Figure 2 below.

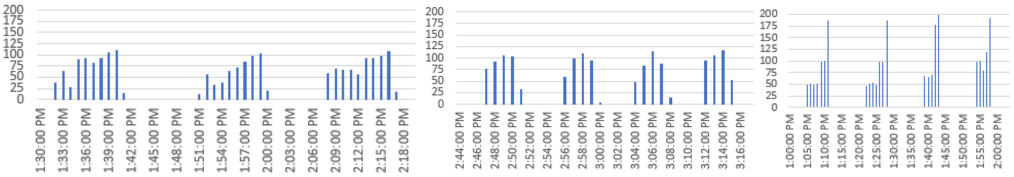

Figure 2: Step and Time data for Long Walk activity (respectively for participants A, B, C).

One might hypothesize the typical Long Walk graph profile would show a natural upward trend, with the earlier slower walking pace taking a longer duration with lower step count, compared with the later faster pace. However, this idealized form is not seen consistently across the participants. Differences in levels of fitness and body size would affect stride and gait of the participants. The variations in time duration and step count between the three participants on this account are clearly visible. The high degree of consistency for each individual participant’s profile is also apparent. These characteristics might be expected to be more prominent in a longer duration and distance task such as the Long Walk activity.

The template construct was now applied to characterize these datasets. For the first step (Data Cleansing), sequences within the data of a period of at least 3 minutes of inactivity before, and again after, a continuously active period of at least 3 minutes, were extracted based on the estimates of Table 1 above.

The next step (Data Analysis) required the time and step parameters for the activity to be refined for all instances which had been preserved by Data Cleansing, from the raw data. Table 2 below shows the characterisation results for these three participants, obtained using the full dataset of eight repetitions each.

Table 2: Parameters for Long Walk Characterisation.

Participant	A	B	C	All
Activity Type 1 Steps (Mean)	696	398	591	561

Participant	A	B	C	All
Activity Type 1 Steps (Std Dev)	52	77	14	32
Activity Type 1 Time (Mean)	10	5	6	7
Activity Type 1 Time (Std Dev)	0	1	1	1

The next step (Habit Category) was achieved by constructing a statistical model for the activity, using the above tabulated parameters. As this was a simple activity, using parameter mean and standard deviation was found to provide a suitable model to include all eight cases, for each participant.

The last step (Habit Envelope) was achieved by combining the three sets of participant parameters to provide an overall inclusion envelope, shown in the column labelled 'All' in Table 2 above. Due to the fairly wide dispersion of the data parameters across the three participants, two standard deviations were chosen around the overall mean to define the activity envelope. This again allowed inclusion of all 24 cases having Long Walk characteristics.

While this characterisation envelope construction used a basic statistical approach due to the intrinsic simplicity of the type of activity, it would be expected that more robust statistical or parametric approaches are needed for cases with more complex patterns, or more highly variable participant data. For example, the skewness in the successive minutes for an instance of this type of activity could be incorporated with an additional parameter based on a higher order statistic.

Short Walk Activity

The Short Walk was a compound activity which commenced with the participant sedentary, then walking to a nearby location at a constant pace, remaining inactive there for at least 1 minute, then proceeding back to the start location and resuming a sedentary state. This 'Type 2' activity thus consists of a two-part walk with an intervening non-walk period i.e. three components. Typical results for four repetitions of the Short Walk are shown for each of the three participants in Figure 3.

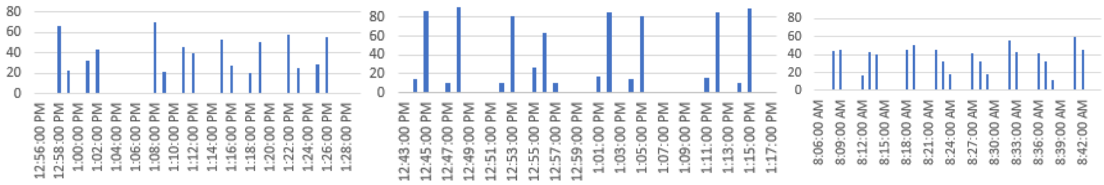

Figure 3: Step and Time data for Short Walk activity (respectively for participants A, B, C).

It can be seen in Figure 3 that the Short Walk activity appears to have less variation than the Long Walk, within and between participant data, and for both the overall step counts and time durations. However, the component step counts in adjacent minutes can vary considerably because of the randomness of the exact starting time within the 1 minute sampling resolution. The short period of inactivity between pairs of walking activities can be seen to be fairly consistent, because it corresponds to a discrete action (i.e. making coffee).

A challenge in identifying and characterising these types of small scale habitual behaviours using step count data arises from the degree of noise in the data. This Short Walk habitual behaviour becomes increasingly difficult to identify when there is noise caused by distractions or interruptions to the individual, such as pausing when encountering a colleague in passing, which can affect the duration and sometimes also the step counts. It is also affected by the quantized time sampling rate which results in almost every 1 minute sample containing a mixture of some inactive time and some active time.

Again following the template construct process using the Table 1 estimates, Data Cleansing consisted of identifying 2 minutes of inactivity prior and post a period of between 3 and 5 minutes containing activity with at least 1 minute of inactivity. Data Analysis required the time and step parameters to be refined, from the dataset: as before mean and standard deviation were chosen. Table 2 below shows these results for these three participants. For the Habit Category, a single standard deviation was found to be too restrictive for Activity Phase step and time parameters, and a choice of two standard deviations was adopted. However a single standard deviation was retained for Internal Inactivity time. For the Habit Envelope, single standard deviation values for all parameters were adopted, resulting in exclusion of four of the 24 individual cases.

Table 3: Parameters for Long Walk Characterisation.

Participant	A	B	C	All
Activity Type 2 Phase 1 Steps (Mean)	81	99	87	89
Activity Type 2 Phase 1 Steps (Std Dev)	9.3	3.5	14.6	5.6
Activity Type 2 Phase 1 Time (Mean)	2.0	1.9	2.1	2.0
Activity Type 2 Phase 1 Time (Std Dev)	0	0.4	0.6	0.3
Internal Inactivity Time (Mean)	1.0	0.9	2.0	1.3
Internal Inactivity Time (Std Dev)	0	0.4	0	0.2
Activity Type 2 Phase 2 Steps (Mean)	80	101	99	93
Activity Type 2 Phase 2 Steps (Std Dev)	6.7	3.7	2.7	2.1
Activity Type 2 Phase 2 Time (Mean)	1.8	2.1	2.4	2.1
Activity Type 2 Phase 2 Time (Std Dev)	0.5	0.4	0.5	0.1

Conclusion

Health behaviour change often involves introducing new 'learned-habits' which may have low retention beyond the initial intervention period. Modifying 'existing-habits' offers a less-intrusive approach and potentially better retained long term change. However, this relies on an ability to characterize and thereby identify or predict instances of such habit occurrences, so that the corresponding intervention can be delivered in harmony with them.

We have described a template construct based on the concepts of a design science research approach, and relying on parametric formulations, which can be used for this type of habit characterization. We have demonstrated how it would be applied to cases of typical office-based habitual physical activities, using data obtained from experimental simulation of the activities by three subjects.

This approach offers potential for the identification and characterisation of habitual behaviours from step count with a simple generic approach to the problem. This would enable low effort interventional tailoring for individuals based on their habits. The paradigm use case for this approach would be to discover periods during a day where opportunities exist to increase steps taken, and deliver the appropriate intervention cue. This could provide more satisfactory outcomes than non-contextual decision logic than typical contemporary consumer style solutions, such as fixed time interval or fixed activity initiation-based approaches.

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[IN REVIEW]

Article

Characterising Health Activity Habits Using Step Count Data: A Flexible Template Approach

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Abstract: This paper describes a template-driven pragmatic approach for characterising habitual human health activity habits in constrained physical environmental settings. A generic design process was undertaken using design science research principles to establish the main structural elements of the template. The application of the template approach was demonstrated by two case studies based on timestamped step count data obtained from Fitbit consumer wearable devices. Case study 1 comprised typical long and short walk habits in an open plan workplace environment, while case study 2 comprised sedentary and mobility habits in both home office and workplace office settings. The associated habit characterisation process and analysis of the results are presented for participants in both studies. The proposed approach offers a utilitarian mechanism for appraisal of such habits using minimal human effort and simple computational techniques.

Keywords: human activity monitoring; step count; habit characterisation; design science

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1. Introduction

Widespread availability of consumer-grade wearable devices to monitor human movement has stimulated much interest in physical activity characterisation using step count data. Common rubrics such as daily attainment of 10,000 steps [1] have been commended as a means to lower non-communicable disease risk factors and benefit an individual's general health and wellbeing [2]. In a typical day constrained by workplace or lifestyle activities, such goals can be difficult to achieve [3]. This has prompted development of health behaviour change interventions and health behaviour change maintenance protocols, to improve activity-based preventive health practices [4].

One popular approach to achieve health behavior change effectively is to identify target points for leverage or "nudging" of actions and so encourage small changes to existing entrenched, repetitive, habitual behaviours [5]. This approach aims at small-scale health behaviour modifications which are more likely to be maintained long term and can be assisted by ecological momentary context-driven interventions. This contrasts with introducing new specific behaviours which are not easily retained beyond an initial period of intervention [6]. Instead it relies on an established strong association of habits with physical activity patterns [7] and related behaviour change [8].

The determination of habits through observation or measurement is a challenge easily confounded by human subjective perception [9]. Typically, quantitatively identifying and characterising habitual behaviour specifically relating to physical activity in individuals, relies on collection of data from multiple high-precision laboratory grade measurement instruments, followed by application of sophisticated algorithms based on artificial intelligence and signal processing techniques [10]. This approach is expensive in time and effort for researchers and intrusive to participants. Physical activity habitual behaviour needs to be recognized and extracted from within a longitudinal series of complex situations. For this to be achieved and for the habits to be properly understood and explained, the habitual components in a dataset must be contextualized [11].

This paper proposes a generally applicable approach which address the above need for identifying and characterising habitual activity behaviour from step count data (and possibly additional parameters). Data of this type is easily collected in real-world settings, using devices such as Fitbit, Garmin, Apple Smartwatch. This approach is likely to be more appealing to participants than the stringent requirements of a laboratory setting, and thus contribute to achieving larger sample sizes and longer data collection periods for such studies.

The next section describes our methodology for establishing the design of a flexible template for identifying habitual health activity behaviours. A design science approach [12] has been adopted to define a problem-centred pragmatic procedure as its artifact, considering that this is a suitable contemporary model for addressing the problem identified above. The design science approach allows for an iterative process of refinement, which will be beneficial for approximating and subsequently refining the characterisation of these types of habitual behaviours.

We then apply the template to conduct data analysis and habit characterisation for the first case study in a typical open plan workplace environment, and for the second case study in a typical home office and in a workplace office setting. We describe the contextual details of the case studies and the data collection process, and provide associated habit characterisation results, to demonstrate the utility of this approach for both activity habit characterisation and sedentary habit characterisation.

2. Materials and Methods

Over the past 15 years the design science approach to research has grown in popularity, as it usefully provides an "interaction between research and practice" [13]. Using this methodology we have defined a mechanism for habitual behaviour characterisation as an action design artifact [14], with the objective of identifying and describing habitual behaviour profiles related to routine physical activity periods for various constrained environment settings.

This involved the evolution of the solution artifact through the design science research iterative process, by which the approach was gradually refined through successive feedback until stability was reached. The final version of this artifact was adopted as the desired flexible characterisation template for subsequent application.

The successive iterations were conducted within the three design science research cycles [15] as follows:

- *Relevance:* the contextual settings of the known habits of interest, associated with high level structural features present in the data;
- *Design:* the determination of values and variability in the contextualized data, to provide categorisation of the known habits;
- *Rigor:* the establishment of thresholds and boundary values for defining the final habit inclusion and characterisation envelopes.

The Relevance Cycle commences with the cleansing of irrelevant data points that are deemed out of scope. In a workplace setting, all the data points outside of known or typical workhours can be culled; additionally, in the first case study all periods of inactivity within the workhours can be reduced to a single value recording the duration of the inactivity time period. The remaining data is regarded as ready for specification of its context, based on a set of heuristic rules that can be derived from subjective observations of the behaviours in that setting.

In the case of the open plan environment chosen for case study 1, this remaining data contains periods of sustained activity (e.g., walking [16]) interspersed with periods of inactivity, in an overall set of many such daily sequences, to form the dominant repeated high level pattern of "inactive-active-inactive". In the workplace setting, this may be interpreted as a simple task like walking to fetch a required item, or walking to a destination point at which a work task is to occur. More complex patterns containing structured patterns of activity and inactivity, such as "inactive-active-inactive-active-inactive", or "inactive-active#1-active#2-inactive" can also be conjectured. If additional parameters were considered, such as time of day, or location data for the person, these patterns could be more exclusively identified and further cleansing to exclude data from consideration could be done, depending on the focus of the study on activity habits or sedentary habits.

In the Design Cycle, analysis of the contextualized data is performed next. This commences with the summarization of step count data in case study 1 or summarization of periods of inactivity in case study 2. In both cases, the Fitbit provided 1-minute time point resolution within each contextual occasion which was detected in the cleaned data. Some activity is continuous and some is interrupted by short periods, of less duration than would be deemed as pure inactivity. Other activity is continuous and uninterrupted, but occurs at different rates of step count for successive time points. If a wide variety of such varying summarised values occurs, applying a Pareto analysis to the 1-minute resolution data-values can help to provide a rapid indication of say 20% of data values that are likely to establish say 80% of the habitual behaviours.

Next the categorisation of the summarised data is undertaken. Each occurrence of one of the patterns determined above is parameterised with its summary values obtained in the data analysis stage, and the range of these parameters is established. Now a rationalization of the categorisation results must be conducted, by excluding outlier or anomaly cases. Again, a wide spread of possible values might be resolved with the use of the Pareto method.

In the Rigor Cycle, for each category determined above, a related performance envelope can now be obtained. This envelope can be more accurately defined, the more parameters that are available, and the more distinctive the separate activities of interest. Where only step count data is available, a looser envelope might be anticipated; if additional parameters such as heart rate or vertical motion were available, this could assist in the tightening of the envelope definition. There can be a significant amount of noise affecting envelope determination, increasing the difficulty and reducing the accuracy of identifying and characterising habitual behaviours.

The final version of the design artifact which has been adopted as central to the flexible template approach, can be visualized as in Figure 1 below. The Relevance cycle corresponds to Context and Data Cleansing functions; the Design Cycle to Context and Data Analysis, plus Characterisation and Habit Categories; the Rigor Cycle to Characterisation and Habit Envelopes.

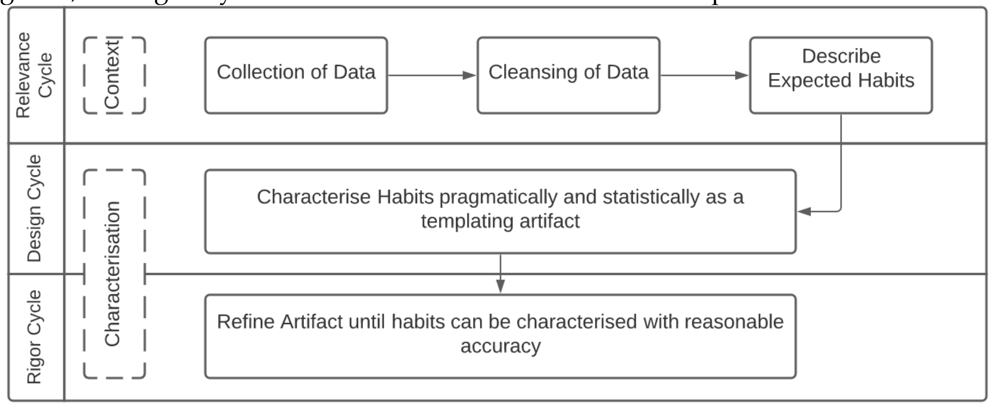

Figure 1: Template for Context to Characterisation process.

3. Case Studies

3.1. Case Study 1

The scenario for case study 1 is a large multi-story workplace environment. The overall structure is of open-plan desk seating around the periphery of each floor, with a row of internal offices delimiting the seating space from the central core space of the building. In the central core are numerous meeting rooms, personal social areas, and a central public space on each level. There are multiple connectivity options within and between levels, consisting of corridors, stairs and elevators. Typical office activities consist of fetching and delivering items, attending meetings, making presentations, using facilities such as coffee machine or bathroom. This contextual information aids in understanding the types of typical movement related physical activities that individuals may undertake in their workday.

In this environment, different individuals may establish their own sets of habits independently, and may choose different activity patterns for the same type of task (e.g. preferring different meeting locations, or taking different routes to the same destination). However, for highly repetitive activities (e.g. bathroom visits), it was noted that individuals tended to take the most direct paths. Indeed this relatively constrained and structured setting lends itself to a limited choice of paths from one location to another, especially if within close proximity. Consequently, it is expected that characterisations of habitual behaviour will be more accurate than in a less constrained setting e.g. outdoors. This is a constrained environment in which sedentary habitual behaviours are often the most dominant, generally for several prolonged periods throughout the working day. It is therefore a good demonstration of the benefit of borrowing the three-stage design science research approach, as only a small percent of daily data relates to actual habits.

The case study data set collected in this setting consisted of two simulated tasks performed with eight repetitions, by three average young adult male human subjects. The simulated tasks were designed to replicate some typical office physical activity habits. These were specifically a simple Long Walk activity, consisting of a single concentrated period of sustained walking from one corner of the building (office space) to the opposite corner (meeting room), and a compound Short Walk activity, with two periods of limited walking (from desk to public space or vice versa) separated by a minor period of inactivity (making a cup of coffee).

All participants were given a uniquely identified fully charged Fitbit to wear for the duration of the data collection exercise, which took about 2 hours in total. Each activity had a predefined path of travel, and the start time and end time were recorded. The activities were undertaken in between multi-minute periods of "passive sedentary" inactivity typical of an office worker, and to ensure that successive repetitions of the same activity were somewhat independent to reduce the learning effect.

The template process for case study 1 is described in the figure below:

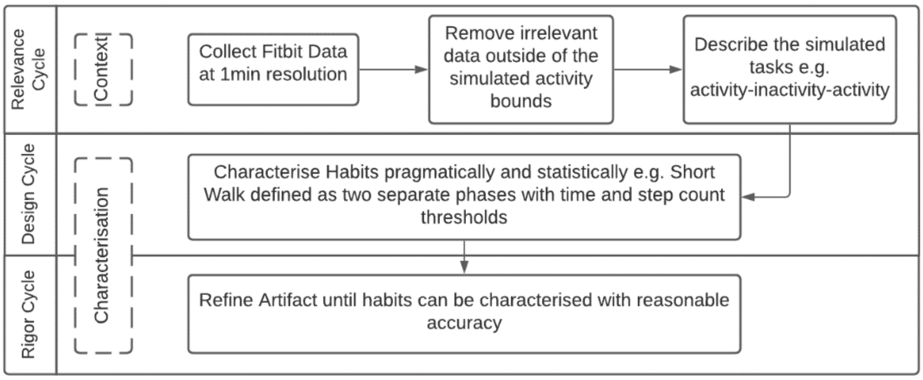

Figure 2: Template for Context to Characterisation process as used in case study 1.

3.2. Case Study 2

The case study 2 scenario covers two different types of workplace environments: the first is an office environment which is very similar to the office environment from case study 1, and the second being a typical single story home environment. At the time of the study participant A (male, 20-30yo) was a university student and a full-time software engineer, and participant B (male, 50-60yo) was a senior academic at a university.

Contextually both participants' roles involved prolonged periods of focused work at a desk as well as more sporadic communication actions to enable workplace meetings in-person when working from the office and video calls when working from the office or from home. One month of data was collected when each participant was working from home during COVID-19 lockdowns in Australia and one month of data was collected when each participant was working from the office.

The primary purpose of this case study was to have a large longitudinal data set to characterise habitual sedentary behaviours over a long time frame. The secondary purpose was the collection of data for two significantly different types of constrained environment locations but with the same type of work being carried out in both locations, to allow comparisons to be made between the two environments for both participants.

The case study data collected was the steps taken at a 1-min resolution for the 9am-5pm timeframe. Both participants were given a uniquely identified Fitbit device to wear for the duration of the data collection period for later analysis to be conducted looking at periods of inactivity (step count of zero for consecutive minutes) that match the short, medium, and long duration sedentary envelopes described in Table 4. The habitual sedentary behaviours were described as follows:

- *Short duration sedentary periods* are periods of work either intentionally or unintentionally interrupted by external distractions. An intentional interruption may be committing to answering emails and then moving from the desk at the completion of that task. An unintentional interruption may be a collegial conversation with the speakers moving away from the desk when working from the office, or answering a knock at the door when working from home.
- *Medium duration sedentary periods* are periods of continuous focused work for a moderate length of time. This may be performing a particular task while at the desk such as typing a document or participating in a meeting (either in-person when working in the office or video conference when working from home).
- *Long duration sedentary periods* are periods of work focus for an extended period of time, likely requiring deep concentration on detail, or a long meeting or presentation without a break.

4. Results & Discussion

The two types of activities undertaken by the participants in case study 1 were predefined with initial estimations of their profiles as shown below in Table 1, based on an observational study.

Table 1: Predefined activity descriptions.

Number	Activity	Estimated Time & Step	Activity Profile
1	Long Walk (single sustained phase)	Activity: >3min >300stp	Inactive >3 min Active Type 1 Inactive >3 min
2	Short Walk (two separated phases)	Activity: >1min <3min >50stp <150stp Inactivity: <2 min	Inactive >2 min Active Type 2 Inactive <2 min Active Type 2 Inactive >2 min

Each Activity will now be considered in more detail, showing the types of variations which may affect habit identification using such measurements, and demonstrate application of the template to them.

4.1. Case Study 1 - Long Walk Activity

The Long Walk was a simple single phase activity (termed a ‘Type 1’ activity) which commenced with the participant sedentary, then walking to a distant location with a deliberately increasing pace, and then resuming a sedentary state there. Typical results for three repetitions of the Long Walk are shown for each of the three participants in Figure 2 below.

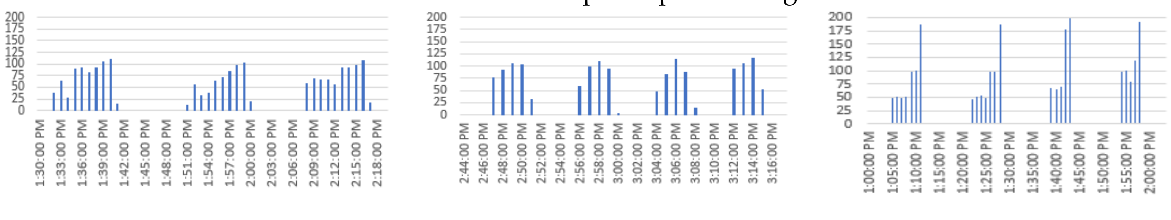

Figure 2: Step and Time data for Long Walk activity (respectively for participants A, B, C).

One might hypothesize the typical Long Walk graph profile would show a natural upward trend, with the earlier slower walking pace taking a longer duration with lower step count, compared with the later faster pace. However, this idealized form is not seen consistently across the participants. Differences in levels of fitness and body size would affect stride and gait of the participants. The variations in time duration and step count between the three participants on this account are clearly visible. The high degree of consistency for each individual participant's profile is also apparent. These characteristics might be expected to be more prominent in a longer duration and distance task such as the Long Walk activity.

The template construct was now applied to characterize these datasets. For the first step (Data Cleansing), sequences within the data of a period of at least 3 minutes of inactivity before, and again after, a continuously active period of at least 3 minutes, were extracted based on the estimates of Table 1 above.

The next step (Data Analysis) required the time and step parameters for the activity to be refined for all instances which had been preserved by Data Cleansing, from the raw data. Table 2 below shows the characterization results for these three participants, obtained using the full dataset of eight repetitions each.

Table 2: Parameters for Long Walk Characterisation.

Participant	A	B	C	All
Activity Type 1 Steps (Mean)	696	398	591	561
Activity Type 1 Steps (Std Dev)	52	77	14	32
Activity Type 1 Time (Mean)	10	5	6	7
Activity Type 1 Time (Std Dev)	0	1	1	1

The next step (Habit Category) was achieved by constructing a statistical model for the activity, using the above tabulated parameters. As this was a simple activity, using parameter mean and standard deviation was found to provide a suitable model to include all eight cases, for each participant.

The last step (Habit Envelope) was achieved by combining the three sets of participant parameters to provide an overall inclusion envelope, shown in the column labelled 'All' in Table 2 above. Due to the fairly wide dispersion of the data parameters across the three participants, two standard deviations were chosen around the overall mean to define the activity envelope. This allowed inclusion of all 24 cases having Long Walk characteristics.

While this characterization envelope construction used a basic statistical approach due to the intrinsic simplicity of the type of activity, it would be expected that more robust statistical or parametric approaches are needed for cases with more complex patterns, or more highly variable participant data. For example, the skewness in the successive minutes for an instance of this type of activity could be incorporated as an additional parameter based on a higher order statistic.

4.2. Case Study 1 - Short Walk Activity

The Short Walk was a compound activity which commenced with the participant sedentary, then walking to a nearby location at a constant pace, remaining inactive there for at least 1 minute, then proceeding back to the start location and resuming a sedentary state. This 'Type 2' activity thus consists of a two-part walk with an intervening non-walk period i.e. three components. Typical results for three repetitions of the Short Walk are shown for each of the three participants in Figure 3.

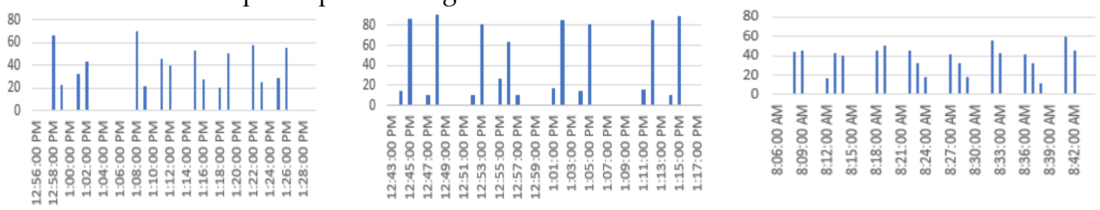

Figure 3: Step and Time data for Short Walk activity (respectively for participants A, B, C).

It can be seen in Figure 3 that the Short Walk activity appears to have less variation than the Long Walk, within and between participant data, and for both the overall step counts and time durations. However, the component step counts in adjacent minutes can vary considerably because of the randomness of the exact starting time within the 1 minute sampling resolution. The short period of inactivity between pairs of walking activities can be seen to be fairly consistent, because it corresponds to a discrete action (i.e. making coffee).

A challenge in identifying and characterising these types of small scale habitual behaviours using step count data arises from the degree of noise in the data. This Short Walk habitual behaviour becomes increasingly difficult to identify when there is noise caused by distractions or interruptions to the individual, such as pausing when encountering a colleague in passing, which can affect the duration and sometimes also the step counts. It is also affected by the quantized time sampling rate which results in almost every 1 minute sample containing a mixture of some inactive time and some active time.

Again following the template process using the Table 1 estimates, Data Cleansing consisted of identifying 2 minutes of inactivity prior and post a period of between 3 and 5 minutes containing activity with at least 1 minute of inactivity. Data Analysis required the time and step parameters to be refined, from the dataset: as before mean and standard deviation were chosen. Table 2 below shows these results for the three participants. For the Habit Category, a single standard deviation was found to be too restrictive for Activity Phase step and time parameters, and a choice of two standard deviations was adopted. However a single standard deviation was retained for Internal Inactivity time. For the Habit Envelope, single standard deviation values for all parameters were adopted, resulting in exclusion of four of the 24 individual cases.

Table 3: Parameters for Long Walk Characterisation.

Participant	A	B	C	All
Activity Type 2 Phase 1 Steps (Mean)	81	99	87	89
Activity Type 2 Phase 1 Steps (Std Dev)	9.3	3.5	14.6	5.6
Activity Type 2 Phase 1 Time (Mean)	2.0	1.9	2.1	2.0
Activity Type 2 Phase 1 Time (Std Dev)	0	0.4	0.6	0.3
Internal Inactivity Time (Mean)	1.0	0.9	2.0	1.3
Internal Inactivity Time (Std Dev)	0	0.4	0	0.2
Activity Type 2 Phase 2 Steps (Mean)	80	101	99	93

Participant	A	B	C	All
Activity Type 2 Phase 2 Steps (Std Dev)	6.7	3.7	2.7	2.1
Activity Type 2 Phase 2 Time (Mean)	1.8	2.1	2.4	2.1
Activity Type 2 Phase 2 Time (Std Dev)	0.5	0.4	0.5	0.1

4.3. Case Study 2 – Sedentary Habitual Behaviour

Characterising sedentary habitual behaviour has been carried out for two different settings and two participants across approximately a 1-month duration for each of those settings with the exception of participant B which has 3 weeks of work from home data (both work from home data sets were collected during COVID-19 lockdowns in Australia). The time period of interest was restricted to 9am-5pm weekdays to match the typical work hours. This was an observational natural study of real-world people, the collection of data by the two participants allows for a realistic representation of typical office workers both in an office setting and working from home environment.

The following table defines the type of sedentary habits that were to be identified within the data set as they are generalisable to both a working from home and working from office situation.

Table 4: Sedentary Habit Types

Sedentary Habit Types	Sedentary Time Duration
Short Duration Sedentary (short spontaneous period of work either intentionally ended or unintentionally ended from external distractions e.g., replying to emails, or working on a larger task but interrupted by a colleague)	5min to 20min
Medium Duration Sedentary (moderate length period of focused uninterrupted work e.g., focusing on a specific task such as typing a document, or a meeting with colleagues)	21min to 45min
Long Duration Sedentary (long period of focused uninterrupted work on one or many tasks, or a large duration meeting with colleagues)	46min to 3 hours

An overview of the instances of the habits for the participants working in the office and working from home are provided below:

Table 5: Working from home Habit Instances

Instances of Habits (working from home)	Participant A	Participant B	Total
Short Duration Sedentary	111	80	191
Medium Duration Sedentary	69	29	98
Long Duration Sedentary	28	15	43
			332

Table 6: Working from office Habit Instances

Instances of Habits (working from office)	Participant A	Participant B	Total
Short Duration Sedentary	230	168	398
Medium Duration Sedentary	67	47	114
Long Duration Sedentary	21	29	50
			562

It is observed from the various instances of habits across both participants and both environments that there are a much higher number of short duration sedentary instances when working from the office compared to when working from home, this is consistent across both participants. It can be concluded that given the longitudinal nature of the data collected, the ability to undertake longer periods of uninterrupted focused work when working from home is somewhat increased compared to working from the office. Further longitudinal studies with a larger officer worker participant sample size would assist in determining if this is indeed the case for many office workers that are able to do their work remotely from home as the participants in this study were able to.

There are much smaller differences in medium duration sedentary and long duration sedentary instances for participant A when comparing work from office and work from home. However, for participant B the number of instances for medium duration sedentary and long duration sedentary is almost double that of working from home when looking at working from office. One explanation may be that participant B had longer duration meetings when working from the office compared to when working from home during the COVID-19 lockdown period.

4.4. Case Study 2 – Participant A Statistics

The following observations are participant A's working from home and working from the office sedentary habitual behaviour statistics:

Table 7: Participant A – Working from home sedentary statistics

Week	Environment	Task Type	Instances	Mean (mins)	Std. Dev (mins)
1	Home	Short Duration Sedentary Instances (minutes)	24	13.625	4.941505667
1	Home	Medium Duration Sedentary Instances (minutes)	18	31.05555556	8.242445541
1	Home	Long Duration Sedentary Instances (minutes)	8	78	27.86190435
2	Home	Short Duration Sedentary Instances (minutes)	33	11.93939394	7.309836669
2	Home	Medium Duration Sedentary Instances (minutes)	16	29.4375	7.247700785
2	Home	Long Duration Sedentary	6	68	31.65438358

		Instances (minutes)			
3	Home	Short Duration Sedentary Instances (minutes)	21	10	5.118593557
3	Home	Medium Duration Sedentary Instances (minutes)	14	28.92857143	7.610360203
3	Home	Long Duration Sedentary Instances (minutes)	8	72.375	17.56569302
4	Home	Short Duration Sedentary Instances (minutes)	33	10.72727273	4.591246612
4	Home	Medium Duration Sedentary Instances (minutes)	21	29.52380952	6.47780092
4	Home	Long Duration Sedentary Instances (minutes)	6	69.83333333	19.28125169

Table 8: Participant A – Working from office sedentary statistics

Week	Environment	Task Type	Instances	Mean (mins)	Std. Dev (mins)
1	Office	Short Duration Sedentary Instances (minutes)	63	9.650793651	4.561970182
1	Office	Medium Duration Sedentary Instances (minutes)	12	29.33333333	5.58135424
1	Office	Long Duration Sedentary Instances (minutes)	6	63.66666667	18.59749087
2	Office	Short Duration Sedentary Instances (minutes)	65	9.846153846	4.644320353
2	Office	Medium Duration Sedentary Instances (minutes)	19	27.42105263	3.834286685
2	Office	Long Duration Sedentary Instances (minutes)	3	56	8.544003745
3	Office	Short Duration Sedentary Instances (minutes)	51	10.1372549	4.458787314
3	Office	Medium Duration Sedentary	19	30.15789474	8.22775221

		Instances (minutes)			
3	Office	Long Duration Sedentary Instances (minutes)	7	65.42857143	16.98879182
4	Office	Short Duration Sedentary Instances (minutes)	51	10.98039216	4.509945437
4	Office	Medium Duration Sedentary Instances (minutes)	17	29.52941176	6.89309117
4	Office	Long Duration Sedentary Instances (minutes)	5	62.4	11.92895637

4.5. Case Study 2 – Participant B Statistics

The following observations are participant A's working from home and working from the office sedentary habitual behaviour statistics:

Table 9: Participant B – Working from home sedentary statistics

Week	Environment	Task Type	Instances	Mean (mins)	Std. Dev (mins)
1	Home	Short Duration Sedentary Instances (minutes)	19	11.73684211	5.445100808
1	Home	Medium Duration Sedentary Instances (minutes)	3	29.33333333	2.886751346
1	Home	Long Duration Sedentary Instances (minutes)	3	70.66666667	14.18919777
2	Home	Short Duration Sedentary Instances (minutes)	43	11.02325581	4.798255497
2	Home	Medium Duration Sedentary Instances (minutes)	18	35.16666667	7.694535876
2	Home	Long Duration Sedentary Instances (minutes)	5	73.8	22.66495092
3	Home	Short Duration Sedentary Instances (minutes)	18	12.72222222	5.788483044
3	Home	Medium Duration Sedentary Instances (minutes)	8	31.5	8.053393251

3	Home	Long Duration Sedentary Instances (minutes)	7	75.28571429	34.509488
4	Home	*No data recorded for week 4 for participant B as work from the office had resumed*	-	-	-

Table 10: Participant B – Working from office sedentary statistics

Week	Environment	Task Type	Instances	Mean (mins)	Std. Dev (mins)
1	Office	Short Duration Sedentary Instances (minutes)	46	8.826086957	3.560925896
1	Office	Medium Duration Sedentary Instances (minutes)	12	36.66666667	6.665151343
1	Office	Long Duration Sedentary Instances (minutes)	10	69.8	19.40675713
2	Office	Short Duration Sedentary Instances (minutes)	30	11.2	4.686002634
2	Office	Medium Duration Sedentary Instances (minutes)	12	32.08333333	6.680478118
2	Office	Long Duration Sedentary Instances (minutes)	8	68.875	10.32939633
3	Office	Short Duration Sedentary Instances (minutes)	35	10.4	5.358884871
3	Office	Medium Duration Sedentary Instances (minutes)	15	28.2	5.01711357
3	Office	Long Duration Sedentary Instances (minutes)	6	61.33333333	15.75648015
4	Office	Short Duration Sedentary Instances (minutes)	57	8.842105263	4.065488346
4	Office	Medium Duration Sedentary Instances (minutes)	8	27.875	3.642506986
4	Office	Long Duration Sedentary	5	63.6	19.91983936

		Instances (minutes)			

5. Conclusions

Health behaviour change often involves introducing new 'learned-habits' which may have low retention beyond the initial intervention period. Modifying 'existing-habits' offers a less intrusive approach and potentially better retained long term change. However, this relies on an ability to characterize and thereby identify and even predict instances of such habit occurrences, so that the corresponding intervention can be delivered in harmony with them.

We have described a flexible template construct based on the concepts of a design science research approach, and relying on parametric formulations, which can be used for this type of habit characterisation. We have demonstrated how it would be applied to cases of typical office-based habitual physical activities, using data obtained from experimental simulation of the activities by three participants in case study 1. We have also demonstrated how it would be applied to a mix of work from office and work from home habitual sedentary behaviours, using data obtained over a long period of time for the two participants in case study 2.

This approach offers potential for the automated identification and characterisation of habitual behaviours from step count with a simple generic approach to the problem. This would enable interventional tailoring for individuals based on their habits with low cost analytical effort. A typical use case for this approach would be to discover periods during a day where opportunities exist to increase steps taken, and deliver the appropriate intervention cue. This could provide more satisfactory outcomes than non-contextual decision logic found in contemporary consumer style solutions, such as fixed time interval or fixed activity initiation-based approaches.

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