MINING REALITY TO EXPLORE THE 21ST CENTURY STUDENT EXPERIENCE

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PREFACE

This thesis is essentially a book of experiences, some my own and some of the students that participated in this research. The authors and philosophers mentioned were all important to me throughout this four year PhD journey. Although this book is intended mainly as a PhD student's research report, I hope it will not simply be relegated to some dusty old shelf. In many ways, this thesis raises more questions than it attempts to answer, and I hope it inspires others to think about higher education research in new and creative ways. As a novice (maybe naïve?) researcher, I have approached this topic with a wondering curiosity; so much about this topic, and the ideas I have explored, were new to me, and have challenged the few preconceptions I had about education. Part of my intent is to stir up in academics the same feelings, to take them back to when they were naïve researchers, full of wide-eyed curiosity, to how they felt, thought and talked, and what extraordinary projects they engaged in.

A **Millennial** is a person reaching young adulthood in the early 21st century. The characteristics of millennials are generally marked by their coming of age in the Information Age, and their comfortable use of digital technologies and social media (Howe & Strauss, 2000).

A **Digital Native** is a person born or brought up during the age of digital technology and so are familiar with computers and the Internet from an early age (Prensky, 2001).

The **Net Generation** is the cohort of young people born between 1982 and 1991 who have grown up in an environment in which they are constantly exposed to computer-based technology. It has been suggested that their methods of learning are different from those of previous generations (Sandars & Morrison, 2007).

The **Google Generation** is the group of people born after 1993 who grew up in a world dominated by the Internet and whose first stop for information is a search engine—most likely Google (Barnum, 2011).

Generation Z is the demographic cohort succeeding the Millennials. Members of Generation Z have used digital technology since a young age and are comfortable with the Internet and social media (Homan, 2015).

The **21st century student…**

ABSTRACT

Understanding student experience is a key aspect of higher education research. To date, the dominant methods for advancing this area have been the use of surveys and interviews, methods that typically rely on post-event recollections or perceptions, which can be incomplete and unreliable. Advances in mobile sensor technologies afford the opportunity to capture continuous, naturally-occurring student activity. In this thesis, I propose a new research approach for higher education that redefines student experience in terms of objective activity observation, rather than a construct of perception. I argue that novel, technologically-driven research practices such as 'Reality Mining'—continuous capture of digital data from wearable devices—and the use of multi-modal datasets captured over prolonged periods, offer a deeper, more accurate representation of students' lived experience.

To explore the potential of these new methods, I implemented and evaluated three approaches to gathering student activity and behaviour data. I collected data from 21 undergraduate health science students at the University of Otago, over the period of a single semester (approximately four months). The data captured included GPS trace data from a smartphone app to explore student spaces and movements; photo data from a wearable auto-camera (that takes a photo from the wearer's point-of-view, every 30 seconds) to investigate student activities; and computer usage data captured via the RescueTime software to gain insight into students' digital practices. I explored the findings of these three datasets, visualising the student experience in different ways to demonstrate different perspectives on student activity, and utilised a number of new analytical approaches (such as Computer Vision algorithms for automatically categorising photostream data) to make sense of the voluminous data generated. To help future researchers wanting to utilise similar techniques, I also outlined the limitations and challenges encountered in using these new methods/devices for research.

The findings of the three method explorations offer some insights into various aspects of the student experience, but serve mostly to highlight the idiographic nature of student life. The principal finding of this research is that these types of ‘student analytics’ are most readily useful to the students themselves, for highlighting their practices and informing self-improvement. I look at this aspect through the lens of a movement called the ‘Quantified Self’, which promotes the use of self-tracking technologies for personal development.

To conclude my thesis, I discuss broadly how these methods could feature in higher education research, for researchers, for the institution, and, most importantly, for the students themselves. To this end, I develop a conceptual framework derived from Tschumi’s (1976) Space-Event-Movement framework. At the same time, I also take a critical perspective about the role of these types of personal analytics in the future of higher education, and question how involved the institution should be in the capture and utilisation of these data. Ultimately, there is value in exploring these data capture methods further, but always keeping the ‘student’ placed squarely at the centre of the ‘student experience’.

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The completion of this thesis is the direct result of the encouragement and support I have received from my family, friends and colleagues. As I reflect upon these past few years, I am humbled by the number of people that cheered me on, challenged me to dig deeper, and pushed me forward. I am truly grateful.

First and foremost, I would like to thank my supervisor, Russell Butson. His mentoring, belief in me and my work, and encouragement were critical to my persistence, without it this dissertation would not be complete. I treasured our conversations and look forward to many more. I would also like to thank my supervisor, Prof. Rachel Spronken-Smith, for her valuable direction and support through the different phases of this dissertation. I sincerely appreciated her time, guidance and thoughtful questions. This work is stronger because of her.

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DEDICATION

This work is dedicated to my parents, Arick and Sunanda, my fiancé, Adon, my brother, Mark, and my sweet little baby, Christian. I have been permanently impacted by your unconditional love, support and encouragement. I love you all so much.

Current systems of education were not designed to meet the challenges we now face.
They were developed to meet the needs of a former age.
Reform is not enough: they need to be transformed.

—

Sir Ken Robinson, *Out of Our Minds*
(Robinson, 2011, p. 49)

CHAPTER 1 : INTRODUCTION

This introduction provides an overview of the study in this thesis, which aims to explore the 21st century student experience using new methods and approaches to capture student activity data. This chapter begins with a background context to the study, followed by its research aims and significance. It then presents the local context of the study, followed by an overview of the thesis structure.

The topic of student experience

Universities are having to adapt to a rapidly changing world. They are being influenced by powerful forces, such as: the proliferation of digitalisation; globalisation; massification; increasing student mobility and diversity; new patterns of financing higher education; and innovations in teaching and learning technologies (Altbach, Reisberg, & Rumbley, 2019; Benckendorff & Zehrer, 2017; Zajda & Rust, 2016; Ramsden, 2008). There is also increasing pressure for New Zealand universities to be more efficient and productive and better aligned to serving national and international imperatives (New Zealand Productivity Commission, 2017).

Likewise, the student body is also experiencing change (Bloch & Mitterle, 2017; Liu & Tee, 2014; Fitzgibbon & Prior, 2010; Ramsden, 2008), driven by a growing demand for 21st century competencies that include: diversity of learning and innovation skills; information, media and technology skills; and relevant life and career skills (Noe, Hollenbeck, Gerhart, & Wright, 2017; Kaufman, 2013; Larson, & Miller, 2011). In the past 20 years, we have witnessed major shifts in the size, demographic makeup, needs, aspirations and expectations of the student population (Thomas, Harden-Thew, Delahunty, & Dean, 2016). Consequently, it is not surprising that there has been a shift in some educational research from a focus on teaching to learning, and more recently to the broad notion of 'student experience' (Altbach et al., 2019). As a construct, 'student experience' comprises aspects of a student's educational experience, engagement, satisfaction, as well as extracurricular influences such as social interactions, living arrangements, finances and more ('student experience' is described in more detail in Chapter 2). As students constitute one of the largest stakeholder groups in higher education, new student realities are likely to play a central role in institutional development and growth, and ultimately impact the very nature of how we define and practice higher education.

The digital age is creating educational conditions that sit outside our historical understanding. Trying to understand this rapidly changing landscape with the research instruments developed to observe and examine a previous era, while common, is problematic. What I am proposing in this study, is the need to approach this highly dynamic and unique period of time by deploying new ways of 'coming to know' (researching) aspects of the students' lived experience. Advances in digital technologies have resulted in a plethora of mobile sensors capable of researching lived experience in ways never before thought possible. I intend to deploy a number of these sensors within a novel research framework to extract rich naturally occurring real-world data, and to evaluate the value of this approach to offer a more relevant and contemporary way of knowing the student experience.

The novelty of the research approach

There is a growing awareness that research into 21st century student experience requires a broadening of concepts and methods (Coates, Kelly, Naylor, & Borden, 2016). First, much of the discourse in higher education revolves around a homogenised and simplified picture of 'the student experience', failing to actively acknowledge or accommodate the richness, diversity and complexity of students' experiences at university (Sabri, 2011). Second, much of the research into student experience is dominated by a narrow range of research methods, namely surveys and interviews. Issues around self-reporting behaviour, generalising student experiences, and low participation rates in student experience surveys have led to some researchers calling for new and innovative data capture approaches, mainly based on observation and the harvesting of digital trace data from student activity (Borden & Coates, 2017; Coates et al., 2016; Cotton, Stokes & Cotton, 2010).

Incorporating new methods into higher education, while novel, may not be as difficult as many assume. For example, there is a substantial body of literature already dedicated to the exploration of human behaviour patterns based on digital traces. Instances of these include the understanding of collective and individual human movement (Sun & Axhausen, 2016); the modelling of urban spaces (Behadili, 2016), or the exploration of social structures (Whelan, Teigland, Vaast, & Butler, 2016). Almost a decade ago, Phithakkitnukoon, Horanont, Di Lorenzo, Shibasaki, and Ratti (2010) created an 'activity-aware map' based on individual cellular data to understand the dynamics of inhabitants for urban planning and transportation purposes. Since then, many research articles have attempted to explore human dynamics based on large mobile databases (e.g., Randhawa & Lomotan, 2018; Yamanishi, Tabei, & Kotera, 2016; Sobolevsky et al., 2015). Another interesting study by Calabrese, Smoreda, Blondel and Ratti (2011) invented the concept of colocation based on the behaviour of telecom network users who called each other frequently and shared the same space at the same time in the city. Salas-Olmedo, Moya-Gómez, García-Palomares and Gutiérrez (2018) explored the digital footprints left by tourists while travelling around cities. By looking at activity data using applications such as Panoramio, Foursquare, and Twitter, they tried to map the tourist densities in different parts of the city of Madrid. Another example is a study by Sevtsuk and Ratti (2010), which showed that the consistency of movement patterns at different hours, days, and weeks could be significantly correlated with people's behaviour while using mobile phones.

In this thesis, I take a broad, holistic view of the 'student experience' of higher education, and propose the use of new, innovative data sources and capture methods to construct rich profiles of university students' lived experiences in the 21st century. The aims of this thesis are twofold: (1) to implement three 'new' methods that have had little prior use in researching student experience, but have shown promise in researching lived experience in other contexts; and (2) to evaluate the usefulness of these new methods for providing insights into the experiences of 21st century undergraduate students. This work is exploratory and not driven by any explicit research questions. My intention is not to 'find out' something specific about student experience. Nor is it to extol the virtues of the particular methods used in this study. Instead, I take my cue from questions and limitations raised in prior literature and look at the technological trends shaping other aspects of our lives. The methods I implement in this thesis are *potentially* useful, but a few of a vast ocean of new ideas and technologies that are changing daily. A recent New York Times article quips that "University campuses are like archaeological digs of innovations that didn't fulfil their promises," and it is the researcher's job to "disprove and dismantle [innovative] ideas" (Marcus, 2020, para. 11-12). It is my intention to keep an open mind throughout this research, ever mindful that innovations too often fall victim to a cycle of "hype, hope and disappointment" (Selwyn, 2013, p. 15).

Research context

This study focuses on the experiences of undergraduate students enrolled in health science programmes at the University of Otago, a research-intensive university in New Zealand. Eighty-five percent of the student population travel to Dunedin from other parts of the country, as well as from overseas (https://www.otago.ac.nz/inbrief/index.html). Most first-year students reside in one of the university's residential colleges, while in their subsequent years of study they live in shared accommodation known as 'flats'. At Otago, there is a large health science undergraduate curriculum including degrees in dentistry, medical laboratory science, medicine, pharmacy and physiotherapy. All health science programmes begin with compulsory first-year papers. Health science courses have a timetable that includes lectures, tutorials, laboratories, assignments, tests, and readings every week, and to succeed students have to conduct a large amount of self-directed study.

Undergraduate health science students typically take four papers over an approximate four-month semester (from the end of February to the end of June). Health science classes are generally demanding, dense with content, and students are primarily assessed on class assignments, projects, mid-semester exams and final exams. A large percentage of students live, work and socialise on and around the main campus area, representing a tightly-knit student community. The pace of the four-month semester is fast; the atmosphere among the students on campus seems to visibly change from a relaxed start of semester to an intense mid and end of semester. Typically first-year health science classes are large (~2000 students enrolling per year, https://www.otago.ac.nz/otago-connection/archives/past-issues/otago110488.html), making it difficult for faculty and students to engage on an individual level.

Local studies

Many studies have explored student experience at the University of Otago, however, from very different perspectives (I elaborate on the various conceptions of 'student experience' in Chapter 2). By far, the majority of studies examine student experiences of the university itself, particularly *academic* student experiences of various teaching and learning approaches and innovations in the classroom (e.g. Daniel & Bird, 2019; Licorish, Owen, Daniel & George, 2018; Ebbeling, et al., 2018). Quite a few studies focus on specific demographics of students and their experiences, such as first-year student experiences (van der Meer, Scott & Pratt, 2018) or the experiences of Māori students (van der Meer, Scott & Neha, 2010).

Less represented are studies that explore extracurricular aspects of the student experience (i.e. outside of the realm of the university and facets of teaching and learning). Nissen, Hayward and McManus (2019), for example, reported on the effect of student debt on overall student experiences, and Jameson and Smith (2011) explored the impact of 'competition' amongst peers in a group of undergraduate health science students.

One study conducted at Otago University that looked at student experience from the perspective of how generational characteristics impact personal experiences was Buissink-Smith, Spronken-Smith and Grigg (2008). This exploratory study examined the characteristics of the Millennial generation of students (born between 1978 and 1995) in a New Zealand context. Their study suggested that the characteristics of Millennials from different cultural backgrounds are unique and as such, contribute to unique student experiences. They concluded by calling for more research into how the characteristics of varying student cohorts influence student experience, particularly as there seemed to be little 'global' consensus on said characteristics.

Looking at the Otago-specific literature, two things become apparent: (1) there is a scarcity of studies that look at the student experience from perspectives that go beyond academic interests; and (2) different student cohorts seem to experience higher education differently. From these two points, it would seem important then to investigate the experiences of this current generation of students at Otago as their experiences are likely to be different again.

Finally, it is worth noting that all the studies listed here rely on perception-based data such as those gathered through surveys and interviews, which many of the authors explicitly state as limitations of their studies—e.g. Jameson and Smith (2011, p. 74) indicating they were only able to collect "subjective participant data", and would have preferred to augment their findings with objective data such as biological measures; or Daniel and Bird (2019, p. 6) noting as a limitation that student experiences of educational technology are "mainly derived from student surveys rather than comprehensive independent analyses", and suggesting in future the use of "alternative methods". One of the main foci of this thesis is an exploration of new methods that take the field of student experience away from a reliance on perception-based methods. I look at the limitations of perception-based methods for collecting accurate experience data in more detail in Chapter 2.

Significance of this study

Given the anticipated changing state of higher education and the shifts occurring in student cohorts, it is important to gain an understanding of current student experience, particularly from a holistic viewpoint that considers the influence and relevance of what often seems to be repetitive, tedious and mundane encounters typical of daily student life. As stakeholders, students play an important part in the process of higher education. For this reason, students, faculty and administrators have a vested interest in understanding what goes on in the daily life of a student. While there is a substantial quantity of research on the topic of student experience, the dominant method used to generate knowledge has been self-reports.

This study attempts to address, firstly the need for a broader understanding of students' lived experiences and secondly, the limitations inherent in self-reported perception data. The thesis aims to explore new data capture methods that may be useful in researching student experience, involving the capture of naturally occurring student activity data through the use of wearable sensors. This exploratory approach will focus on the capture of:

1. Movement data from a smartphone GPS app to determine daily movement traces of students and the places they visit and spend time in;
2. Photographs from wearable auto-cameras to generate a photographic record of the student's contextual environment; and
3. Computer usage from a desktop application to capture virtual activities/events.

As this study is exploratory, it is difficult to predict specific outcomes likely to emerge from this research. Nevertheless, this study has at least three potential significant contributions. First, I want to trial a variety of new data capture methods, not widely used in higher education research, and highlight the benefits and challenges of these new approaches. Second, I hope to extract some meaningful data about student activities/experiences that may be useful in providing a more holistic definition of 'student experience'. Third, I hope my investigation will act as a catalyst to promote interest in the exploration of new methods of research and promote a more contemporary understanding of student experience in higher education. And, for me personally, as an emerging researcher, I hope my journey into 'uncharted territory' will lead to unexpected discoveries that help guide my thinking and academic growth in the future.

Thesis structure

The thesis is structured in three parts: (1) the theoretical and contextual foundation; (2) empirical evidence comprising three related sub-studies; and (3) overall discussion of the findings, and concepts and ideas raised by this research (Figure 1.1).

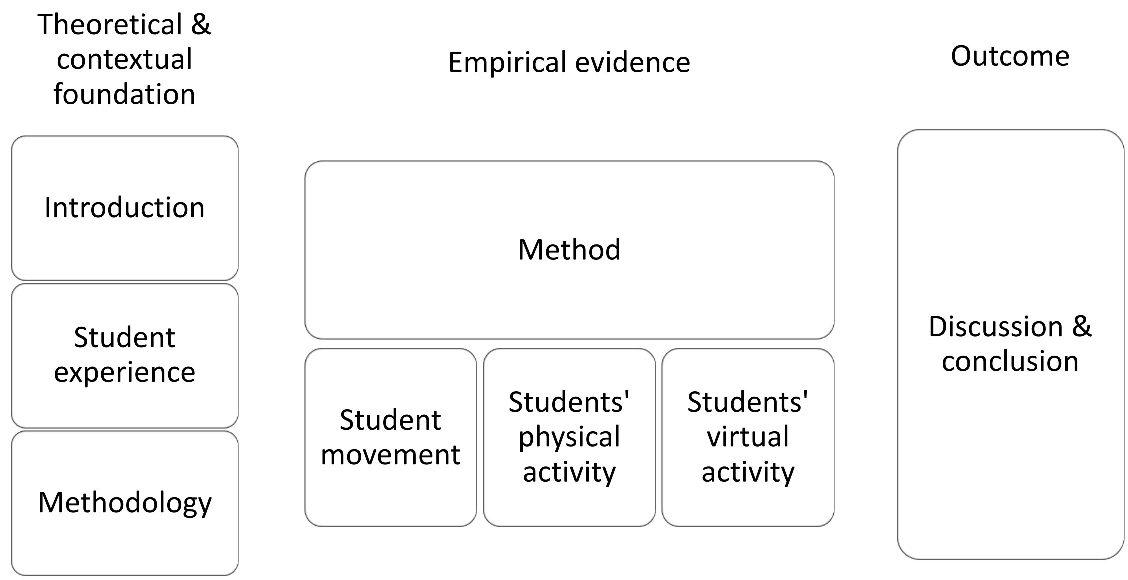


Figure 1.1 Thesis structure.

In Chapter 2: Student experience, I explore the literature on how the student experience has been researched in higher education so far. I define 'student experience' as it is currently understood in the literature, before stating the main themes that emerged from the review of the literature. I discuss the current dominant methods of researching student experience and note the limitations with these. I then outline new research methods for a better understanding of this topic and provide a brief discussion about the potential of these emerging methods.

In Chapter 3: Methodology, I outline my ontological and epistemological assumptions, as well as the exploratory research approach that is reinforced by these beliefs and assumptions. I also highlight several influential writers and thinkers who have helped guide my exploration. This chapter thus provides the overarching methodological ideas that underpin this study.

In Chapter 4: Method, I describe the overall data collection and analysis procedures, based on the research methodology. This chapter illustrates the ways datasets were created and developed. Information about the participants is provided, and the details about the data collection and the analysis techniques are presented, along with the quality assurance measures put in place throughout the course of the study. The chapter concludes with a summary of the methods used in this study.

Chapters 5, 6 and 7 are the three empirical sub-studies. Each adopts a particular lens to address the influences on student experience: student movement, student activity, and virtual student behaviour. Chapter 5 explores space and place by investigating the GPS movements of students in the university setting. Chapter 6 explores students' physical activities and context using photographs. Chapter 7 investigates the virtual environment by probing the daily computer activities of students. Each of these chapters acts as an independent report, outlining the data capture method, analyses and findings.

Finally, in Chapter 8: Discussion and conclusions, I consider the findings of the three sub-studies in light of the wider literature. By triangulating the three datasets for one student, I develop a conceptual framework for analysing the holistic student experience. I discuss the overall challenges of implementing these new continuous data capture techniques in higher education research, including logistical challenges associated with capturing and analysing large data sets, and ethical considerations of these 'student monitoring' approaches. I evaluate and critique the usefulness of the new methods for providing new insights into student experience. I contemplate the broader societal implications of capturing these types of 'student analytics' and question the role of the institution in being a curator of extensive profiles of student data. I also provide commentary on the future of higher education and theorise how student experience data could feature as a personal development and self-reflective tool for 21st century students.

Summary

A key educational concern of the modern university is understanding the elements that underpin higher education, in particular the 'student experience' of higher learning. To date, our understanding of students' experiences has been primarily based on perception-based data generated through the use of questionnaires and interviews. However, such approaches can be limiting as they may fail to accurately capture student activities and behaviours in the physical reality. Recent technological advances mean we can now capture continuous, naturally occurring behaviour data, which have the potential to paint a more holistic picture of what it means to be a 21st century student.

This chapter has provided an overview of the study, illustrating its purpose, significance, rationale, and context. In the next chapter, I present a background on the current understanding of 'student experience', propose new directions for conceptualising what it 'means to be a student' in the current educational landscape, and explore how traditional methods of researching student experience ultimately fall short of capturing the breadth and depth of student data available.

To the casual observer,
these children may appear just to be waving firebrands at a couple of caged tigers,
but to me they are learning what they live and living what they learn!

—

J. Abner Peddiwell, *The Saber-tooth Curriculum*
(Peddiwell, 2004, p. 73)

CHAPTER 2 : STUDENT EXPERIENCE

The term 'student experience' is widely used in higher education literature to describe a variety of aspects of the educational experience, from student engagement to student satisfaction and more. The definitions range from narrow conceptions of a student's experience of learning in the classroom (Ainley, 2008), to more comprehensive constructs that consider, for example, the impact of a student's accommodation or finances on their total experience of higher education (Krause, 2017). In recent years, researchers are suggesting that these varying definitions are not in competition with one another, but rather all contribute to a holistic, or total, view of the student experience. Moreover, the interplay of these various factors is also influential on how students experience higher education.

In this chapter, I will explore what 'student experience' means in a modern New Zealand context. I will bring together a range of definitions from the literature and examine them against the backdrop of the current higher education landscape, in the hope of extrapolating a holistic understanding of the undergraduate student experience and the role it plays in 21st century higher education. Further, I will explore a variety of new methods and methodologies for capturing and analysing student data that support this new conceptualisation of 'student experience' that have been previously unavailable to researchers.

What is Student Experience?

Student experience is a problematic term as there is no clear consensus on what such a research area encompasses. Everything from student engagement to student satisfaction falls under the general umbrella of 'the experiences of students'. Over the years, student experience has been researched from many perspectives—for example, from a teaching and learning perspective, studies have looked at student engagement (Reeves, Kiteley, Spall, & Flint, 2019; Crane, Kinash, Bannatyne, Judd, & Eckersley, 2016; Temple, Callender, Grove, & Kersh, 2016); student success (Irvin, & Longmire, 2016; Smith, &

White, 2015); the changing nature of higher education (Fulford, 2018; Buzwell, et al., 2016); and strategies for improving teaching and learning (Henderson, Selwyn, & Aston, 2017; Layer, 2016). Other studies have examined student experience in terms of the impact of ancillary functions of the institution, such as the role of university accommodation (Cheng & Chan, 2019; Holton, 2016), the configuration of learning spaces (Morieson, Murray, Wilson, Clarke & Lukas, 2018; Deed, & Alterator, 2017; Pepper, 2017), and the level of pastoral care for student well-being (Cameron & Siameja, 2017; Berger & Wild, 2016). Most of this research can be said to focus on only a narrow set of student activities and behaviours; namely, those that pertain to the *institutional* context, such as student learning and study practices, or student satisfaction of courses (Benckendorff, Ruhanen, & Scott, 2009). Even highly cited seminal works in the area of student experience, such as Pascarella and Terenzini's *How College Affects Students* (1991), is concerned primarily with the role that the institution plays in shaping student attitudes and behaviours.

Interestingly, one of the earliest mentions of 'student experience' as a singular concept (introduced by Harvey, Burrows and Green, 1992) also suggests that student experience should extend beyond the academic aspects of student life to incorporate all aspects of a student's engagement with their time at university. This, which Harvey et al (1992) term the 'total student experience', encompasses not only the academic aspects of teaching, learning and curriculum but also extracurricular aspects of everyday student life (Tan, Muskat, & Zehrer, 2016; Harvey et al., 1992).

When thinking about student experience from a holistic point-of-view, it is important to acknowledge that the number of formal 'contact' hours at university only makes up a small portion of a student's total university experience. Several authors (Bliuc, Goodyear, & Ellis, 2017; Ding, 2017; Macaskill, & Denovan, 2013) have, for instance, emphasised the non-contact hours of a student's life as a time in which they develop their identities, make career decisions and set life goals. There is growing evidence supporting the challenges faced by undergraduate students concerning their career, as well as life planning (Chandler & Potter, 2012; Krause & Coates, 2008; Lowe & Cook, 2003; Lam & Kwan, 1999). In recent years, researchers are once again broadening their conceptualisation of what 'student experience' means. Krause (2005) argues that understanding of the 'student experience' should encompass the entirety of a student's engagement with the institution, from initial contact through to graduation and beyond. And, recent studies by Krause (2017) and Jones (2018) acknowledge that learning in higher education not only takes place in the classroom but includes a whole range of experiences, including aspects of a student's living arrangements and accommodation, safety and security, and finances and part-time work. These researchers emphasise that conceptualisation of student experience should encapsulate both academic and non-academic activity, in a range of contexts both on and off-campus, including things like social inclusion and post-graduation expectations.

Acknowledging that the term 'student experience' has been adopted by many researchers and applied to several different research areas, it is necessary to hone this literature review to the most relevant studies. Since the focus of my study is on a holistic student experience, I have chosen to focus on studies that take a similar focus—that is, studies that provide or take a wide perspective on the various aspects of student experience, rather than those that focus on only one topic. For this reason, I have selected three key papers that review and consolidate the extensive literature on student experience and provide frameworks and inventories of key features. These articles all emphasise a holistic view of student experience, but make use of different frameworks, and identify different influences on students, thus providing a comprehensive basis to frame the current study. The three review articels are: Benckendorff et al.'s *Deconstructing the student experience: a conceptual framework* (2009), Borden and Coates' *Learning analytics as a counterpart to surveys of student experience* (2017), and Jones' *The student experience of undergraduate students: towards a conceptual framework* (2018).

Benckendorff et al. (2009)—Deconstructing the student experience: a conceptual framework

Benckendorff et al. (2009) suggest that conceptions of the student experience are complex, multifaceted and difficult to define. As such, developing an understanding of student experience will be different from one institution to another as the concept is influenced by things such as the particular needs of different student cohorts. They describe the contemporary notion of student experience as:

> a phrase that encompasses not only the academic aspects of teaching, learning and curriculum but also student lifestyle and extracurricular activities, academic advice, support and mentoring, and work experiences (Benckendorff et al., 2009, p. 84).

The authors discuss a number of challenges to understanding the student experience, including the idea that many academics base their understandings on their own experiences. However, student profiles have changed considerably in the recent years, and there is more diversity amongst the student cohort as a consequence of unique pathways, life experience, ethnicity, location, study style, ambitions and expectations. Benckendorff et al. (2009) recommend that each university must understand the needs and experiences of its students. The objective of the article is to provide educators with an understanding of the key debates and themes related to student experience in higher education.

The article attempts to 'deconstruct the student experience' by taking into consideration the different aspects that contribute to student experience in higher education. Based on a wide-ranging review of the literature, Benckendorff et al. (2009) develop a conceptual framework of dimensions that influence the student experience, grouped broadly under four dimensions. First, the *institutional dimension*—representing the largest body of research into the student experience, this dimension focuses on how institutions and staff can enhance the learning experience of students. Second, the *student dimension*—influenced by individual student characteristics, this dimension focuses on the observed quality of the student experience, and outcomes such as retention and student satisfaction. Third, the *sector-wide dimension*—being part of a broader system of institutions, universities themselves are affected by sector-wide changes that are developed as a consequence of competition or cross-institutional collaboration. Fourth, the *external dimension*—this dimension focuses on the external trends and variations such as, government policies, technological innovations and economic pressures that influence the student experience.

Through their review, Benckendorff et al. (2009) demonstrate that the notion of the student experience is influenced by rapid changes and diversity in student cohorts, resulting in a complex and continually evolving phenomenon. They conclude by suggesting that to provide quality educational experiences and respond to changing student cohorts and institutional structures, it is critical for educators to stay well-informed of the latest developments in the area of student experience. This requires recognising that contemporary student experience is about more than just teaching and learning. Academics need to be able to respond to a diverse student cohort while simultaneously coming to terms with changes across the broader higher education system.

This thesis is a direct response to Benckendorff et al.'s (2009) call to extend the notion of student experience beyond the traditional focus on curriculum, assessment and pedagogy to include the everyday, mundane activities of students. For instance, I recognise that many 21st century students are employed in part-time employment, some up to 20 hours a week; these students may be prone to disappointment with their 'student experience' if they are unable to organise their classes around their work commitments. It is important for the university to recognise that aspects such as these are all contributing to the students' experience of higher education.

Borden and Coates (2017)—Learning analytics as a counterpart to surveys of student experience

Students today source identity-building experiences from a broad range of study, lifestyle, and employment opportunities. Such change drives a need to revisit underlying assumptions about who students are, what they seek from higher education, the expectations that shape their experience, and how institutions can best help students reach their potential. To study the experience of students in the 21st century, Borden and Coates (2017) reiterate the importance of shifting away from general statements about the broad experience of groups to a more individual focus.

Borden and Coates (2017) present insights from a research project designed to improve the 21st century student experience. By identifying new data sources and approaches for measuring the student experience, their research describes new conceptions for understanding higher education students. In a multi-institutional study involving six institutions from Australia and two from the United States, Borden and Coates (2017) develop a framework that outlines four dimensions of a successful student experience: (1) student success, (2) student identity, (3) information use, and (4) change leadership. They also provide a detailed inventory of nine attributes of the student experience (Borden & Coates, 2017, pp. 95-97). These attributes are:

- **value**—e.g. financial, social, educational, professional, personal;
- **belonging**—e.g. enabling participation and engagement (vs alienation);
- **identity**—higher education allows people to extend or change themselves, and gain professional attributes (e.g. 'bedside manner' or 'management capability');
- **discovery**—e.g. encounter and create new ideas;
- **achievement**—e.g. getting into university, passing units, getting good marks, completing courses, getting employment;
- **connection**—e.g. make connections between people, ideas, experiences; develop networks; collaboration in communities;
- **opportunity**—e.g. academic and professional opportunities and prospects;
- students should feel their experience is **enabled** and **personalised**, they acquire competency and capacity to flourish, with information, support, guidance as and when needed.

Borden and Coates (2017) highlight the need for a highly individualised interpretation of student identity as part of the proposed model of student success. Furthermore, generalising the experience of a small representative group to the entire student population does not serve any student well and may be prone to existing biases. The authors note that "rather than viewing students as belonging to one group or another, we need to understand that each student's identity is a unique composite of demographic characteristics such as gender, race, ethnicity, religion, regional origin, and so on" (p. 100), suggesting a need for new thinking and conceptualisation of the student experience. They further promote the ideas of 'profiles and journeys' as useful tools for employing this approach for better understanding individual student profiles and personalising the student experience.

Borden and Coates (2017) also introduce the concept of 'student analytics', a term that encompasses "new perspectives on how data could be used to enhance a broader conception of the higher education experience" (p. 92). Urging a move away from reliance on traditional student experience surveys, the article posits that analytics can provide an objective means of quantifying different (arguably more relevant) aspects of student experience, to inform institutional decision-making.

In this thesis, I build on the knowledge gained from Borden and Coates' (2017) research and outline methods for assessing student experience at the individual level, and through the use of data analytics. By adopting an idiographic view of student identity, I hope that this type of research approach will lead to a more nuanced, personalised or individually focused understanding of student activity. Acknowledging the need for greater granularity of student information, I intend on using naturally occurring activity data from students that support the theoretically framed approaches discussed by Borden and Coates (2017). The analysis of these types of student data will produce new insights to enhance the individual student experience.

Jones (2018)—The student experience of undergraduate students: towards a conceptual framework

Jones (2018) also proposes a conceptual framework to better understand the undergraduate student experience. His research seeks to identify the main factors that form the student experience. The article provides a literature review of studies that present extensive theoretical and empirical evidence on student experience in higher education. Employing Bronfenbrenner's Ecological Systems Theory (1977, 1994, 1999), Jones provides a model which suggests that undergraduate student experience is influenced by the interaction between the student and their environment.

Bronfenbrenner’s Ecological Systems Theory (henceforth, EST) depicts the environment as a system of nested structures, ranging from immediate face-to-face interaction with another person to general all-encompassing cultural belief systems. The key term of Bronfenbrenner’s theory is ‘ecology’ which is the area of biology that deals with the relations of organisms with one another and their physical surroundings. EST organises contexts of development into four levels of external influence—microsystems, mesosystems, exosystems and macrosystems—and these levels describe the nested networks of interactions that create an individual's ecology. Each of these levels inevitably interacts and influences each other in every aspect of the individual’s life.

This theory allows us to understand how the relationships a student has can affect their university experience and other aspects of their lives. A student, for example, typically finds themselves simultaneously enmeshed in different ecosystems, from the most intimate home ecological system, moving outward to the broader university system, and then the most expansive system of society and culture itself. Figure 2.1 provides an example depiction of EST within the context of higher education, showing hypothetical influences on student experience.

In Figure 2.1, we see the student placed at the centre of the ecological model, with the four systems emanating outwards. Taking each system in turn, from most immediate to least:

- **Microsystem** applies to the institutions and groups that most immediately and directly impact an individual’s development. A microsystem, therefore, entails any specific interaction that occurs between the developing person and one or more others. A university student, for example, might have a microsystem involving: family flatmate/friend, a sports team, a lab group, or a student club.
- The next level is that of a **mesosystem** which consists of interactions between and among two or more microsystems. For example, peer culture on campus comprises such a mesosystem.

- Beyond this lies the **exosystem**, which involves links between a social setting in which the individual does not have an active role, and the individual’s immediate context. In other words, the exosystem comprises an environment which has an impact on the developing individual but does not contain him/her. The university administration represents such a system.
- Finally, the **macrosystem** describes the culture in which individuals live. It is the totality of an individual's micro, meso and exosystems and entails the realm of developmental possibilities for him/her. Macrosystems are temporally and culturally exclusive to that individual and are dynamic rather than static, i.e., the macrosystem evolves over time, because each successive generation may change the macrosystem, leading to their development in a unique system. The macrosystem places the individual in the context of his/her personal developmental ecology.

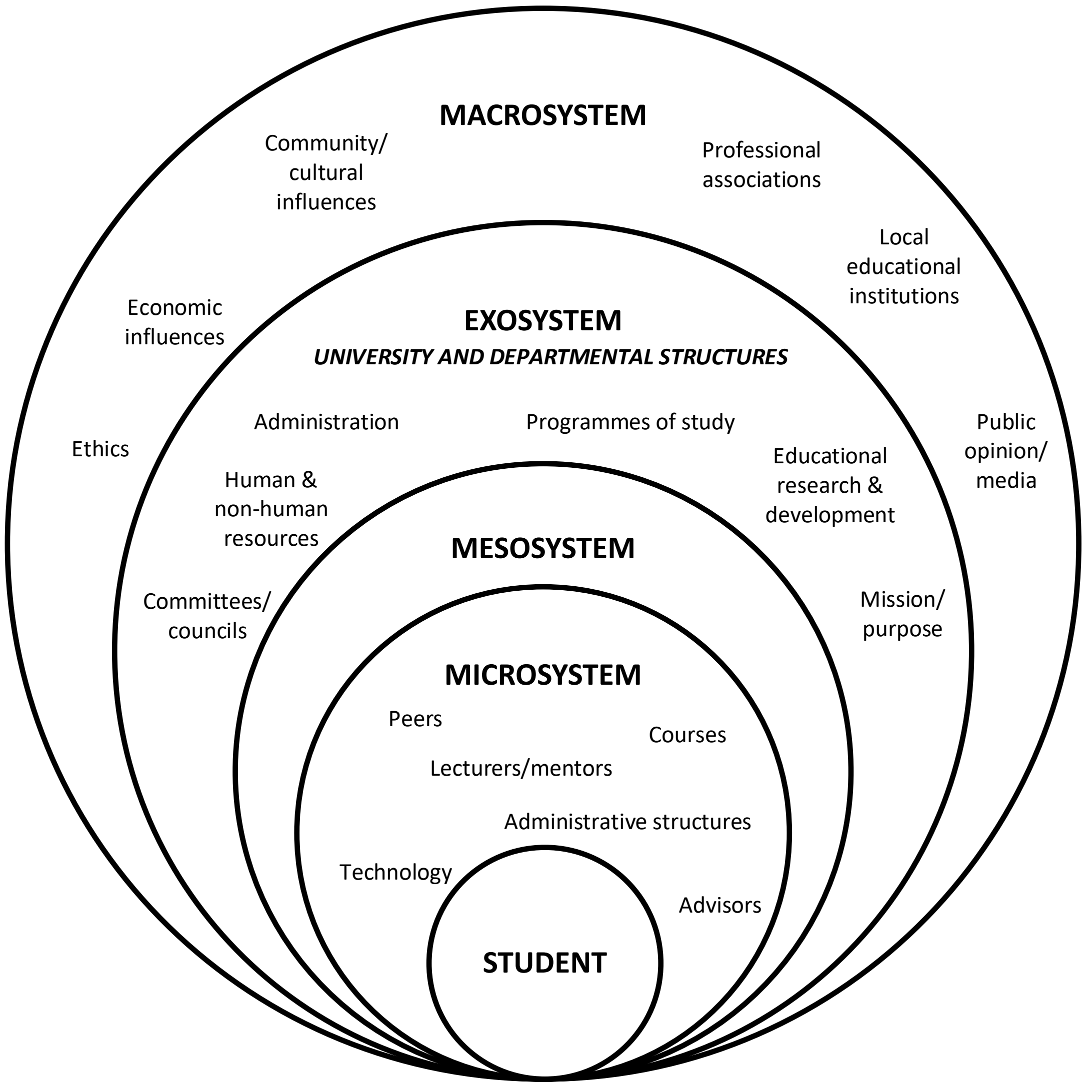


Figure 2.1 Depiction of Ecological Systems Theory (EST) for student experience, showing the four different levels—microsystem, mesosystem, exosystem and macrosystem—that form the students' ecosystem.

Jones (2018) adapted EST to categorise seven core components or microsystems that are critical to the undergraduate student experience. These include: student expectations, transition, peer networks, social background, degree programme, extra curricula activity and life after graduation. Jones' research suggests a broadly defined model of student experience where learning and development take place as a result of meaningful interactions between the student and the key microsystems.

EST encapsulates the context-specific person-environment interaction that becomes apparent as the most likely to have influence on the course and content of following psychological developments in all domains, including cognitive growth (Jones, 2018). This theory rejects the common assumption in many research studies that developmental attributes (e.g., knowledge, achievement, etc.) can be measured and examined out of the context of an individual's life. As a focus of this thesis is the exploration of student behaviour in a higher education setting—e.g., patterns of student activity (physical and virtual), social interactions, or movement—EST would seem to provide an excellent model for conceptualising different contextual spheres of influence on the overall 'student experience' of an individual.

According to this theoretical framework, each system contains roles, norms and rules which may shape an individual's identity; in our context, we are interested in the roles, norms and rules which influence the overarching 'experience' of the student. As an ecosystem, each of the four sub-systems influences and is influenced by the other systems; no system operates in isolation. Viewing student experience through this lens—that is, as a complex interplay of relationships at differing levels of developmental influence—again reinforces the assertion that we need to research student experience from a holistic standpoint. In effect, EST argues that it is not useful to examine a student's academic experiences removed from the context of their personal, social, and cultural backgrounds; one cannot effectively interrogate a student's technological experiences in the classroom, for instance, removed from a deeper understanding of their technological experiences *generally*.

Summarising current thinking on student experience

From each of the three review articles described above, I have taken away a different point that has influenced my general direction in researching the student experience. From

Benckendorff, et al. (2009) I note the need to continuously investigate the diversity of experiences of different student cohorts (echoing the conclusion of Bussink-Smith, et al. (2008) that different student contexts will invariably result in different experiences). From Borden and Coates (2017) I take up the idea of utilising personal 'student analytics' to inform conceptions of student experience, and the need to move away from relying (solely) on perception-based and generalised survey data. From Jones (2018) I appreciate the adaptation of EST to student experience to provide a more holistic view of the different influences on student life at university.

I should note that it is not my intention throughout the rest of this research to directly *apply* any of the frameworks or inventories derived from these articles. I do not wish to critique the student experience attributes published by these authors, nor to compile my own list of 'new' attributes (indeed, taking the holistic view of student experience that I am, such a list would be unending). And, I do not intend to use frameworks such as EST as a template onto which I will transcribe specific student experiences that I observe throughout this research. Instead, EST (and, really, all of the ideas discussed in these articles) provide 'reference points' to ground my investigation of student experience and steer my research in general directions.

Keeping these overarching ideas in mind (namely, that 'student experience' is a unique, personal and contextual construct for each student), the next section outlines current methods for researching the student experience. I examine the most commonly used methods and note their limitations for capturing the kinds of data that would inform an idiographic, holistic perspective of student experience. I then discuss the potential of new technologies to capture these data and provide insights on aspects of student experience previously unreached by researchers.

Methods for researching the student experience

There is a growing awareness that research into 21st century student experience requires a broadening of methods and concepts (Coates et al., 2016). To date, much of the literature around student experience is dominated by perception-based methods such as surveys and interviews, which are proving inadequate for capturing the complexities and individuality of student experiences in contemporary higher education (Borden & Coates, 2017; Coates, et al., 2016; Cotton et al., 2010). Issues around self-reporting behaviour, generalising student experiences, and low participation rates in student experience surveys have led to some researchers calling for new and innovative data capture approaches, particularly based on observation and the harvesting of digital trace data from student activity. This research builds on these studies by expanding the lens on what we consider the 'student experience' of higher education, proposing new, innovative data sources and capture methods to construct richer profiles of students in the 21st century.

Perception-based research methods

There is a long tradition of using surveys to research student experience (Borden & Coates, 2017). This is likely due to surveys being relatively easy to administer and analyse (Tight, 2012). In fact, higher education research, in general, relies heavily on surveys and interviews as its primary means of data collection—indeed, many studies have suggested that higher education researchers stick with only a narrow range of methods and resist the exploration of others (e.g., Wells, Kolek, Williams, & Saunders, 2015; Rios-Aguilar, 2014; Tight, 2013; Kelly & Brailsford, 2013; Scutt & Hobson, 2013; Hesse-Biber, Hesse-Biber, & Leavy, 2006). As Kellehear (1993, p. 159) writes, higher education tends to "fetishise and concentrate undue attention on the spoken word".

This is not to say that such methods have no merit in higher education research; on the contrary, questionnaires and interview-based research approaches can provide rich datasets of a participant's views, thoughts and perceptions. Problems occur, however, when perceptions are equated with practice or behaviour: what you *think* you did may not be what you *actually* did. Several researchers have raised concerns over the inaccuracies that post-event, perception-based data can pose for research into actual behaviours or practices (e.g., Sim & Butson, 2014; Cohen, Manion, & Morrison, 2007; Arksey & Knight, 1999; Kellehear, 1993). Reporting specifically on student experience research, Cotton et al.

(2010) provide a succinct list of the challenges associated with perception-based survey data, namely:

- **selectivity** (i.e., students reporting experiences they feel 'fit' the research);
- **recollection** (i.e., students are unable to recall details about experiences); and
- **rationalisation** (i.e., reporting events in a certain light, perhaps in opposition to what actually transpired).

An example illustrating this discrepancy was a study by Sim and Butson (2014), who showed that what students say they do with their computers, and what they actually do when their activities were monitored, varied considerably.

Observational methods

To move away from the aforementioned limitations of perception-based methods in researching student experience, some authors argue for observational methods to be used more widely. Cotton et al. (2010) outline the benefits of employing observational methods for collecting student activity data, including the use of direct observation, stimulated recall using captured *in situ* data (such as audio recordings), and participant-generated activity diaries. They write that observation provides an objective record of events and can be used to triangulate any perception-based data gathered as well. Maddox, Lingham and Bates (2017) observed student behaviour in a library setting to better inform space design and generally improve students' library experiences. They recorded patterns of student activity and augmented their research with photograph data of student study spaces in the library. In the end, they concluded that observational methods offered a richer data source than traditional metrics for evaluating library use, such as the number of books loaned or user surveys.

In both these cases, the authors praised the use of observational methods for researching aspects of the student experience, for generating rich, objective datasets, and for providing reference points to compare against any perception-based data also collected. However, both studies also note the limitations of such methods, in particular the complex and time-consuming nature of recording behaviour. The required ‘presence’ of the researcher during the entire data collection phase (as opposed to, say, the relatively low effort required in administering a survey), is a costly endeavour that few researchers are likely to be able to resource.

Learning analytics

Recently, the field of learning analytics has emerged in response to the preponderance of survey data to understand student learning in higher education, valuing instead the digital activity data generated automatically by students in their day-to-day pursuits. Learning analytics measure, collect, analyse and report data about learners and their learning, typically for better understanding the learning process and for improving the environments in which it occurs (Booth, 2012; Ferguson, 2012). While much of the literature on learning analytics has adopted this definition, the meaning and aims of this research field are still contested. One earlier definition suggests that learning analytics is the use of intelligent data, learner produced data, and analysis models to ascertain information and social connections for predicting and advising student’s learning (Siemens, 2010). However, this definition was later criticised by Seimens (2010) himself saying that “learning analytics—at an advanced and integrated implementation—can do away with pre-fab curriculum models”; and by other researchers such as, Sharkey (2010) who maintained that learning analytics does not aim to ‘predict success’, suggesting it does not and cannot measure learning.

A more holistic view was provided by the framework of learning analytics by Greller and Drachsler (2012) who proposed a generic design framework that can act as a useful guide for setting up analytics services in support of educational practice and learner guidance, in quality assurance, curriculum development, and in improving teacher effectiveness and efficiency. Around the same time, Chatti, Dyckhoff, Schroeder, and Thüs (2013) also presented a systematic overview on learning analytics and its key concepts through a reference model based on four dimensions, namely: (1) data, environment, context (what?); (2) stakeholders (who?); (3) objectives (why?); and (4) methods (how?). The broader term ‘analytics’ has also been defined as the science of examining data to draw conclusions, and when used in decision making, to present paths or courses of action (Picciano, 2012). From this perspective, learning analytics has been demarcated as a particular case of analytics in which decision-making aims to improve learning and education. Another approach for defining learning analytics is based on the concept of analytics interpreted as the process of developing actionable insights through problem definition and the application of statistical models and analysis against existing and/or future data (Cooper, 2012; Powell, & MacNeil, 2012). From this point of view, learning analytics emerges as a type of analytics (as a process), in which the data, the problem, and the insights are learning-related.

More recently, Gašević, Dawson, and Siemens (2015) argued that computational aspects of learning analytics need to be linked with existing educational research for learning analytics to deliver its promise to understand and optimise learning. Johnson et al. (2016) defined learning analytics as an educational application of web analytics designed for learner profiling, a process of collecting and analysing data from individual student interactions in online learning activities. As a result of this research, learning analytics are now being used for a number of purposes, including understanding how course resources are being used (e.g., Kruger & Doherty, 2016; Ferguson & Clow, 2015; Vozniuk, Holzer, & Gillet, 2014), to more easily see how well programmes are functioning (e.g., Harrison, Villano, Lynch, & Chen, 2015; Méndez, Ochoa, & Chiluiza, 2014), to examine micro and macro patterns of student and instructor behaviour (e.g., Pachman, Arguel, Lockyer, Kennedy, & Lodge, 2016; Adjei, Botelho & Heffernan, 2016; Slade & Prinsloo, 2013), and to inform learning system designers on how to improve user experiences (e.g., Laurillard, 2016; Kruger & Doherty, 2016; Muller, 2008).

While learning analytics represent a move towards using continuous digital trace data from students (as opposed to self-reports or observational methods), the problem is that they capture data only within a narrow range of contexts, namely *institutional* contexts. As raised, student experience comprises more than just what happens ‘in the classroom’, and therefore learning analytics offer a good starting point for expanding our methods, but we need even more innovative methods to fully capture the richness of the students' lived experience.

Summary

In this chapter, I explored the term 'student experience' to incorporate the everyday behaviours and activities of undergraduate students and how this links to their higher education experience. Research reporting on students' university experience has increased in recent years, but the focus has been mainly limited to the on-campus experiences of undergraduates. Growing interest from the research community has come with increased, though still limited, awareness of students' everyday practices. Analysing the contemporary literature reveals that student experience encompasses not only the academic aspects of a student's time at university but also aspects of their everyday living practices. This is defined as the total student experience. The many different definitions of the term 'student experience' in the literature highlight that there are multiple influences and locations in which the student experience unfolds (Jones, 2018). Analysing the student experience requires a broader and more flexible theoretical perspective that reflects these multiple dimensions. Additionally, the current understanding of the importance of students' practices in relation to their student experience is mainly based on perceptions rather than actual practice data. The discrepancies found between perception and practice data in the studies signals the need for a substantial shift in the way to understand and gather data in this emerging field. The study reported in this thesis was undertaken to offer some new understandings and insights into aspects of student experience. In the next chapter, I outline my ontological and epistemological stance, and elaborate on various 'peripheral' influences (not specifically 'student experience' related) that have all played a role in guiding my thought processes throughout this research.

We see the world not as it is,
but through a veil of conceptions.

—

Sir Ken Robinson, *Out of Our Minds*
(Robinson, 2011, p. 147)

CHAPTER 3 : METHODOLOGY

Formally, methodology embodies the systematic expression of the theoretical and conceptual frameworks that guide the design, methods and analysis adopted in academic research (Howell, 2012). However, this definition fails to capture the all-important vitality that drives research: that is, the need to know, the curiosity to enquire. I recall as a child, I had a natural curiosity about so many things. I had a fascination with figuring out how the world worked, incessantly asking questions of any available adult. In hindsight, I now see my questioning was symptomatic of a deep need to 'know stuff', a need that is still very strong today. I have come to associate my inherent need to 'inquire and interrogate' as something akin to the formal terms of ontology, epistemology and methodology. As a postgraduate, I have been trained to frame such concepts (methodology, epistemology and ontology) in research-orientated ways. However, it is only recently that I have become aware that these concepts characterise, not the research, but me as a researcher—they are personal. As a result, I have begun to articulate who I am as a researcher within these concepts.

So who am I as a researcher? It strikes me as I am investigating 21st century students, that I am also a 21st century student. I grew up in the digital age. I do remember the days of dial-up Internet; however, I also know the joys of broadband. My ability to use the Internet to find answers to problems has helped me immensely. As an emerging millennial researcher, I have a deep desire to work at the forefront of new knowledge, exploring processes and phenomena currently beyond traditional understanding. Sometimes it seems to me that my research could pursue almost limitless avenues. Because of my constant access to the Internet, and subsequent exposure to a never-ending tide of new ideas, my ideas and practices around research are greatly affected by a hotchpotch of educational and personal beliefs. It could be argued that this is inevitable as we transition from the industrial to the digital era. As a digital-centric millennial, I accept this transition defines who I am as a researcher and influences the choice of research ideas and practices I adopt. Below I share some of the more important ideas that have affected me as a 21st century student, and as a millennial researcher.

My ontological and epistemological stance

Ontology is the metaphysical exploration of existence (Scotland, 2012); meaning that it involves the (philosophical) understanding of what it is like to be or to exist. It asks questions like ‘what is an object?’, ‘what does it mean to say something exists?’ and ‘if it exists, what are its essential features: that constitute its identity?’ I embrace a relativist ontological position. As I continue to read and learn about this ontological approach, I find many correlating intersections between its various layers and how these link with the topic I explore in this thesis: namely, the 21st century student experience.

I was intrigued by the concept of relativism and thought it was worth exploring. The label ‘relativism’ has been linked to many different beliefs and perspectives; the abundant use of the term ‘relativism’ in contemporary philosophy means that there is no ready consensus on any one definition. In saying that, to orient my position, I find the definition by Baghramian and Carter (2018, p. 1) useful:

> Relativism, roughly put, is the view that truth and falsity, right and wrong, standards of reasoning, and procedures of justification are products of differing conventions and frameworks of assessment and that their authority is confined to the context giving rise to them.

From this definition, relativism to me is the notion that opinions are relative to variations in perception and consideration. According to relativism, there is no absolute, objective truth; instead, each viewpoint has its own truth. Relativism considers that human beings are not able to explicitly access the world ‘out there’ (Bernstein, 2011). I believe that indeed there is an external world but would argue that we can only directly access representations of the world in our consciousness. For me, the phrase ‘beauty is in the eye of the beholder’ gives a better idea of relativism—beauty, for example, is not absolute; instead, it is created and given meaning to by individuals. My focus is, therefore, on the everyday activities of people, specifically the day-to-day activities of undergraduate students.

Epistemology is a branch of philosophy concerned with the theory (or nature) of knowledge (Scotland, 2012). Epistemologists do not accept that people can ‘just know things’. They ask questions like ‘what is knowledge anyway?’, ‘how is it acquired?’, ‘what do people know?’ and ‘how do we know what we know?’ My epistemological belief has its foundation in relativism. Taking a subjectivist approach, my epistemological position determines a vital responsibility for the individual, inferring that knowledge cannot exist without people to create it. Knowledge is fundamentally subjective, as each individual will create their world in an exclusive way, contingent on their background, the social influences acting on them, and so on.

Suffice to say then, it is the social constructivist view that makes the most sense to me. Social constructivism is based on a relative ontology meaning that the truth about ‘what is what’ is socially negotiated (Duit & Treagust, 1998). In conjunction with this, my subjectivist epistemological position concludes that in social constructivism, the true meaning of knowledge is internally constructed. Knowledge is created by interaction with the environment so individuals can make sense of their world through activity and exploration. Social constructivism differs from constructivism in that it takes into account that language and culture also influence how individuals make sense of their world and, since language and culture are social experiences, knowledge is co-constructed with others in social situations.

One of the core lessons this teaches me is that every learner is an individual, will approach learning their own way, and construct meaning that is unique to them. So, as a social constructivist, I believe that to understand students and their behaviours, we have to be aware of their experiences and culture and recognise that they do not just potentially *see* the world differently but *experience* it differently too.

Exploratory research

Adopting a relativist and social constructivist perspective on research and the nature of 'truth' has led me to an exploratory research approach. For me, exploratory research, by its very nature, represents an inquiry into concepts and topics in an innovative form. The purpose is to gain new appreciations and identify and develop insights about the existential characteristics of something. The objective is to gather preliminary information that will help define problems and maybe suggest hypotheses (Kotler, & Armstrong, 2010). Through social-based exploratory research, we seek to find out how people get along in the setting under question: what meanings they give to their actions, and what issues concern them. The goal is to make sense of 'what is going on here?' rather than address explicit questions.

Reiter (2017) provides some considerations for the application of an exploratory approach in social science research that I have attempted to keep in mind throughout this thesis. First, exploratory research should be conducted in a transparent, honest and self-reflexive manner. In an attempt to adhere to this tenet, I aim to highlight the many influences on my thinking around this topic, both directly and indirectly relevant to my overall discussion. I feel it is important to share these as it helps to orient the reader with my particular worldview, and hopefully contextualise any inherent biases in my research. Second, fundamental to exploratory research is a gradual reformulating of theories and hypotheses. As mentioned previously, my aim is not to 'find out' or 'confirm' something (as my ontological stance on the nature of an objective 'truth' precludes this). Rather, I intend to 'make more sense' of something dynamic, complex, and socially constructed (in this case, 'student experience'), by collecting empirical data, subjecting them to various enquiries based on various conceptual perspectives, and re-evaluating my original ideas in light of new discoveries.

To add meaning to data I have collected in this thesis, I have embraced this idea of 'sensemaking'. Sensemaking has been defined as "the ongoing retrospective development of plausible images that rationalise what people are doing" (Weick, Sutcliffe, & Obstfeld, 2005, p. 409). More simply, sensemaking involves the process of assigning meaning to experiences. The practice of sensemaking is associated with an interpretive perspective of communication (Kramer, 2017), which emphasises how meaning is socially created through interaction. Using sensemaking as an interpretive lens, I try and make sense of individual experiences.

Sensemaking is a necessary part of any human activity research because most events are equivocal, which is to say that experiences can be interpreted in multiple ways. The idea of sensemaking allows for the management of the ambiguousness of experiences that are unusual than anticipated by choosing one explanation for the experience out of the many possible explanations (Kramer, 2017). The dedication to a certain meaning affects future activities, as the process of sensemaking persists. This process will allow me to explore how individual student activity contributes to their experience of higher education.

As stated, one of the principal criteria of exploratory research is the continuous refinement of assumptions and hypotheses through the collection of empirical data. 'Empirical' refers to that which can be experienced with the senses, and in the context of research, it refers to data that can be observed and documented (Pickett, 2018). These data need to be submitted to rigorous and transparent analyses before the process of identifying them as evidence for passing judgements or providing solutions.

It is important to note that while this thesis is empirical (grounded in evidence as opposed to relying purely on theory and logic), it does, at times employ reasoning for clarity and synthesis with broader concepts. To reason is to have the capability of deliberately making sense of things, ascertaining and confirming information, using logic, and modifying or qualifying practices, institutions, and beliefs created from new or existing evidence (Kompridis, 2000). It is directly related to subjects such as philosophy, science, language, mathematics, and art, and is generally believed to be a differentiating ability retained by humans (MacIntyre, 2013). Reasoning, like perception or instinct, is one of the ways by which rationale moves from one belief to another. For example, reasoning is the process by which logical individuals comprehend sensory information from their surroundings. As a part of executive decision making, reasoning is also strongly identified with the capacity to self-consciously transform, with regards to 'goals, beliefs, attitudes, traditions, and institutions', and hence with the ability for independence and autonomy (Kompridis, 2006).

In particular, exploratory data analysis lends itself to *abductive reasoning*, what Ho (1994) refers to as the 'logic' of exploratory data analysis. Abductive reasoning is a process of understanding various points of views or variables and combining them to form a more inclusive representation of the problem (Burnore, 2013). The process of abductive reasoning begins with an incomplete set of observations and proceeds to the likeliest possible explanations for that set. Abductive reasoning yields the kind of decision-making that does its best with the information at hand, which is often incomplete. For example, a medical diagnosis is an application of abductive reasoning, based on a set of symptoms. The abductive process can be creative, intuitive, and even revolutionary (Thagard, & Shelley, 1997). For example, Einstein's work was not just inductive and deductive but required creative leaps of ingenuity and vision that hardly seemed warranted by the empirical data he could readily observe. Indeed, so much of Einstein's work was carried out as 'thought experiments', that some of his peers discredited it as too farfetched. Nevertheless, now his remarkable conclusions about space-time continue to be verified experimentally.

Using abductive reasoning, social science researchers begin by observing social behaviour or questioning social actors in detail and then providing clarification for what has been found. Researchers are often interested in unpacking 'what is going on' and 'how do people interpret these experiences?' or 'why do people do what they do?'. Rather than testing a hypothesis, the point is to try and make sense of some social phenomenon. Researchers may even put off formulating a research question until after they begin to collect data—the idea is to let the question/s emerge from the situation itself (Brewer & Hunter, 1989). In this thesis, the purpose of using abductive reasoning is related to the use of methods that capture significant quantities of relatively unstructured data or that take a field of inquiry in a new direction.

In summary, my chosen approach to research is exploratory in nature, grounded in empirical data and guided by abductive reasoning. My interest, my passion, is to explore to determine the nature of a situation and/or problem. It has been suggested that exploratory research is 'preliminary research', which forms the foundation of more conclusive research later. It can even help in establishing the research design, sampling methodology and data collection method (Singh, 2007). When conducting exploratory research, researchers should be willing to change their direction as a result of a revelation of new data and new insights (Saunders, Lewis, & Thornhill, 2012). Therefore, by using an exploratory research design, my aim is not to provide the final and conclusive answers to questions, but to explore the research topic with varying levels of depth. As discussed earlier, in exploratory research, it is important to be honest and transparent. Having thus considered my ontology and epistemology, as well as an exploratory research approach and my own personal characteristics that influence my research, I now turn to theoretical influences.

Theoretical influences

In a further effort to be transparent in my approach to research, in the following sections, I discuss the primary influences on my thinking and methodological approach. While not all of these have been formally adopted as part of this study's 'method', nonetheless each of the following influences has nudged me throughout this PhD, and the essence of these ideas can be seen in my final design.

Influence 1: Rand, and the individual

I recently read Ayn Rand's novel, *The Fountainhead* (Rand, 1943). It is a remarkable book, a defence of the individual creative spirit. It is about a perfectionistic young architect who prefers to struggle in obscurity rather than concede his artistic and personal vision:

> To sell your soul is the easiest thing in the world. That's what everybody does every hour of his life. If I asked you to keep your soul—would you understand why that's much harder? (Rand, 1943, p. 436).

The book follows his struggle to practice modern architecture, which he believes to be advanced—the protagonist battles against an establishment that values traditional approaches and denies his modern practices. The primary theme of *The Fountainhead* is individualism versus collectivism, not in politics but within a man's soul (Rand, & Peikoff, 1999). Rand defines individualism as the moral stance, political philosophy, ideology, or social outlook that emphasises the moral worth of the individual (Wood, 1972). At the core of Rand's philosophy is a belief that unfettered self-interest is good and constitutes the ultimate expression of human nature.

As I read Rand's work, I found her ideas empowering; they taught me to rely on myself. As an individualist, I promote the practice of individual aspirations and wishes and so appreciate autonomy and self-determination, and believe that interests of the individual should take precedence over the group. In this way, I connect and understand individualism as a lifestyle where there is a propensity towards self-invention and experimentation as opposed to tradition or prevalent mass opinions and actions.

Influence 2: Goffman, and multiple identities

One way to understand human behaviour is through Goffman's dramaturgical theory of viewing individuals as actors on a 'social stage', who vigorously invent an impersonation of themselves for the benefit of spectators, and, eventually, themselves (Goffman, 1959). When we perform in the social world, we put on a 'front' to cast a particular representation of ourselves—this is our 'social identity'. We create this front by manipulating the setting in which we perform (e.g., home, classroom, work, etc.), our appearance (e.g., clothes, hairstyle, accessories, etc.) and our manner (e.g., emotional responses to situations). In the social world, we are called upon to act out numerous fronts contingent on the social stage on which we observe ourselves and the groups of performers with whom we are acting—thinking of students, in a classroom situation or at home with flatmates would be typical examples of social stages which require individuals to put on such a front. On these social stages, we undertake characteristics in relation to other group members and cautiously control the impressions we emit to conform to society and/or achieve our personal objectives (Goffman, 1959).

Impression management entails projecting an 'idealised image' of ourselves, which requires hiding various characteristics of a presentation, such as the effort that goes into putting on a front, and usually concealing any personal benefit we will get from an interaction. Unfortunately, because spectators are continually on the look-out for the signals we give off (so that they can know who we are) "performers can stop giving expressions, but they cannot stop giving them off" (Goffman, 1959, p. 108). This means that we must always be on our guard to exercise 'expressive restraint' when on the social stage. There are a lot of things that can go wrong with our presentation which might reveal the fact that we are not the person our performance implies we are—for example, we might lose physical control (hunch), or make errors with our clothing (a messy appearance). Performing our social roles is rather challenging, and so in addition to the front-stage aspect of our behaviours, we also have back-stage zones where we can practice our activities in the world.

A number of the roles we play challenge each other, and so we need to keep audiences separate; some performances are only meant for certain audience members. For example, a student might act studiously while on campus but more carefree while amongst friends off-campus. Most audience members, however, are diplomatic and willingly stay away from back-stage zones where we practice for our social performances. If we ever 'fall out of character' they incline to employ 'diplomatic inattentiveness' to save the situation (Goffman, 1959).

Goffman's theories of socialisation differ from other perspectives, such as the Marxist point-of-view. Marxism, for example, argues that institutions socialise students to accept authority and hierarchy passively, thus preparing them for exploitation later in life

(Goffman, 1959). By applying Goffman's theory to students, we could perceive students might just be acting out the acceptance of hierarchy to get through the system with as little hassle as possible. At the same time, back-stage they may think university is not particularly important, and they may not accept the structures and forms of higher education as relevant past the completion of the degree.

From a researcher's perspective, the significance of Goffman's theory lies in the fact that to understand people; we need to engage in naturally occurring behaviour data analysis to get back-stage with them. In this way, we can see people's true selves when they stop performing. If a researcher simply gave people a survey to complete, or even if they had a detailed discussion with them, they could be perceived by the respondent as a member of an audience, and the results we get could just be a performance put on for the benefit of the researcher. Ultimately, Goffman's dramaturgical perspective on human interaction suggests that it is best to study human activity by focusing on individuals and their efforts to maintain their identities in public.

Methodological influences

The following section introduces the key influences I draw on for developing a new research method.

Influence 1: Idiographic research

To explore the student experience requires the capture of holistic data about individual student activity. To do this, I employ idiographic methods of data capture and analyses, in natural settings, in real-time (or close to real-time occurrence), and on repeated time occasions. Accordingly, my research design is based on using personal student analytics within an idiographic research design. The term 'idiographic' is derived from the Greek word 'idios', which means 'own' or 'private'. Therefore, idiographic research concerns analysis at the individual level (Cone, 1986) rather than by a cohort or group (nomothetic). The term 'nomothetic' comes from the Greek word 'nomos' meaning 'law'. Researchers who adopt a nomothetic approach are mainly concerned with studying what we share with others. Nomothetic research tends to employ aggregation of individual data to ascertain generality across classes or groups; outliers or exceptions are usually deemed undesirable and removed through various statistical methods. Idiographic research, on the other hand, welcomes exceptions as these define the uniqueness of the individual. In this thesis, I take an idiographic approach to research, focusing on the individual and emphasising the unique personal experiences of human nature. The idiographic approach does not try to devise laws or generalise results to others.

Idiographic methods investigate rather than assume that each individual will have similar relations between variables (Conner, Tennen, Fleeson, & Barrett, 2009). Thus, an ideographic approach yields' within-person' patterns, each unique to one individual. Using this approach, I aim to identify patterns of behaviour within each students' spaces, activities and movements, over time and contexts.

Influence 2: Reality Mining

The core of the new methods used in this thesis is the use of 'sensor-based' systems that offer continuous feeds of personal data over prolonged periods. Until recently, capturing activity or behavioural data (particularly over extended periods) has been relatively untenable, as systematic observation of lived experience data is a complex, time-consuming and logistically challenging endeavour. However, recent technological advances in wearable sensor-based devices are enabling simple, continuous capture of data streams from psychological, physiological, and environmental dimensions.

Reality Mining (Eagle & Pentland, 2006) has emerged in recent years as a means to investigate activities and behaviours of people in extraordinary detail and with exceptional spatio-temporal precision. Reality Mining involves the harvesting of digital traces generated by intelligent mobile devices such as smartphones or wearable devices, providing extremely fine-grained data about what we do, where we go, and with whom we interact. This continuous and simultaneous sampling of an individual's life provides for comprehensive, descriptive and predictive models of a range of dynamic processes, such as social interactions, use of technology, and behavioural patterns. Even the mundane, random, and arbitrary actions of daily-life patterns can offer meaning-bound and purposeful insights when socially, spatially and temporally contextualised (Magnusson, Burgoon, & Casarrubea, 2016).

Propelling this data-driven approach is the proliferation of powerful, affordable wearable devices and self-surveillance apps. For example, wearable devices such as fitness trackers (e.g., FitBits, Apple Watches), and miniature personal cameras (e.g., Narrative clips or GoPros) allow wearers to easily collect continuous, naturally occurring information about their daily lives. The evolution of the smartphone has also seen a proliferation of apps that allow passive tracking of life activities, notably in the form of geolocation data (e.g., GPS apps such as MapMyRun or EasyTrails and auto-cameras). Wolf and Kelly (2014) suggest these technologies are fuelling the desire for self-knowledge through self-tracking, typified in an emerging social movement recognised as the 'Quantified Self'. Similarly, Bolanos, Dimiccoli, and Radeva (2017) talk about the popularity of visual lifelogging through the use of wearable cameras, and the rise in the construction of personal narratives from daily visual data.

The emergence and increasing refinement of personal miniature tracking technologies afford the harnessing of Reality Mining for smaller, idiographic studies (Cheung et al., 2017; De Groot, Drangsholt, Martin-Sanchez, & Wolf, 2017). In the context of higher education, wearable devices offer the potential to facilitate personal insights into the role of student spaces, activities and schedules. Accumulated spatio-temporal data would allow for detailed analysis of different student behaviours and experiences over their time at university, creating profiles of patterns and relationships that accurately define a student's lived experience.

Within the university setting, adopting a Reality Mining approach, grounded in idiographic data, means it is possible to construct a comprehensive depiction of student life from data that captures what students do, what places they visit and for how long, and what events take place within these spaces. Rather than mining their data covertly, I aim to situate the individual at the core of this research by fostering transparency and collaboration through shared insights of their data. As mentioned, a core feature of this approach is the need to acknowledge that each student's experiences are unique, to explore and learn from the distinctiveness of their own lived experience.

Influence 3: Space – Event – Movement (SEM) framework

One way to understand spatially integrated perspectives for the analysis of human activity patterns is through a synthesis of spaces, events and movements (SEM). Developed by an architect, writer and educator Bernard Tschumi, the SEM framework (Tschumi, 1976) explores the use of space, event and movement in the context of architectural design. His statement "there is no space without event" (Tschumi, 1996, p. 139), sparks a deep conviction in me to know about the dynamic character of how people (in my context, students) go about living in various spaces. I believe that space is socially constructed by the event taking place within it. Therefore, educational space is defined by the educational activity taking place within it. Accordingly, the university is a form of an ecosystem, characterised by movement as well as by the spaces and inter-social experiences of people. Consequently, it becomes a discourse of events and spaces.

The SEM perspective conceives and represents an individual's activities, behaviours and movements in a day as a continuous series of events spaced over time. The number and location of daily activities that can be performed by an individual are restricted by the amount of time available and the space-time constraints associated with various obligatory activities (e.g., work, study, entertainment) and joint activities with others (Hornsby & Yuan, 2008). Therefore, SEM not only highlights the importance of space for understanding the geographies of everyday life, but it also allows researchers to examine the complex interaction between the space and the event taking place and their joint effect on the structure of an individual's activity patterns, in particular, situations (Hornsby & Yuan, 2008).

Although used widely in other disciplines such as architecture, urban planning and tourism, the SEM framework has not been widely used as a framework in human behaviour research. Some exceptions include the work of Kwan and Schwanen (2016) who offer a reflection on the rise of mobilities and their relation to pre-existing research traditions, specifically transportation geography; Walters (2010) who refers to SEM as a concept to connect the supermarket space with social events that take place there; and Miller and Wu (2000) who explore the use of GIS software for measuring space-time accessibility also in transportation planning and analysis. The limited development of SEM methods is likely due to the absence of comprehensive individual-level data and analytical means that can accurately represent the intricacies of an individual's environment (e.g., the movement network and spatial distribution of activities). Another difficulty is that individual movement in space is a multifaceted trajectory with many interacting elements. These take into account the setting, timing, interval, sequencing, and type of activities. This feature of activity patterns has made the concurrent analysis of its many aspects challenging. However, with growing obtainability of georeferenced individual-level data such as Global Positioning System (GPS) data, it is now more feasible than ever before to operationalise and implement SEM constructs.

Influence 4: Students as collaborators

When thinking about the students that were part of this thesis, I realise that I have been blessed by their contribution to the research in several different and unanticipated ways. They have commented on the process, shared ideas, emailed things to me unsolicited (e.g., linking me to blog posts and online articles they thought might inform my research), offered to meet over coffee to discuss the data, and all voluntarily and unprompted. As a result, I have become aware of information I would have otherwise been oblivious to without these additional eyes and ears. What then would be a suitable term to describe their contribution to the research? 'Participant' does not quite seem to do the job. Some studies have used the term 'co-researcher', particularly in respect of research which sets out to be 'participatory' (Bergold & Thomas, 2012). However, in these studies, the intention from the beginning is to implore the participation of individuals who will fill the role of co-researcher; the studies have been planned as such. Co-researchers may even be included in the planning process, preceding data capture, analysis and interpretation, and ultimately the production of a report. Differing levels of participation are possible, signified by the authority co-researchers have in shaping the outcomes (Arnstein, 1969). I have to admit that I did not set my research up that way. I never went out and looked for individuals who would take on specific roles; I know only too well how time-poor most health science students are and indeed felt pangs of guilt even when requesting them to give up an hour for a chat. In what unfolded, students contributed if and when they felt able, at times to suit them and on their terms. As a result, there was less sense of compulsion or commitment, and instead one of professional pursuit and encouragement. And having just written that, I believe the term 'collaborator' might better define the role of students in this study.

Feminist research

I have returned to this section much later in my journey—it is only after reflecting on all of the influences mentioned above that I have come to realise my research is characteristically feminist. I do not mean that it is concerned with 'gender' issues, but rather that the same characteristics of feminist research are recognisable in my methodology. First, feminist research celebrates methodological diversity, being interdisciplinary and transdisciplinary (Sandford, 2015); it also recognises that researcher bias is inevitable, and ensures it is, therefore, upfront and visible (Letherby, 2003). These principles characterise the exploratory approach I have adopted for this study. Second, feminist research is concerned with exploring lived experience, particularly from multiple standpoints (Brooks, 2007), which clearly follows my own thinking about idiographic research. Third, feminist research is overtly political—at its simplest, it is research that seeks to illuminate a woman's perspective within embedded patriarchal structures; however, transcending the issue of 'gender', feminist research can be seen as research that represents the experiences of the oppressed and presents a counter-perspective to the established structures of authority. As Brayton, Ollivier, and Robbins (2014, para. 5) write, "[Feminist research] actively seeks to remove the power imbalance between research and subject." The central ideas of my research directly challenge the traditional institution of higher education and are principally concerned with empowering the students. This is evident in my aim to include students as collaborators and my exploration of personal development movements such as the 'Quantified Self' (elaborated on in Chapter 8). Indeed, in my later discussion chapter, I become somewhat critical about the established structures of the university and question how (and if) these new research methods can effectively fit within them.

Summary

In this chapter, I outlined several influences that have shaped my research methodology. From my ontological and epistemological views on the lack of objective truth, and an embracing of a social constructivist and relativist worldview, I have ultimately adopted an exploratory design for this project. While this means I do not have explicit research questions, I do have a general social phenomenon of interest (student experience) and intend to collect empirical data to help in 'making sense' of this phenomenon. Abductive reasoning also factors into my overall design as I explore my data and refine my initial assumptions about the topic.

I also listed a wide variety of thinkers and concepts that have played a role in my process of 'sensemaking'. From Rand's political writing about the power of the individual (and my subsequent embracing of a strongly idiographic research perspective) to Goffman's presentation of identity (which speaks to my desire to move away from research that relies too much on 'perception-based data); these are the ideas that form the foundation of my exploration. In terms of methodology, Reality Mining and the SEM framework have guided me to collecting continuous, naturally occurring student activity, with a specific focus on spaces, events and movements. I have also embraced the notion of 'students as collaborators', rather than merely participants. And, in bringing together all of these influences, I have realised that these things which at first seemed disparate, in actuality embody a feminist research perspective.

I understand how:
I do not understand why.

—

George Orwell, *Nineteen Eighty-four*
(Orwell, 1984, p. 72)

CHAPTER 4 : METHOD

In this chapter, I outline the main methods of data capture for this doctoral study. As discussed in Chapter 2, one of my aims is to capture naturally occurring, idiographic (i.e., pertaining to individual students, rather than generalised) data of student activities to better inform a holistic perspective of student experience. I also want to investigate the potential of new and emerging technologies to enable that data capture. While the research is exploratory in nature (and therefore without explicit research questions about student experience), I do have some guiding concepts and theories that help to inform what sorts of data I will capture, and what sorts of methods I will employ. For example, Tschumi's (1976) Space-Event-Movement (SEM) framework encourages me to look at the spaces students come to occupy during their time 'as a student', and what activities they perform in these spaces. As such, I want to track the day-to-day movements of students and will use GPS (Global Positioning Satellite) traces from a smartphone-based app to achieve this. Because I am taking a holistic view of student experience, I am equally interested in investigating the day-to-day activities that students engage in both *on* and *off-campus*. The GPS traces will give some insight into the activities of students (inferred from the spaces they visit), but I will also use wearable auto-cameras (that take a picture automatically every 30 seconds) to create photo narratives of their daily routines. Finally, to investigate this current generation's digital tendencies, I will use computer tracking software to log students' virtual activities.

Therefore, in this thesis, I will present the findings of three new data capture methods that have the potential to enhance our understanding of various aspects of 'student experience'. The datasets generated by these methods are:

1. GPS traces collected from smartphone-based GPS apps to capture student movement;
2. Digital photos from miniature wearable auto-cameras to capture interaction and activity data; and
3. Computer usage log data from computer tracking software to capture the virtual activities of students.

These datasets serve to illustrate the possibilities of the new methods. In the sections below, I will describe the participants of this study and the fieldwork protocols followed in gathering these datasets. Specific methods, details of analyses performed, and the findings pertaining to each dataset are reported further in Chapters 5, 6, and 7, respectively.

Participants

The participants for this study were 21 undergraduate students enrolled at the University of Otago, Dunedin, New Zealand. A description of the study and invitation to participate was sent via email to all full-time undergraduate health science students at the University of Otago, through the Graduate Research School, and the Division of Health Sciences, as well as via a Facebook post on the Otago University Students Association and Otago University Health Science Library pages (see Appendix A for email invitation). The invitations outlined the project and criteria for selection, as well as contact details for interested students seeking more information. The email also included a copy of the information sheet and consent form (Appendices B and C, respectively). Students who met the criteria were grouped based on their level of study. Overall, 54 students responded to the request for participation, and a convenience sample of 21 students was then invited to attend a briefing/training session. At the completion of this session, each student was asked if they would like to be involved in the study. If required, any replacements were drawn using the same process from the original list. Among the 21 students selected for the study, four were first-year, two were second-year, and 15 were third-year students. The course demographics were as follows: four health science first-years, three from medicine, six dentistry and eight pharmacy students. In terms of gender, two participants were male, and 19 were female. This study was approved by the University of Otago Ethics Committee (Ethics #16/160, see Appendix D for ethics application and Appendix E for letter of approval).

Fieldwork protocol for devices

Each participant was provided with a GPS app, a small clip-on auto-camera and software for computer usage tracking. The data were captured continuously over an approximately four-month period (a single semester, from the end of February 2017 to the end of June 2017). The period of daily data capture for each of the sub-studies was defined as 'waking up' to 'bedtime' and varied for each individual according to their routine. The research consisted of a trial period followed by the formal data collection stage. These stages are described in more detail below.

During the trial period, participants signed the consent form to join the study. Each student was invited to a session explaining the use of the devices and the research itself. Prior to signing the consent form, we detailed the type of data being collected by the devices. Students were trained to use the camera and the apps. The devices required little attention from students following the initial set-up; that is, data collection happened automatically in the background as students went about their days. Students were also shown how to access and review their own data. A short profiling questionnaire was administered during the trial session to collect demographic information about the students and their courses.

After the trial period, students carried their devices with them throughout the day over the entirety of the first semester. Automatic sensing data was collected and uploaded to the cloud, either daily or weekly. Given the richness and volume of data captured, only the top five participants with the most data captured in each of the sub-studies were selected for subsequent analyses. The specific methods for each of the sub-studies are detailed further in the next three chapters.

Establishing rapport with students

As well as the formal data capture methods mentioned above, I also had weekly informal discussions with the students regularly to probe aspects of their weekly activities. These sessions lasted from anywhere between 30-50 minutes. As one of my aims in this project was to include the students as collaborators, I thought it essential to build rapport with them and ensure they were active participants in the research process. The precise nature of the interaction was not determined in advance but depended on how the discussion developed. These discussions also allowed me to create a friendly and approachable environment where the students felt comfortable sharing information about themselves.

Focus group style, informal group discussions were chosen to capture student perceptions rather than structured interviews. The reason for this was to allow the students to speak openly about their views and opinions regarding their lived experience. The informal discussion enabled me to return to the same topic numerous times, allowing the student to produce information with stimulated memory (Keijzer-Broers, Nikayin, & De Reuver, 2014; Van den Herik, & de Vreede, 2000; Caplan, 1990). With the discussion being more like an everyday conversation, a safe and relaxed environment was created within the space of the discussion; unlike a highly structured interview where the respondent may feel stressed or hurried, and may not respond accurately if they feel the need to move on to the next question (Keijzer-Broers et al., 2014; Krueger & Casey, 2014). It was hoped that the use of an informal method would encourage free and open dialogue. However, unstructured discourse can result in a variety of responses that may lead the discussion off-track. It was, therefore, vital that I was judicious in regulating the conversations.

Because these discussions were conducted based on a loose structure, they allowed me to interact with individuals and ask different types of questions to generate responses associated with the different types of data. The questions were open-ended and usually structured around the data collected for that particular week. This unstructured approach provided flexibility as questions were adapted and changed depending on the students' answers. This approach also allowed the participant to respond with in-depth explanations, in their own words, to provide their perspective on the research process. Hence, I was able to gain a better understanding of the situation from the participant's point-of-view and ask for clarification if required.

It is important to note that these sessions were not initially intended to be used as a formal method of data capture, and as such were not included in the ethics application, or introduced to students as a formal method. Later, I did consider using the focus group sessions as a means of validating some of my assumptions and findings around the usefulness of the other data capture methods; however, ultimately I determined this would not have been an ethical research practice, as the students were under the impression that these sessions were informal and effectively a 'safe space' to voice any concerns or ask for further information. Changing the purpose and nature of these sessions partway through the research could have undermined my intention to build rapport with the students and include them as collaborators.

Data management

To keep consistency in the data collected, it was crucial, not only on my part but also the students', to 'keep up' with the data management, (e.g., regular uploading and storage of data). For example, if I noticed students' cameras were not uploading data (suggesting cameras were not plugged in at night), or there were significant gaps in weekly GPS data (suggesting students perhaps left their phones at home during the day), or no computer activity, I would send a text/email reminder to remind them to use the devices, and upload the data regularly.

To promote compliance and data quality, we offered some incentives to all the participants. First, all students received a full paid version of the GPS app for continued future use. Students also received a backup battery pack for their phones to use during the study, which they were allowed to keep. At the end of the study, $200 compensation was provided to all students who collected data over the entire study period.

Ethical considerations

Students' privacy was a significant concern for this study. To protect students' personal information, we fully anonymised each student's identity with a random user ID (e.g., sem21) and kept these separate from all other project data so no data could be traced back to individuals. All students were given an email address and password based on their personal IDs to use with the apps and software, to ensure they did not have to use their personal details in signing up new accounts. During the data collection phase, data was stored temporarily on these password-protected applications before being transferred to secured servers for storage and later analysis. Specific data storage and security procedures are further detailed below.

Only the members of the research team had access to the datasets and were responsible for data storage. On completion of the study, students were presented with both a complete and abridged version (i.e., a summary report) of their GPS and camera data. Any personal information held on the devices was destroyed at the completion of the study, although the data derived from the research will be kept for up to five years.

Photograph and GPS data: data captured from both the wearable camera and the mobile app was temporarily stored either on the camera or the participant's smartphone. Participants synced data nightly to a secure web application and a password-protected email. The data were then downloaded to a high capacity storage server for later analysis.

Computer usage data: computer activity data were manually transferred to the high capacity storage server from the participant's computers at the end of the data collection period. These data were downloaded and analysed on a secure password-protected computer.

The intent of the study was to be transparent. Students had continuous daily access to all the information they provided throughout the study period and at the completion of the study. Requests for access to this information could be raised at any time and were discussed at regular discussion sessions. These weekly discussions were also guided by honesty and transparency.

As this study involved human participants, ethics approval was sought from the University of Otago Ethics Committee before data collection (the ethics application and approval letter are included in Appendices D and E, respectively). The ethical use and care of the data, as well as the ethical treatment of students as participants, were integral to the research design, planning and implementation of the whole study. Of particular concern were issues related to privacy, particularly in terms of perceived surveillance and the capture of personal data (these ethical challenges are elaborated on in Chapter 8). As this thesis is guided by an idiographic approach, and the focus is on individual student's data, we wanted to be able to show their images and unique traces. However, students were also provided with a consent form on which they were given options regarding their anonymity (Appendix C).

Summary

In this chapter, I introduced the three core datasets that form the basis for the three empirical sub-studies; namely, GPS traces from a smartphone app, photostream data from a wearable camera and computer usage data from computer tracking software. It then provided details on the participants, including their year-levels, degree programmes and gender. This was followed by a description of the fieldwork protocol for the three data capture techniques and also provided information on establishing rapport with the participants, data management and ethical considerations of this study. The following chapters 5, 6 and 7, demonstrate the use of the three new methods (GPS traces, wearable cameras and computer tracking software, respectively) introduced in this chapter to research student experience. Each chapter discusses details around implementation, findings and limitations specific to each method.

Not so many years ago, the word 'space' had a strictly geometrical meaning:
the idea it evoked was simply that of an empty area…
To speak of 'social space', therefore, would have sounded strange.

—

Henri Lefebvre, *The Production of Space*
(Lefebvre & Nicholson-Smith, 1991, p. 1)

CHAPTER 5 : DETECTING SPATIOTEMPORAL PATTERNS OF MOVEMENT IN UNDERGRADUATE STUDENTS

Introduction

A significant aspect of this research into the student experience is exploring student activities and spatial patterns in relation to the physical and the built environment; that is, *where* do students spend their time, and *how* do they spend their time in these spaces? To provide insights on these questions, this chapter presents an investigation into the capture and interpretation of student movement data (via Global Positioning System, or GPS, traces), helping to paint a picture of spatial patterns of student activities. Taking the view that all student experiences influence overall 'student life', and that extracurricular activities, in particular, can have a considerable impact on a student's learning and personal development (Jones, 2018), this chapter seeks to explore the spatial and temporal patterns of student activities both on and off-campus. The idea of examining student spaces and activities (events) is drawn from Tschumi's (1976) Space-Event-Movement (SEM) framework, and the real-time collection of GPS data comes from Reality Mining (Eagle & Pentland, 2006).

The structure of this chapter is as follows: first, it discusses the concepts of 'spaces' and 'places' as important constructs of an individual's daily life and provides examples of using GPS data to research the movements of people to determine spaces and places of significance. It then briefly describes the potential of GPS data to better understand the movements of students specifically, both on and off-campus and offers examples of how this information could be useful to both institutions and students. Finally, it describes the work carried out as part of this doctoral study—I outline the methods of collecting GPS data from a cohort of undergraduate students and present a range of examples of how this data can be analysed and presented.

It is important to note that while this PhD research study collected other types of data to understand student behaviour, the focus of this chapter is solely on movement analysis from GPS data. No other factors or layers of data, such as images, computer use, social interaction and activity detection, will be discussed in this chapter. The chapter focuses only on movements of undergraduate health science students at the University of Otago. The chapter aims to analyse patterns of movements and their relationships with spaces and their use. The purpose is to demonstrate the utility of such tracking methods, the sort of data that can be captured easily and unobtrusively, and the types of analyses that can be performed on the resulting data.

Space and place

The concepts of 'space' and 'place' are essential components of the lived experience of an individual (Farrugia, 2015). Much has been written about the distinctions between the two concepts (e.g. Lefebvre, 2004; Soja, 1989), and it is beyond the scope of this thesis to engage with the philosophical and political commentaries that accompany such writing. However, these concepts offer us, in their very simplest definitions, two ideas to investigate further with regards to the student experience—'space' as the physical, concrete environment in which students move (*where* do they go), and 'place' as the mental and social meanings attributed to certain spaces (as manifested in *what* they do in these spaces). Essentially, we are interested in exploring what spaces students choose to spend their time in, and what practices and behaviours they exhibit in these spaces.

Most spaces and places have commonly understood purposes (and associated behaviours, norms and expectations) for the majority of the population—e.g. public parks, a library, or a bus stop. However, there are also microgeographic spaces that have particular significance to a smaller, localised community; a 'neighbourhood' offers an example of one of these types of 'microgeographies', carrying special meaning to a select group of individuals who live there (Matthews, Limb & Percy-Smith, 1998). The idea of microgeographies has been used to examine space use and space behaviour of individuals residing in different settings. For example, a New Zealand study by Ivory et al. (2015) used the concept of microgeographies to investigate physical activity across different places and people, suggesting that 'place' can both condition and be shaped by human behaviours. We can surmise that there likely exist microgeographies particular to the ‘student’ population; the university campus being an obvious example that springs to mind.

Finally, there exist also personal places and spaces which hold significant meaning for specific individuals only. While there is no way to anticipate the myriad personal spaces with which each student has an association, we can suggest ‘home’ or ‘bedroom’ as likely possibilities in this category.

Traditionally, capturing detailed information about human spaces, places and microgeographies has been challenging due to the nature of data collection—traditional methods of finding out what spaces people come to inhabit, and what they do in these spaces, has been based on manual data collection methods (such as interviews, surveys, and diaries), and often rely on participants’ ability to recall their movements accurately. For example, Lau and McKercher (2006) conducted a research study to understand tourist movement patterns, and employed surveys, interviews and written diary accounts by participants. They concluded that their research was “inhibited by the difficulties of gathering useful and detailed itinerary information from tourists” (p. 40). Generally, techniques incorporating post-recollection methods to collect such data are of limited effectiveness and efficiency compared to the digital capture of continuous contextual information (Toha & Ismail, 2015; Lau and McKercher, 2006).

GPS data

New technologies are enabling advances in tracking and understanding these microgeographies of human behaviour. Wearable GPS technologies and GPS-enabled smartphone applications have allowed researchers to more accurately and less invasively follow individuals/participants' movements (Shoval & Ahas, 2016), allowing for the collection of continuously occurring natural behaviour data over any given period. GPS-based tracking has been used on numerous occasions in a variety of ways, for example, research in tourism (Zheng, Huang, & Li, 2017; East, Osborne, Kemp, & Woodfine, 2017) and urban planning (Laranjeiro et al., 2019; Korpilo, Virtanen, & Lehvävirta, 2017). These studies have already shown their extensive use and their ability to provide a reliable platform to collect GPS data from phone apps. They demonstrate that GPS-tracking has many strengths: it is unobtrusive and highly accurate (Yun & Park, 2015); it has the potential to provide continuous tracking of individuals with rich information on their movement patterns (Hardy et al., 2017). These technologies can be used to track the number of people that enter a building (e.g. Schautz, van Dijk, & Meisert, 2016; Moussouri & Roussos 2015; Yoshimura et al. 2014; Yalowitz & Bronnenkant 2009), movements across large cities (e.g., Kellner & Egger 2016; Thimm & Seepold 2016), and to study movement behaviour over extended periods (e.g. Spangenberg, 2014; Birenboim, Anton-Clavé, Russo, & Shoval, 2013; Shoval et al., 2011). Moreover, an increasing understanding by users that many apps track movement and mine personal information has arguably relaxed perceptions of privacy (Hardy et al., 2017), in comparison to earlier research.

Student movement data

For higher education, tracking student movement can provide considerable insight into the spaces and places specific to *students*, notably where they go in their daily routines, and how long they spend in these locations. From this data, we can learn much about an individual student's microgeographies, and their behaviours and practices to address questions such as 'what spaces are important to this student?', or 'are there patterns in their daily routines?' By aggregating movement data from multiple students, we can also start to build up a picture of what places are generally important to all students, what places are important to particular demographics of students, and determine interactions between students. While I will be exploring in much more detail later the reasons why this type of investigation is worth undertaking, I will briefly outline the main benefits here to prime the reader for the rest of the chapter.

For institutions, this type of information can be valuable in a few different contexts. One of the more apparent applications is the utilisation of campus spaces and amenities. Universities spend considerable resources building and outfitting spaces on campus for students (Acker & Miller, 2005). From library and study spaces to cafes, restaurants and other social spaces, the design of the physical campus environment is an essential component of the student experience. Particularly as institutions attempt to improve their physical environment to compete with increasing virtual and mobile learning opportunities (e.g. Coulson, Roberts & Taylor, 2015), designing campus environments that meet student needs is critical.

Institutions can also use student movement data on campus to monitor student engagement with university life. For example, a recent article in the Washington Post describes how some colleges are using the GPS functionality of some students' phones to track student movements for class attendance (Harwell, 2019). As the article reports, "if [colleges] know more about where students are going … they can intervene before problems arise" (para. 11). And, while attendance in class is one application of this kind of tracking, there are other contexts where this information could also be useful, such as student well-being and pastoral care. As a recent example, in September 2019, a university student was found dead in his campus accommodation in Christchurch, New Zealand; the student was discovered several weeks after his death, prompting questions around how such an event could have occurred unnoticed (Roy, 2020). Keeping track of student movement patterns, and automatically detecting anomalous movements (or the absence of movements for a set period) could provide a mechanism of monitoring students for the purposes of pastoral care.

Movement tracking also offers insights to student utilisation of spaces *off-campus*, which would also be of interest to institutions. From a teaching and learning perspective, it would be worth knowing whether or not students choose to study in spaces off-campus, and if so, why? Knowing what spaces in the city and surrounding areas are popular with students generally (or what spaces are popular with specific demographics) would be valuable information for institutions for marketing and recruitment purposes.

For students, comprehensive movement data offers a chance for reflection on movements and activities, and time spent in specific locations, providing opportunities to optimise routines and increase efficiencies in their day-to-day lives. As part of the Quantified Self movement (Wolf & Kelly, 2014), tracking one's movements uncovers precision timings for activities (which can be over- or under-estimated in the absence of data), which can then be evaluated and refined according to personal goals (I will discuss the Quantified Self movement in more detail later in Chapter 8).

Previous research on investigating student movements

Despite the value of investigating spatiotemporal patterns of student activity to gain a fuller picture of the student ecosystem, little prior research has been conducted examining student movements using GPS data. However, there are a couple of exploratory studies that have used GPS traces to investigate student movement patterns, which are worth noting here. Mohareb and Omar (2018) conducted a study to understand the pattern of movement of students at a university in Tripoli, Lebanon, noting that different cohorts of students exhibited different patterns of movement throughout the city and that different parts of the city were utilised more or less by students at different times. They concluded their work could be useful for city infrastructure planning, particularly around health services. Wang, Huang and Shan (2015) captured the GPS trajectories of college students to understand their activity trends based on their time spent in certain locations ('stay points'), and advocated for the use of GPS data mining over more traditional forms of data collection (such as questionnaires and interviews). Both these studies demonstrated the potential of GPS data to illustrate student movement and behaviour; however, both were very exploratory in nature and only collected short samples of student movement data (one week, and 15 days respectively). In this chapter, I build on this previous work by collecting student movement data over a prolonged period (one semester or approximately four months). The details of this data collection are outlined below, followed by a description of the findings.

Method

This section outlines the selection of technology to capture GPS data, as well as details of the actual data collection and data analysis (for more information on study setting and participants refer to Chapter 4).

Fieldwork protocol

Before the commencement of data collection, over a period of several months, the research team considered and tested various types of technology and apps that could provide GPS data. Athlete monitoring devices such as the 'VX sport system' (https://www.vxsport.com/) were initially considered, which would give accurate physical location data of participants. However, this was dismissed, given that students would have to carry an extra device around with them, with the risk of losing it or forgetting it at home, and both the students and the researchers would have to download specialised software to be able to view and analyse the data. The team then considered mobile phone apps as an option. The development and rapid proliferation of GPS-enabled smartphones offered a convenient data collection tool for this project, as participants already carried these with them. This meant that we could minimise the cost of the data collection (e.g. by not having to procure specific collection devices) and minimise the inconvenience to participants (e.g. by not burdening them with a secondary device to carry around). Typical GPS receivers embedded in smartphones are capable of providing a user's location (latitude and longitude) to within about 5–15 metre accuracy with an update frequency typically every second.

After testing and trialling several GPS apps over three months, one app was chosen: EasyTrails (available for both Apple and Android phones, http://www.easytrailsgps.com/). This app could be easily installed onto participants' personal phones, passively tracking their movements in the background and allowing them to view the data at all times. EasyTrails is a space-based navigation application system that provides high-quality location and time information. Once turned on, this app ran passively in the background and users typically did not have to interact with it. GPS points were captured continuously whenever the app detected the phone was 'moving' (via accelerometer and gyroscope sensor readings). Each GPS point was captured as a timestamp, with corresponding latitude, longitude, and altitude (although altitude was not used in this study). Table 5.1 shows an extract of a GPS dataset.

Table 5.1 Sample dataset of GPS points collected by a student.

Timestamp	**Latitude**	**Longitude**	**Altitude**
509656340.651598	-45.863878	170.517255	30.045467
509656348.999124	-45.863842	170.517205	27.262555
509657395.000186	-45.863969	170.517136	53.405106
509657411.000187	-45.863876	170.517144	47.783035
509657994.998600	-45.863845	170.517193	49.701595
509658691.999641	-45.863834	170.517060	45.074650

Data collection

Students downloaded and used the GPS app on their personal smartphones. The app was trialled with each participant during a training period of three to six weeks (starting in February 2017), and the formal data collection period took place in semester 1, 2017 (approximately end of February 2017 to end of June 2017). The hours of having the apps turned on were from 'waking up' to 'bedtime' but varied due to individual use and circumstances. Continuous sampling of GPS data can drain the phone's battery life much faster than usual; to overcome this challenge, participants were provided with backup power banks that they could connect to their phones when running out of battery. It was also explained to all participants at the time of recruitment/training that their phone and power banks needed to be charged every night and the researcher would also send a weekly reminder about the importance of keeping the devices charged.

Within the app, a display screen showed the participants their most recent GPS track data, which could then be exported as a CSV (comma-separated values) file via email. All students were provided with secure email addresses and passwords to protect their privacy. They had access to all the data to view, edit, or delete any files before it was submitted to the researchers for analysis. Participants were also invited to attend an informal discussion each week, which lasted from 30-50 minutes. These sessions gave them a chance to comment on the data collected and discuss any logistical issues. Notes were produced from these meetings and were used as reference materials for the researcher, but these data are not reported in this analysis.

Data quality

One limitation of using GPS to track movements is that this approach does not work inside buildings as GPS uses satellites to pinpoint locations—movement data is lost in any places shielded from the satellites (e.g., inside buildings). However, this was determined to be an acceptable limitation for this study for a few reasons. First, the primary purpose of tracking student movements was to determine which spaces and places were significant to these participants, and it was not necessary to capture detailed information about movements *within* buildings to identify important 'spaces'. Second, student activity data was also being captured from the wearable cameras (discussed in Chapter 6). Finally, this investigation was guided by previous studies using GPS traces, where this limitation was determined to not be a significant factor.

Data analysis

The primary means of analysing the GPS data was by plotting the latitude and longitude points onto maps of the study region (Dunedin, New Zealand). I used an open-source JavaScript library called Leaflet (https://leafletjs.com/) to plot geographic markers of the student data, which allowed me to explore their patterns of movement. The basic algorithm for plotting the data was as follows:

1. Read in each point of longitude and latitude data from the CSV file.
2. Plot a 'marker' on the map corresponding to each point.

The appearance of the markers was then altered after plotting, depending on the type of visualisation desired: for instance, the transparency of markers was increased to produce heatmaps of activity, or multiple markers in the same location were clustered to reduce 'noise'. The data were also divided and aggregated in various ways to produce different visualisations and illustrate different aspects of student movement (all of these details are provided in the next section, Findings).

Findings

I will now report the general findings of the GPS data capture from the students. Overall, 548,270 total data points were captured from 20 students, with an average of 27,414 points per student (note that student 11 had issues with their data capture which resulted in unreadable files; they have been excluded from further analysis). Student 15 captured the most data points (73,514), with 13 students capturing over 20,000 data points. Student 3 only captured 886 data points. Table 5.2 shows the total number of points captured by each student.

Table 5.2 The total number of data points captured by each student.

Student	**Number of data points captured**	**Student**	**Number of data points captured**
15	73,514	**10**	24,236
6	49,916	**16**	22,371
1	44,223	**8**	20,227
20	42,126	**14**	17,942
19	40,562	**5**	14,853
18	39,985	**7**	14,145
17	36,771	**2**	12,688
4	28,799	**9**	6,246
12	28,310	**21**	5,568
13	24,902	**3**	886

To illustrate the types of analyses possible with this data, I will use a subset of the student data; specifically, I will use the five students with the largest number of data points (students 15, 6, 1, 20 and 19).

Preliminary exploratory visualisations

Figures 5.1 shows the initial exploratory plotting of GPS traces using Leaflet. These visualisations were made to 'get a sense' of the data before performing any specific aggregations or divisions (note: any specific adjustments to the appearance of markers will be discussed as needed—if no such details are provided for a particular figure, the GPS points were simply plotted on the map 'as is'). First, Figure 5.1 shows all the GPS points captured by student 1 during the entire data collection period.

As can be seen in Figure 5.1, most of the student's movements are concentrated in the city centre—unsurprisingly, this is where the university campus and accommodation buildings are situated. However, we can also see that over the entire semester, the student movements spread over a most of the surrounding area, and even extended far outside of the city limits (the paths leading out to the left and top right of the map). Next, Figure 5.2 (a-g) shows the daily GPS traces from student 1 over the first week (seven days) of their data collection.

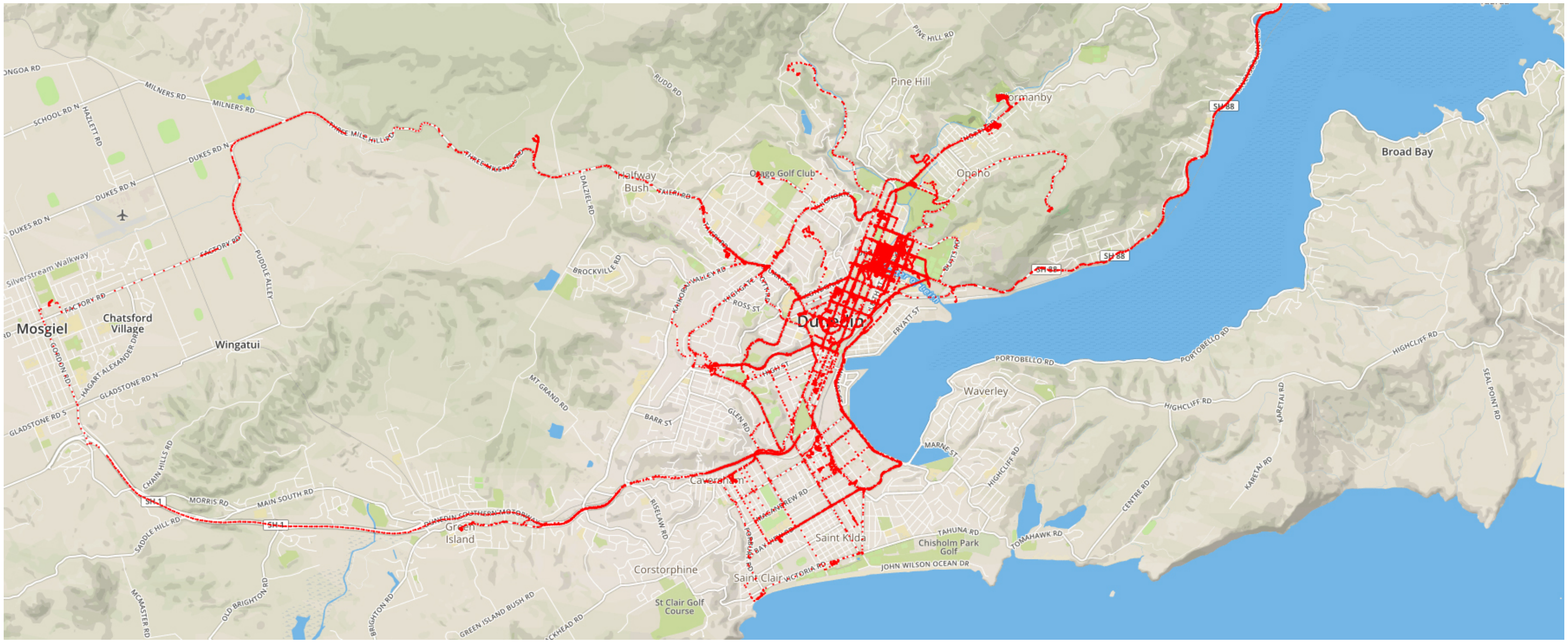


Figure 5.1 Visualising the raw GPS data from student 1 over the entire data collection period (one semester), on a map of the study area (Dunedin, New Zealand).

Figure 5.2 GPS traces from student 1 over the first week (seven days) of the data collection period.

By splitting the data into separate days and plotting the GPS traces of each day, we can start to discern patterns and routines (and anomalies) in student movement. While all of the day traces shown in Figure 5.2 (a-g) show variations in movements, there are some discernible patterns. For example, in images 5.2 (a), and (c-g), a distinct 'L' shaped pattern in the top left corner of the student's traces is visible. Notably, the same pattern is not visible in Figure 5.2 (b). While we do not have any more information on why this day exhibits a different pattern than the others, the point here is that we can *detect* a different pattern, and this may provide useful insights in some contexts (see Chapter 8 for further discussion on the potential for students to utilise their own data).

Figure 5.3 shows all of the GPS points from the five students (15, 6, 1, 20, 19) combined onto a single map—each student has been given a different coloured marker (blue, purple, red, orange and green respectively), and the transparency of the markers has been increased to produce a heatmap of activity; that is, multiple markers overlaid in the same area will appear darker than markers appearing in isolation, showing more clearly the 'hotspots' of frequent student activity.

By dividing the data into different subsets, I was able to visualise various aspects of the students' movements. For example, Figures 5.4 (a) and (b) show the differences in movement/activity hotspots of student 1 during the day (9 am - 5 pm) and in the evening (5 pm - 10 pm), providing two maps of student 1's spaces and their movement profile during the different periods of the day.

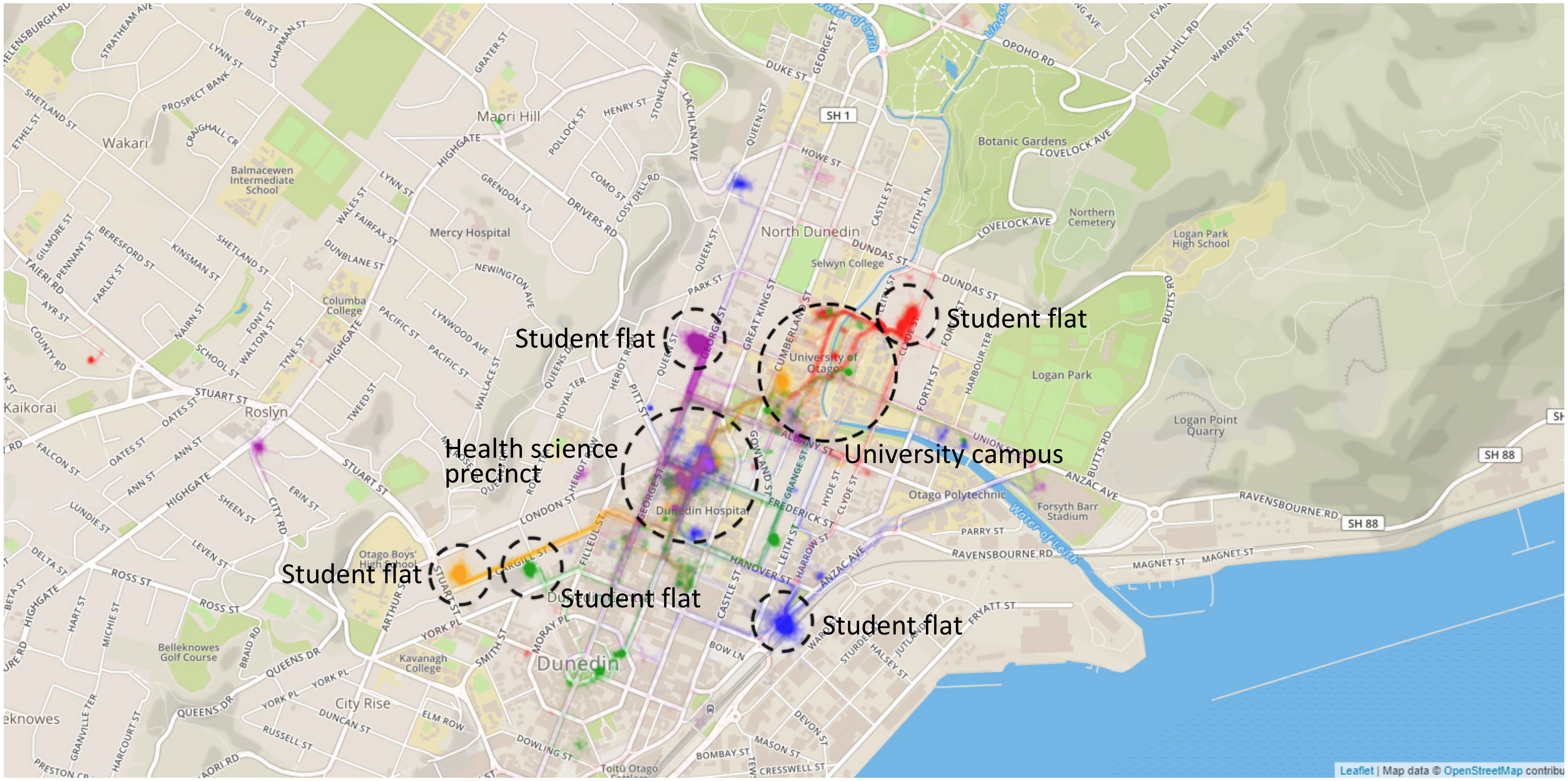


Figure 5.3 Combined movement in the study area. Aggregated track-points from five students over one semester indicating the general movement in the study area. The figure gives an intuitive view of the movement in the area. Clusters mark frequently visited spaces, which we recognised as the students' flats, the central campus buildings and the health science precinct (identified by black dotted circles).

Figure 5.4 The movement pattern of student 1 in the study area over one week during (a) the day (9 am - 5 pm) and (b) the evening (5 pm - 10 pm).

The first thing which is apparent in Figure 5.4 is that this student shows much more movement activity during the day than the evening. The student's movements are also concentrated around the campus area (centre of the image) during the day and are concentrated outside the main campus area during the evening. This pattern is not unexpected as we would assume the student to be attending classes on campus during the day and visiting non-university related spaces during their free time (in the evening).

Comparisons between students

Visualising the movements of different students allows us to compare and contrast different patterns of activity. For example, in Figure 5.5, we compare the movements of two students—student 1 (red) and student 6 (purple)— over one week.

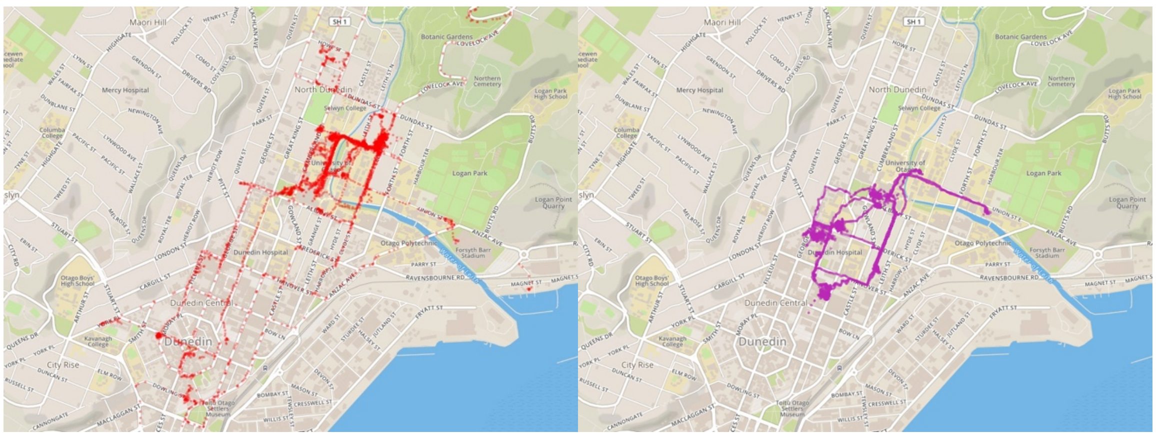


Figure 5.5 Two maps showing two different students' movements and hotspots of activity (student 1 is the red trace, and student 6 is the purple trace).

As seen in Figure 5.5, student movement patterns vary considerably among individual students. Student 1's (red) movement extends over a larger area of the city, whereas student 6 (purple) is confined to a much narrower area. Student 1 shows a dark hotspot around the campus area (centre of the image), but then several smaller hotspots dotted around the city, with lighter trails connecting them; it is hard to discern any obvious patterns in student 1's movements, suggesting a highly mobile and flexible daily routine. Student 6, on the other hand, has a narrower pattern—they travel more directly between four key points (which we identified as home, main campus, health science precinct and gym), and rarely vary their routes. This suggests student 6 is more regimented in their daily routine. While we do not make any value judgments on whether either approach is more beneficial than the other, it does serve to illustrate the individuality of student routines.

Stay points and interesting locations

Another analysis possible is to determine ‘interesting locations’ from the student GPS data (Khetarpaul, Chauhan, Gupta, Subramaniam, & Nambiar, 2011). Here, an ‘interesting location’ is one in which the student has spent an extended period of time, rather than simply passing through. To do this, I followed the approach outlined in Khetarpaul et al. (2011)—from the student data, I calculated ‘stay points’, whereby a student has spent more than 20 minutes covering a 200-metre distance (or less). All the students’ GPS points were compared, and only those meeting the above criteria were plotted. Table 5.3 shows the total number of stay points calculated for each student.

Table 5.3 The total number of GPS and stay points for each of the five students.

Student	Total # GPS points	Total # stay points
15	73,514	276
6	49,916	97
1	44,223	603
20	42,126	172
19	40,562	117

I then plotted the stay points on a map and used a clustering algorithm to aggregate nearby points; this was done because the GPS devices will record slightly different latitude and longitude values even for the same location, due to the sampling interval and fluctuations in signal strength. Aggregating nearby points results in a single ‘location’, that is more easily discerned on the map. Figure 5.6 shows each student’s stay points plotted and aggregated into location clusters.

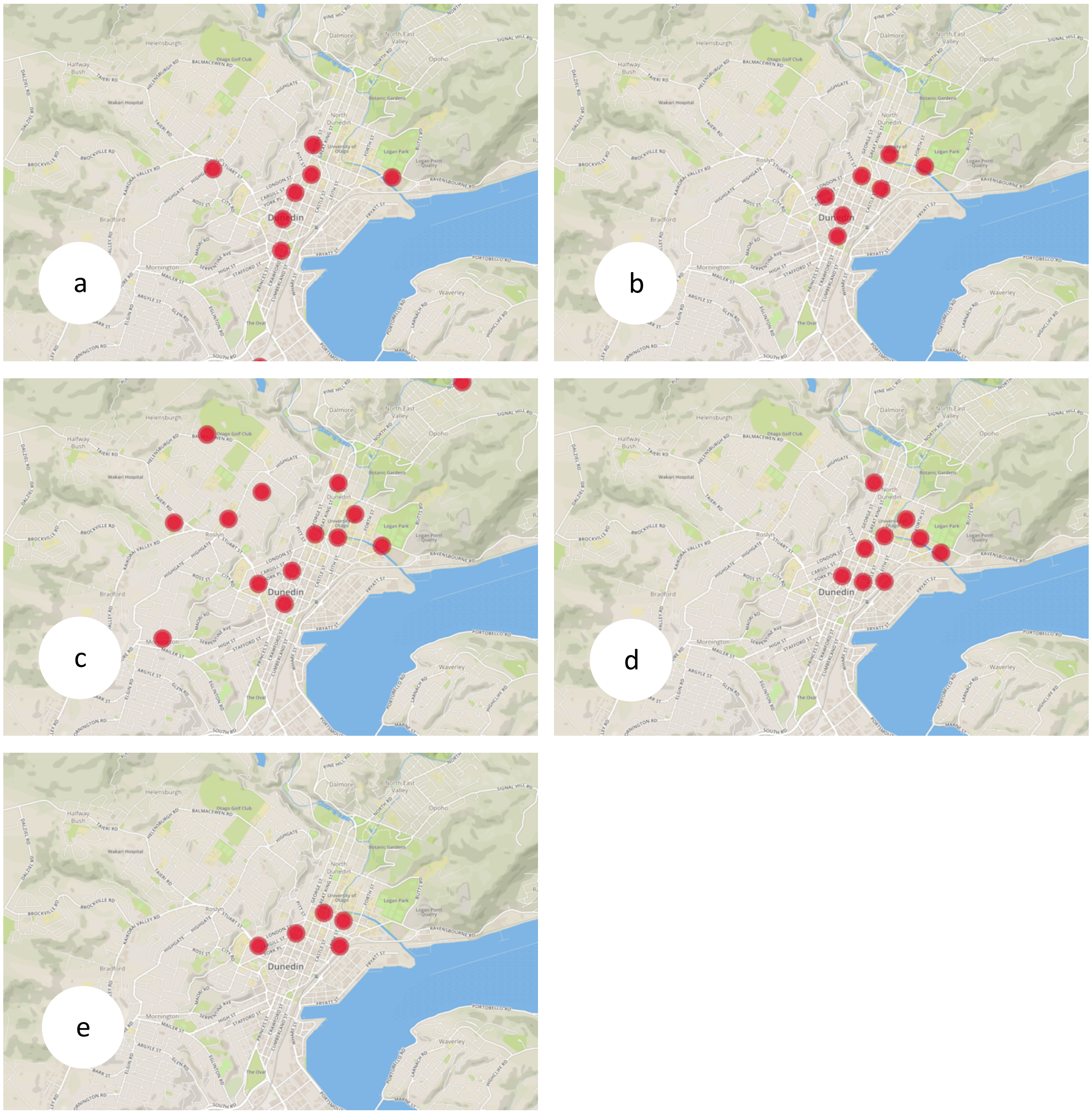


Figure 5.6 Stay points from five students: 15 (a), 6 (b), 1 (c), 20 (d), and 19 (e).

In Figure 5.6, the red circles indicate stay points, or locations frequented most by each student; we can postulate that these are the places that ‘mean’ something to the students. Examining these clusters in more detail, and we see that these are typically university buildings (where they attended class and the campus library) and the students’ residences. The next most frequented locations included the university gym, friends’ houses, and family homes (for the local students). The infrequently visited locations were scattered around the city, and it was impossible to determine the exact nature or reason for the 'stay' at each location.

Finally, also from Khetarpaul et al. (2011), I was able to determine the locations that were generally 'interesting' to all students. This involved finding the locations that were frequented by multiple students only—such analysis helps to remove personally identifying location data, such as a student's residence, which is likely to be frequented by one student only. In this case, I determined an 'interesting location' to be one that was visited by at least three of my five students. Figure 5.7 shows the 'interesting locations' in the city, again plotted using a clustering algorithm to aggregate nearby points.

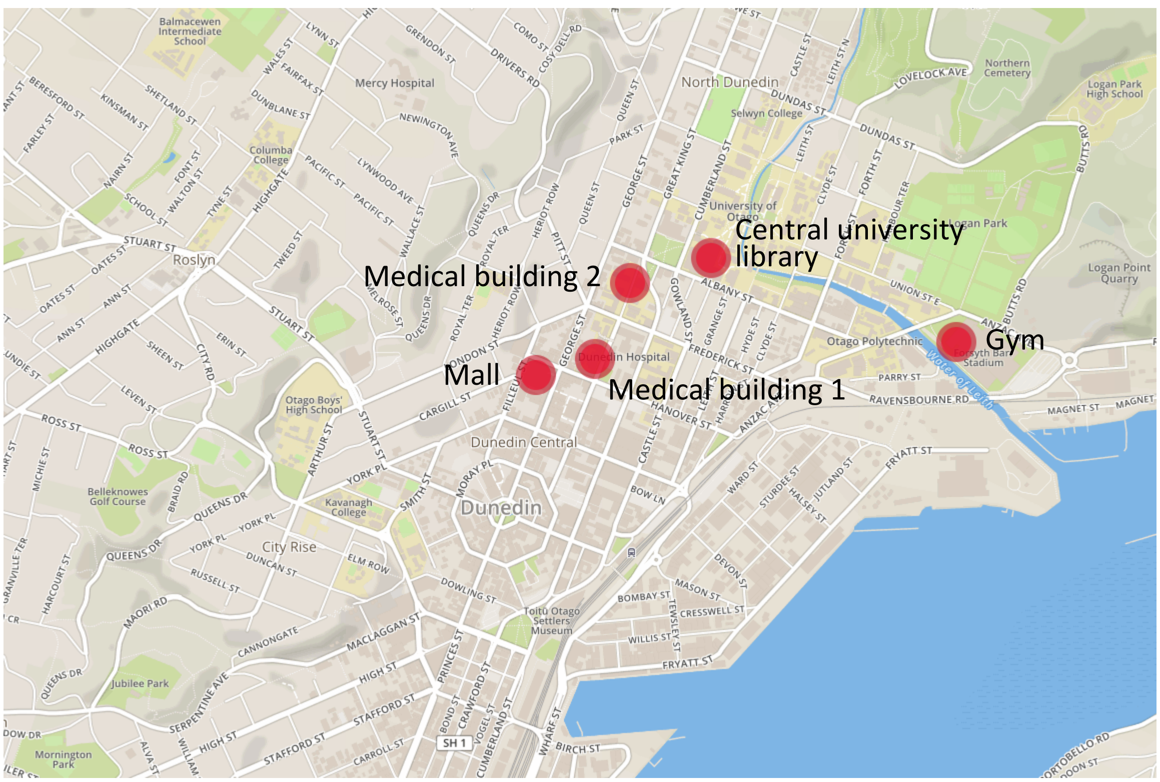


Figure 5.7 Interesting locations of all five students.

As seen in Figure 5.7, five core interesting locations were detected. These were identified as the central university library, two medical buildings situated near the hospital, the university gym, and the city mall. Again, the findings are not surprising—the medical buildings and central library denote common study spaces for health science students, while the gym and mall represent the shared social spaces. For institutions, repeating this type of analysis with different student groups could reveal the spaces significant to different student demographics. Moreover, student populations could be split along other defining characteristics (e.g., socioeconomic status, gender, first-in-family, or students who drop out of study) to identify patterns and possibly predict at-risk student behaviours—for instance, Hanewicz (2009) identifies retention patterns based on a student's proximity to campus spaces.

Discussion and conclusions

Given the paucity of fine-grained spatiotemporal data on student experience, together with the possibilities afforded by new GPS technologies, this chapter aimed to develop a method to capture the space and movement patterns of the undergraduate students. I explored the use of smartphone-based GPS tracking apps for understanding student movement behaviour in a university setting. This chapter has shown that GPS data can be used to capture accurate real-time data, to highlight spaces, movements and activities that define the students' lived experience.

This study also illuminated a number of analyses possible with this type of data. Individual student's data can be viewed daily or weekly to determine recurrent patterns of movement, and we can even separate different times of day (e.g., day movements vs evening movements). Comparing students illuminates differences in individual student behaviour, again emphasising the importance of an idiographic perspective with regards to student experience. Finally, we can also determine spaces that hold shared significance to multiple students (microgeographies).

Assuming that human beings perform behaviours based on habits (Mohareb & Omar, 2018), it could be inferred that these patterns describing past and present behaviours could define future behaviours as well. Movement patterns of human beings have been of interest in many different behavioural analysis research (e.g., Laranjeiro et al., 2019; Zheng et al., 2017; Moussouri & Roussos, 2015). Many studies have attempted to understand individual patterns of movement of people based on their location information. For example, Song (2016) conducted a probabilistic space-time analysis of human mobility patterns to be able to construct personal human mobility models from an individual's positioning data. These patterns of individual movement data can be constructed using the raw GPS location data obtained from individuals (Kim & Song, 2018).

From this study, a uniquely rich dataset emerged as a result of gathering continuous naturally occurring student movement data using a mobile phone-based GPS tracking app. This elicited data that illustrated where different students went and how they moved between spaces both on and off-campus. From a development perspective, this data will assist institutions with the design and planning of spaces around campus to better align with the students' needs/requirements. The fine-grained nature of the GPS data will provide places such as libraries, gyms, lecture theatres, and cafés on campus insights into how much time students spend in these spaces, which services are used the most, and what new services are required. Up until now, research into understanding this type of student behaviour has relied on methods such as questionnaires and post-event recollection interviews and has been limited both spatially and temporally.

There are, however, limitations in this method of capturing spatio-temporal patterns of student behaviour. First, I was limited by the available apps at the time of this research. I wanted an app that was available on both Apple and Android smartphones, so this reduced the number of options available to me. In the end, while the app captured the relevant data, I was limited by how much I could customise it, such as, setting the sampling interval or the data formats that I could export for analysis. Also, the GPS app on the smartphone was susceptible to fluctuations in the sampling interval, due to occasionally losing satellite signal, which likely resulted in some data loss.

Another limitation is that many of the analyses were drawn from other studies and may not be specifically designed for a higher education context. For example, the detection of 'stay points' in the GPS data being based on an algorithm of *general* movements throughout a city; perhaps the definition of what constitutes a 'stay point' or 'interesting location' (in terms of time spent in a single place) is different for students.

GPS technology offers a small window on students' everyday movements. The app revealed where a student goes, what route they took, and how long they stayed. Although we can infer activities that a student might be engaged in at certain locations, GPS traces do not tell us exactly what these students are doing. To address that shortcoming, we employed another technology that captured student activity data using a wearable camera. Many research projects (Talavera, Radeva, & Petkov, 2017; Aghaei, Dimiccoli, & Radeva, 2016; Bolanos et al., 2016) have used this technology, in which participants wear a miniature auto-camera that records what they are doing throughout the day. The use of these wearable auto-cameras is elaborated on in Chapter 6.

People take pictures of each other,
Just to prove that they really existed,
Just to prove that they really existed.

—

The Kinks, *People Take Pictures of Each Other*
(Davies, 1968, track 15)

CHAPTER 6 : PHOTOGRAPHS TO OBTAIN INSIGHTS INTO STUDENTS' LIVES AND EVERYDAY CONTEXTS

Introduction

This chapter explores the use of photographs as a form of evidence to investigate the 'lived experiences' of a group of undergraduate students studying at a research-intensive university. As mentioned in the preceding chapter, we can infer a lot about student activities from the spaces they come to occupy—for example, a student seen to be spending a lot of time in the library could reasonably be assumed to be studying. However, such a gross classification has limited usefulness. Therefore, the specific aims of this chapter are to capture a more fine-grained representation of students' activities via photograph data and to evaluate the usefulness of this method for developing a better understanding of the student experience. Again, the investigation of student activities (events) forms a component of the Space-Event-Movement (SEM, Tschumi, 1976) perspective, and the automatic generation of photographs is another example of passive gathering of naturally occurring data (Reality Mining, Eagle & Pentland, 2006).

University students are a social group that tend to have complex and unique spatiotemporal behaviour (Busari, Osuolale, Omole, Ojo, & Jayeola, 2015). With substantial independence in the campus environment, students are autonomous in their decision making concerning their everyday activities, with little control from university authorities. They live, study, and socialise with their peers and colleagues; as such, the daily decisions of one student are regularly affected by the decisions of others. Typically, most undergraduates are school leavers of a similar age and are open-minded and generally receptive to new ideas from peers and colleagues with various backgrounds and mixed interests (Wood, 2015). Furthermore, the intermittent nature of the class schedule allows them to be involved in various activities not only in the evening or at night, but also for almost the entire day. All these factors mean that university students have complicated daily schedules, resulting in complex spatiotemporal patterns of behaviour.

It would be fair to say that much research into 'student experience' fails to capture or represent the rich tapestry of experiences that encompass a student's daily experiences. For example, much of the contemporary research on student experience is focused on experiences in the taught environment, i.e. the various classroom settings, such as lectures, labs and tutorials, effectively ignoring the spaces in between. Some studies do attempt to capture student activities outside of academia. For example, Richardson, King, Olds, Parfitt, and Chiera (2019) investigated how the first-year university students at an Australian university use their time, concluding that "there are strong associations between how students use their time and health, well-being and academic success" and "a better understanding of how students allocate their time on a day-to-day basis will enable more effective support for students in making these changes" (p. 1). Haque et al. (2018) also attempted to assess the quality of life of medical students at a Malaysian university using a cross-sectional study design, finding that university medical students possess a good quality of life within the 'optimum educational environment'. However, there is a paucity of such studies, and for those that have been done, the methods have been limited.

I felt that a deeper understanding of student experience could be gained from broadening the investigative net. Building on the previous chapter, having determined *what* spaces are significant to students, I was curious to find out if we could better interrogate *what happens* in these student spaces. It was this perspective of rethinking student experience in a more holistic way that inspired me to postulate new ways of capturing the richness of these experiences. I wanted to probe the rhythms and routines of daily student life. This would require a method allowing the harvesting of data continuously and naturally over extended periods. In this way, I would focus on what it was that students *actually* do, i.e. their lived experience, rather than asking them what they *think* they do (Sim & Butson, 2014; Paretta & Catalano, 2013).

Capturing the lived experience in this way is centred on revealing and interpreting human behaviour and practice. It involves producing detailed descriptions of everyday life that can be used to interpret and elucidate webs of meaning. This entails collecting naturally occurring contextual-behaviour data, for example, in the form of photographs through wearable devices such as small clip-on auto-cameras. These devices provide rich data for analysis, providing insights on human behaviour with great nuance and detail, allowing us to uncover unexpected findings that may have been hidden by our implicit assumptions regarding context and interpretation.

This chapter is organised as follows: first, I describe how capturing data about everyday activities can be useful in understanding the 'lived experience' of an individual. Second, I provide a rationale for the use of photographs to capture daily activity data. Finally, I describe the work carried out as part of this doctoral study—I outline the methods of collecting photograph data from a cohort of undergraduate students and present a range of examples of how this data can be analysed and presented.

Activities of Daily Living (ADL)

Activities of daily living (ADL) are routine activities people engage in on a day-to-day basis. The concept of ADL was originally proposed by Katz, Ford, Moskowitz, Jackson and Jaffe (1963) and has been added to and refined by a variety of researchers since that time (e.g. Noelker, Browdie, & Katz, 2013). Health specialists frequently use an individual's ability or inability to complete ADL as a measurement of their functional level, especially in regard to people post-injury, with disabilities and the elderly (e.g., Compagnat et al., 2019; Hopman-Rock, van Hirtum, de Vreede, & Freiberger, 2018; Debes et al., 2016). Another application of ADL is in younger children who often require help from adults to perform everyday tasks, as they have not yet developed the skills necessary to perform them independently. Some examples of ADL include eating, working, cleaning, getting ready in the mornings and other socialising and leisurely activities (Fuentes-García, 2014). Several research studies, generally involving surveys, have collected data on the ADL status of individuals (e.g., Taylor, Lynch, & Ureña, 2018; Kinosian et al., 2018; Grov, Fosså, & Dahl, 2017). Although basic characterisations of ADL have been suggested, what particularly forms a specific ADL for each individual may differ. Adaptive equipment and devices may be employed to improve and augment independence in accomplishing ADL.

Some activities of daily living such as cleaning and maintaining the house, moving within the community, preparing meals, shopping for groceries and necessities, or using a phone or other form of communication, are not essential for fundamental functioning, but they let a person exist autonomously in a community (Fuentes-García, 2014).

ADL for personal development

Personal development encompasses activities that increase awareness and identity, improve talents and potential, develop human capital and enable employability (Maslow, 1981), which also align with the goals of higher education for students. The personal development process includes the enhancement of the following activities: self-knowledge, health, strengths, aspirations, social relations, enhancing lifestyle, quality of life and time-management, among others (Maslow, 1981). When these are measured, goals can be defined for future changes and/or advances in their personal needs and ambitions.

Before the emergence of static and wearable sensors, people's daily habits were manually recorded. For instance, ADL were manually annotated by either individual users or specialists, as shown by Andersen et al. (2004) who recorded the habits of living of hospital patients. In their study, Andersen et al. (2004) manually recorded information about the ability of an individual's ADL performance, intending to classify the patient as either dependent or independent. For small scale studies, manual recording of data can be quick and easy. However, for studies with large datasets, this type of data gathering can become a very cumbersome and time-consuming practice. With large amounts of digital data, it is crucial that you can file, find and store documents in a fast and effective way. There are more efficient ways in today's growing technological world that cannot only help collect large amounts of naturally occurring data but also help to keep it organised with a higher productivity level. Lifelogging is one such method prevalent today.

Lifelogging

Lifelogging is a movement that first appeared in the 1960s as the process of recording and tracking personal activity data generated by the daily behaviour of an individual (Ferdous, Chowdhury, & Jose, 2017). By recording people's own view of the world, lifelogging provided a new lens and advanced a step forward to the desired and personalised analysis of the lifestyle of individuals. The objective perspective offered by the recorded data of what happened during different moments of the day represented a robust tool for the analysis of the lifestyle of people. The development of new wearable technologies has now further advanced lifelogging as an everyday practice and allows individuals to automatically record data from their daily living. Through the analysis of recorded visual data, information about the lifestyle of the camera-wearer can be obtained and retrieved.

The recent explosion of wearable digital devices presents us with a fertile landscape to employ various data mining approaches (Framingham, 2019). Recent studies have claimed that the use of wearable technology will intervene the lives of the users, and can have a positive impact on daily behaviours, for instance, by reducing sedentary behaviour and encouraging exercise (Stephenson, McDonough, Murphy, Nugent, & Mair, 2017). Tapping into these rich data sources could reveal previously unknown dynamics concerning physical and social networks, activity patterns, and the flow of information between individuals (de Montjoye, Quoidbach, Robic, & Pentland, 2013; Noulas, Scellato, Lathia & Mascolo, 2012). Knowing more about this can help people become more self-aware, better organised and health-conscious by automatically recording their daily activity.

Use of photographs

Photos are an ideal way of capturing rich observations of people, places, and events and sometimes even moods and feelings *in situ* (Warren, 2002). They can augment the ability to research, describe, and symbolise the world of a person. Whether it is as a tool of assessment, a stimulus to trigger responses, or a means of displaying cognitive models and presenting results, the use of images in research is not a new methodology, but neither is it widespread. Often described as a "waif on the margins" (Harper, 2002, p. 15), photography has encountered considerable scepticism and criticism within the higher education research community—it has only recently started to gain some creditability as a valid research method (Kortegast et al., 2019; Metcalfe, 2015; Frith, Riley, Archer & Gleeson, 2005). Such wariness has been attributed to doubt over the validity of images, which are ambiguous and open to multiple, subjective interpretations. However, the demise of objective, absolute reality thinking within higher education, has resulted in a growing interest in visual data as a way of understanding multiple realities (Guillemin, 2004). This has led to an acceptance that visual methods can provide valuable and valid data about issues of concern to the social sciences (Kortegast et al., 2019; Metcalfe, 2015; Bagnoli, 2009; Frith et al., 2005). More recently, interest has grown in performing qualitative research which focuses on the visual images themselves to explore people's experiences and meaning-making (Kortegast et al., 2019; Metcalfe, 2015; Frith et al., 2005).

While the use of images in such ways has enriched our view of individuals in their everyday environments, past methods involved the researcher taking the photos, so it was inherently subjective in what was captured. However, if the participant is capturing photos continuously, this provides a more objective and holistic dataset of activity. For instance, the capture of objective information about the participant's physical world provides a clear view of what activities the participant is actually involved in (e.g., reading on a laptop or reading a textbook), without filtering relevant environmental information. My intention was not to use photographs just as a tool to assist with discussions or interviews—that is, as an 'add-on'—but rather as an important method of eliciting and understanding experience in its own right.

Traditionally, analysis of photographic data has relied on the manual counting of physical details present and the interpretation of implied intentions and meanings (e.g., Frith et al., 2005). The physical demands of manual counting and coding mean there is a limit to the size of photographic datasets that can be manually analysed. In the case of photographs, there is also the limitation of the photo capturing device. Unlike video, photographs are reliant on a person taking a photo at the desired time. This requires a substantial investment by the participant, and the images taken will depict the participants' point-of-view or egocentric vision (Dimiccoli, 2018). The use of wearable auto-cameras alleviates these issues by introducing the first-person point-of-view—once clipped and switched on, these wearables require no further input from the participants or the researcher, and continuously capture photographic data from the participant's perspective. The ease to which these devices can systemically capture continuous streams of images, in any context, situates them within a distinctive group of technologies capable of revealing lived experience in a manner previously unthinkable. However, creating meaning from a potentially massive collection of unstructured egocentric visual data presents significant challenges. In the following sections, I provide details on the wearable camera used in this study and how this was used to capture and analyse ADL from a group of undergraduate students.

Method

Photographic data were captured through the use of an automatic clip-on camera. These photographs were used to create an inventory of the student's ADL. In the following sections, I describe the data collection process and the final dataset captured.

Devices

In this study, I used small clip-on, forward-facing auto cameras (see Figure 6.1 for an example of the camera used in this study), programmed to take a photo every 30 seconds. The key advantage of these devices was the ease of which they could be deployed, and the generation of an egocentric perspective of the daily activities of a person, since by wearing them attached to the chest they capture a first-person point-of-view of the environment where the user spends time.

Figure 6.1 An individual wearing a Narrative Clip camera.

In this study, the photographs were generated by the students using a Narrative Clip 1 (http://getnarrative.com/). This camera has a resolution of 5 megapixels, and auto-captures photographs every 30 seconds. The camera's angle arc is 70 degrees with an aspect ratio of 2560 × 1920px. The angle arc and relatively large resolution size mean the camera can capture large amounts of details. An inbuilt sensor turns the camera off when placed face-down on a flat surface or when it is in complete darkness to save battery power. It has an internal memory of 8GB, which can store around 6000 pictures on the device itself; images can be downloaded from the device when connected to a computer, and Narrative provides a cloud storage service for persisting images. Figure 6.2 shows samples of a recorded photo sequence from a Narrative Clip. As can be seen in Figure 6.2, the camera records the environment where the user spends their time, which can be used to study and infer their behavioural patterns.

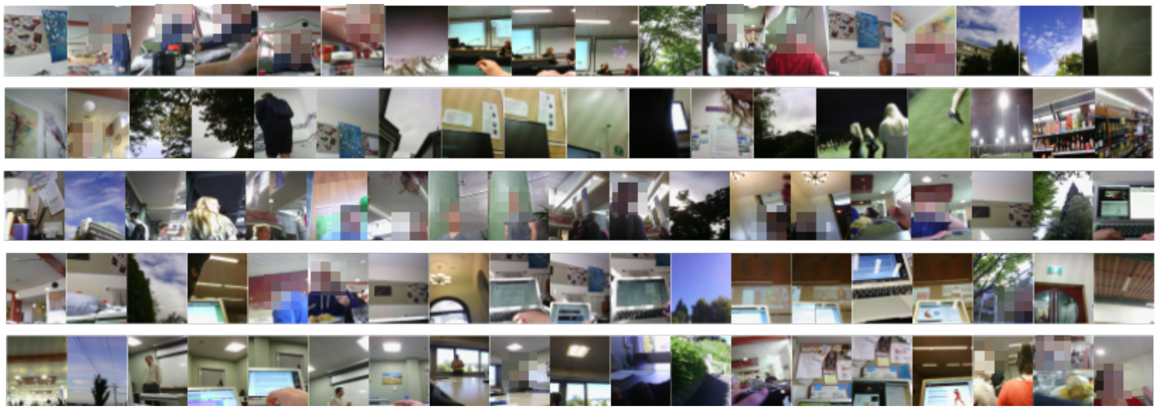


Figure 6.2 Example of recorded images from the Narrative Clip (reduced in size for displaying here).

The collection of photos generated by the Narrative cameras represent detailed inventories of these students' ADL. Data collection took place over approximately four months (i.e., the academic semester). In this chapter, analysis is focused on egocentric images recorded by five undergraduate students who wore the camera throughout the day.

Analysis

This next section describes how the images were analysed. The analysis in this chapter was done in collaboration with colleagues from the Department of Mathematics and Computer Science at the University of Barcelona. For my part, I captured and cleaned the students' data and produced the figures showing their categorised activities. The team in Barcelona were responsible for processing the images and the categorisation of the egocentric photostreams (using Computer Vision techniques, described in detail below). Specific approval was gained from the students regarding the analyses of the images captured from the wearable auto-camera, as these data were being shared with researchers from outside of the University of Otago. All data were transferred to the Barcelona team as anonymised datasets, cleaned of any identifying information.

Computer Vision

Artificial intelligence has witnessed a huge growth in connecting the gap between the proficiencies of humans and machines, and one of many such areas is the field of Computer

Vision. Computer Vision is an "interdisciplinary scientific field that deals with how computers can be made to gain high-level understanding from digital images or videos" (Tono, Tono & Zani, 2020, p. 300). It seeks to automate jobs that the human visual system can do. The aim for this field is to allow machines to see the world as humans do, observe it in a similar way and even use the knowledge for a variety of tasks such as image and video recognition, image analysis and classification, media recreation, recommendation systems, natural language processing, etc. As a scientific discipline, Computer Vision research involves studying the theory and technology for building artificial systems that attain data from images or multi-dimensional data. During the last few years, the field of Computer Vision has benefited by advances in the Convolutional Neural Networks (CNN) (Khan, Rahmani, Shah & Bennamoun, 2018).

A CNN is a deep learning algorithm which takes an input image, assigns importance to various aspects/objects in the image and can differentiate one from the other. CNNs are, therefore, statistical models designed to learn patterns from visual data for classification purposes. A CNN can capture spatial and temporal dependencies in an image through the application of relevant filters. The design 'fits' better to the photograph dataset due to the decrease in the number of parameters contained and transformability of weights. In other words, the network can be trained to recognise the complexity of the image better. The role of CNN is to condense the photos into a form which is simpler to process, without losing characteristics which are crucial for getting a good prediction. This is important for not only recognising features in a single image but also when applying it to massive datasets, such as the one in this study.

Due to the growing availability of wearable cameras, the field of Computer Vision is advancing rapidly. Egocentric photostreams are now being evaluated and analysed for their application in various new disciplines, in addition to the several different applications already presented in the literature. For example, social relations analysis and characterisation by facial detection and tracking have been demonstrated by Aghaei (2017) and eating habits have been addressed by Bolanos et al. (2016) to describe a healthy individual lifestyle.

This research used a CNN named VGG-16 previously trained on a set of 18,674 images targeting 21 different egocentric categories (Simonyan & Zisserman, 2014). VGG-16 is a CNN model for large-scale image recognition. The model achieves 92.7% top-5 test accuracy in ImageNet, which is a dataset of over 14 million images belonging to 1,000 classes (Simonyan & Zisserman, 2014). However, VGG-16 can be slow to train and has a large network architecture, due to its depth and number of fully connected nodes, which means deploying VGG-16 can be a time-consuming task (in the context of machine calculations). However, when compared with the time needed to *manually* classify thousands of images, VGG-16 is an excellent and efficient tool for analysis.

As described, Computer Vision is an interdisciplinary field with an ultimate goal to understand the visual world of individuals. In recent years, it has achieved notable progress due to the advances in hardware and the development of new methods of analysis. Advances in the field of Computer Vision research (i.e., automatically extracting meaningful information from images based on defined rules, such as facial recognition) means it is now possible to efficiently analyse thousands of photographs and identify key features such as social interactions (e.g., Aghaei et al., 2016), or inferred sentiment (Talavera et al., 2017).

To gain a better understanding from egocentric datasets, it is vital that the data gathered are contextualised with respect to the individual participants and their specific contexts. The challenge was the development of a set of algorithms that could be used to search and document particular actions that could render a meaningful picture of this lived experience. The appearance of human faces and characteristic objects are among the factors that helped determine the significance of an image (Khosla, Raju, Torralba & Oliva, 2015). As shown in Figure 6.3, this study focused on finding informative images (via rich image selection), temporal events (via activity recognition), and images where social interaction was probable (via face detection).

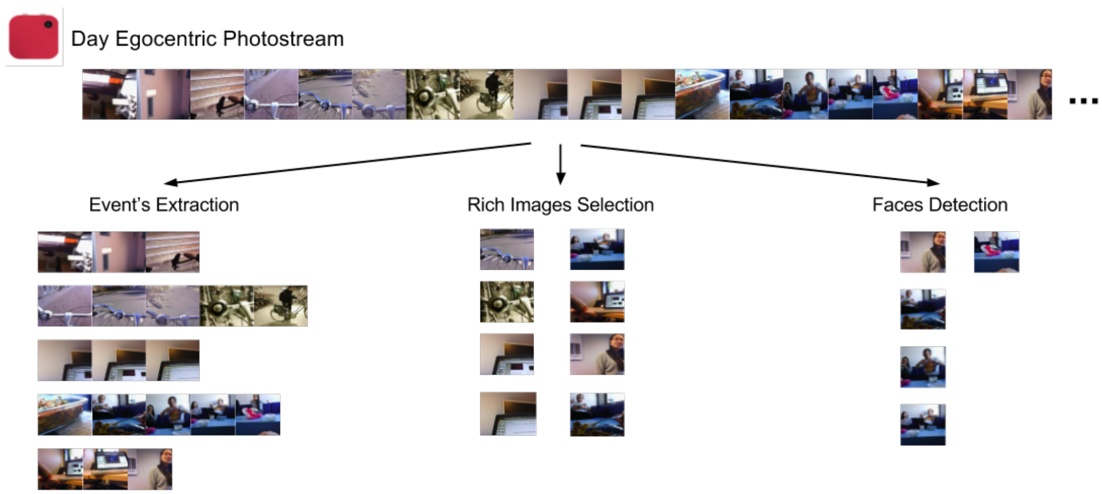


Figure 6.3 Information that is extracted with Computer Vision Tool from egocentric photostreams.

The following section details how the information is extracted from recorded images by applying existing Computer Vision methods.

Rich image selection

The first step in analysing the image data was the selection of 'rich' images. This was done by utilising techniques that recognise objects within an image; the number of objects in an image acts as a measurement of the 'informativeness' of the photo. The free motion of the camera often leads to non-intentional image capture; thus, an image selection algorithm was needed. Here, the algorithm for rich image selection used was proposed by Peláez (2017), which detects objects in images, extracts features (such as faces), and classifies the image according to the objects and features found. Figure 6.4 shows a brief outline of the rich image selection algorithm.

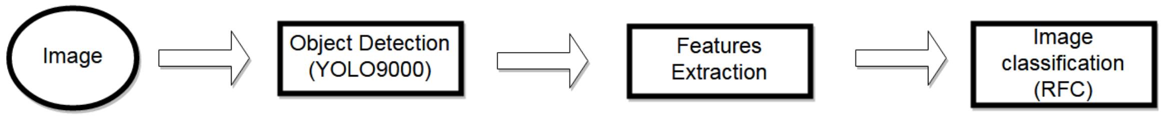


Figure 6.4 Outline of the algorithm for rich image selection (Peláez, 2017).

The algorithm is sensitive to the appearance of human faces and characteristics, as well as other recognisable objects. Rich images are, therefore, defined as images containing a higher number of objects. This allowed us to avoid images with low semantical content (e.g., blurred, dark or other occluded images are discarded from the dataset). This method requires the algorithm to divide the images into patches. In patch-based classification, patches of the image are analysed, and attributed specific classes based on the contents of the patch. Finally, the entire image is classified based on what is found in the patches. Essentially, patch-based classification takes into consideration the salient features in a section of the image and determines which category best describes the features detected. Specifically, for every patch, the algorithm:

- Counts the number of objects it contains. The number can range from 0 to the maximum number of objects found in the image (no limit).
- Attempts to classify the objects based on a predetermined list of 9000 common objects. The algorithm attributes a class and a 'confidence' value (i.e., a percentage value of how 'sure' the algorithm is that the object in the photo resembles the reference object).
- Determines variance of colour, from 0 when the image is of a single colour and without a defined limit.
- Detects whether it contains people. It can only be 0 or 1, 0 indicating there is no person and 1 that at least one.

Activity recognition

Using activity recognition, I aimed to recognise the ADL of individual students from a series of observations on their actions and the environmental influences impacting these actions. Since the 1980s, this research field has captured the attention of several different disciplines due to its strength in providing personalised support for many different applications and its connection to many different fields such as medicine, human-computer interaction, or social science. Activity recognition can involve the automatic classification of images in one or more activity categories (Dimiccoli, Cartas & Radeva, 2019). The importance of egocentric activity recognition has been particularly popular because of its potential health applications, for example, monitoring the lifestyle of people with memory impairment (Oliveira-Barra et al., 2019).

Sensor-based activity recognition integrates digital traces produced by human-technology interaction with novel data mining and machine learning techniques to profile a wide range of human activities (Mukherjee & Bhattacharya, 2018; Gravina, Alinia, Ghasemzadeh & Fortino, 2017). Wearable and mobile devices provide powerful digital trace data to enable activity recognition to provide a profile of an individual's activities during everyday life. However, it is still a challenging task to understand the naturally occurring, continuous behaviour of individuals through photos taken by wearable cameras.

I refer to the different activities of an individual in a day as events and consider that they are composed of a group of sequential images that represent the same scene or environment. Thus, from the egocentric photostreams from individual students per day, events were extracted by applying the temporal segmentation method introduced by Dimiccoli (2018)—an event is classified as a group of images that last a minimum of 3 minutes, which is translated to at least six images per event. Images are represented by a combination of global visual features extracted by a CNN, and semantic features extracted by auto-tagging technology called Imagga (http://www.imagga.com/solutions/auto-tagging.html). In the case of this study, the tool is based on deep learning and was trained from an extensive collection of human-annotated images. It is able to recognise various objects in an image, which can be used as descriptors. Hierarchical clustering techniques are applied over the extracted features, merging similar images in a cluster. The general processing pipeline used in this study is shown in Figure 6.5.

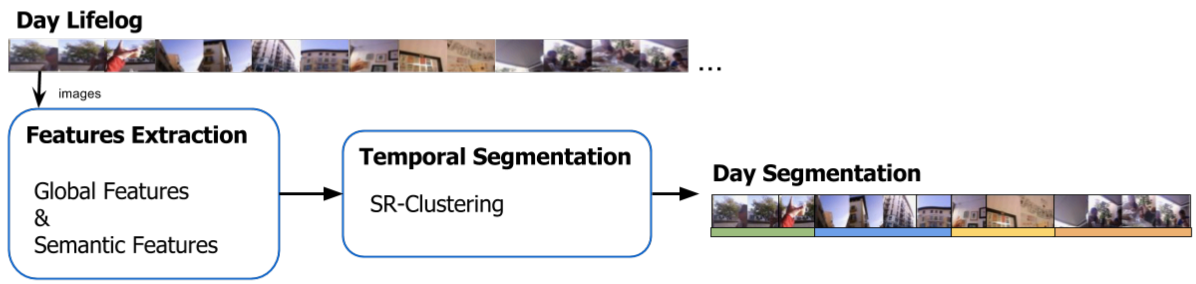


Figure 6.5 General pipeline of the SR-Clustering method.

Cartas, Marín, Radeva, and Dimiccoli (2017) introduced a dataset of 21 egocentric actions of daily activities performed by multiple users. For the analysis of this data, I refer to the CNN classifier introduced by Cartas et al. (2017) for the classification of the recorded egocentric photostreams into ADL. This network was trained on a set of 18,674 images targeting 21 different egocentric activity related categories: *Public Transport, Driving, Walking outdoor, Walking indoor, Biking, Drinking together, Drinking/eating alone, Eating together, Socialising, Attending a seminar, Meeting, Reading, TV, Cleaning and chores, Working, Cooking, Shopping, Talking, Resting, Mobile,* and *Plane*. Most of the categories are self-explanatory; however, a couple can be clarified further: *Working* in this context means 'working on the computer'; *Attending a seminar* includes classes, labs and tutorials; and *Mobile* means using a mobile phone.

From the photographic record, the students' contextual environment was inferred over the data capturing intervals by recognising the activities they engaged in throughout the day. Activity recognition was employed to automatically classify each image into one of the 21 given activity classes. However, some dimensions could also be categorised under multiple categories, e.g., *Shopping* and *Socialising*, or *Eating* and *Walking*.

Findings

I will now report on the findings of the photo data capture from the students. First, I report on the general findings of all students such as the total number of images captured, followed by examples of the image classification from a subset of the students. As mentioned, the first step of the analysis was to select useful images from the data, using the rich image selection tool. The total number of ‘rich’ images captured was 288,059 from 21 students, with an average of 13,717 photos per student. Student 14 captured the most photos (29,790), with 14 students capturing over 10,000 photos (Table 6.1). Student 18 only captured 11 photos.

Table 6.1 The total number of photos captured by each student.

Student	Number of photos captured	Student	Number of photos captured
14	29,790	**9**	11,067
4	27,090	**6**	10,758
10	26,367	**19**	10,385
13	23,594	**11**	9,272
1	21,859	**21**	7,863
17	19,147	**3**	5,954
20	17,650	**12**	4,063
16	16,561	**15**	2,919
2	15,053	**8**	2,849
7	12,965	**18**	11
5	12,837		

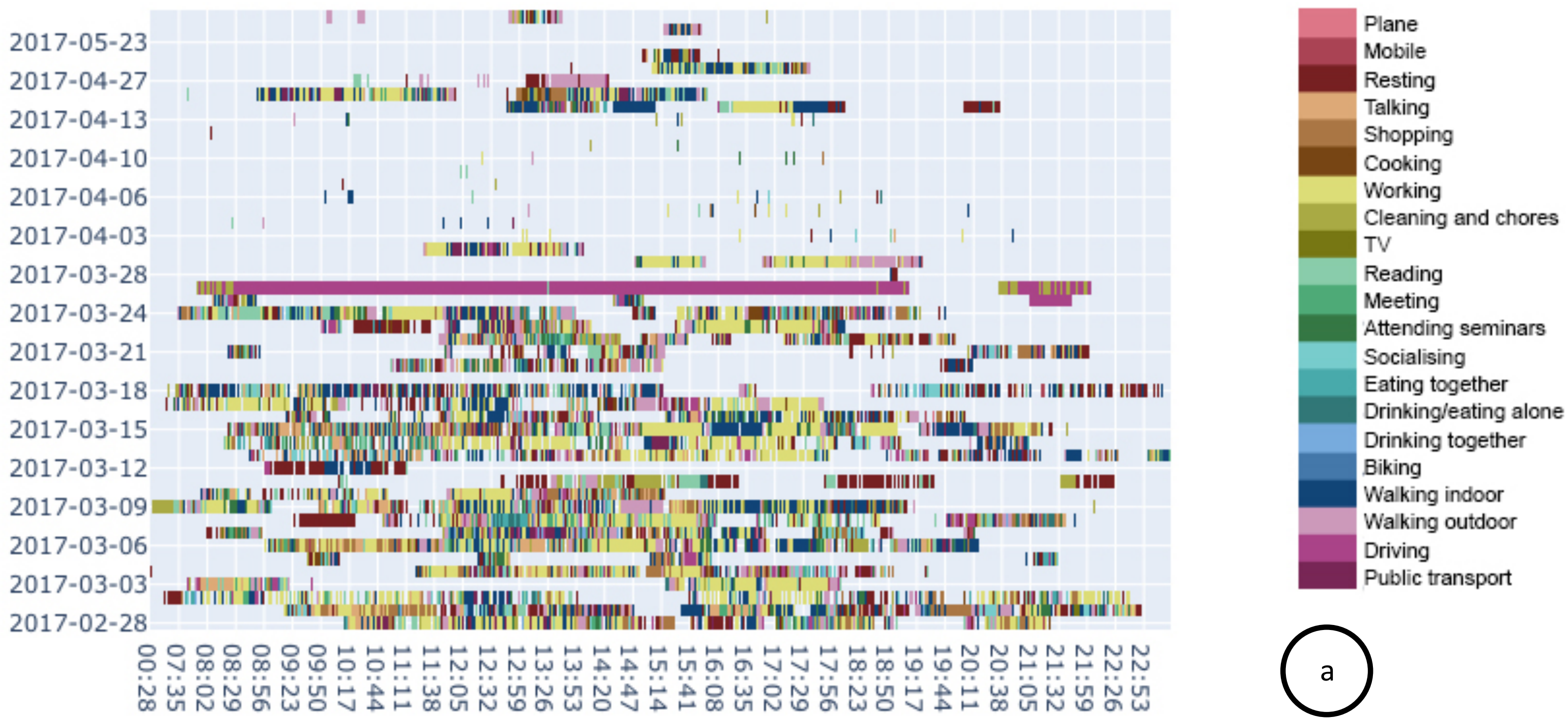
To illustrate the types of analyses possible with this data, I will use a subset of the student data; specifically, I will use the five students with the largest number of photos (students 14, 4, 10, 13 and 1).

Preliminary exploratory visualisations

Figure 6.6 (a-e) shows heatmaps of the five students' (14, 4, 10, 13 and 1) categorised activities throughout the semester. Figure 6.6 (a-e) helps us get a first impression about the daily activity patterns of students 14, 4, 10, 13 and 1, and how these vary over a semester. Immediately, we can see that these students engage in a rich tapestry of activities, further emphasising that academic behaviours make up only a small fraction of 'what it means to be a student'. Because there are so many activities captured in these images, it is difficult to see what is going on. For this reason, Figure 6.7 (a-e) shows a count of all the activities detected in each students' (14, 4, 10, 13 and 1) photostream.

Count of student activities

As seen in the five graphs, *Working* (on the computer) was among the most frequent activities. As noted earlier, these students were expected to exhibit a high degree of digital behaviour. Also, prevalent to high degrees were *Reading, Resting* and 'movement' (that is *Walking indoors* or *Walking outdoors).* Interestingly, *TV, Socialising, Eating and Drinking together*, were among the less frequent activities. The combination of *Reading* and *Working* activities suggests that students are likely engaging in academic behaviours. However, we cannot be sure of this as we do not know from this data what exactly the students were working on. Therefore, in the next chapter (Chapter 7), I will examine their digital behaviours in more detail, through the use of computer application tracking software.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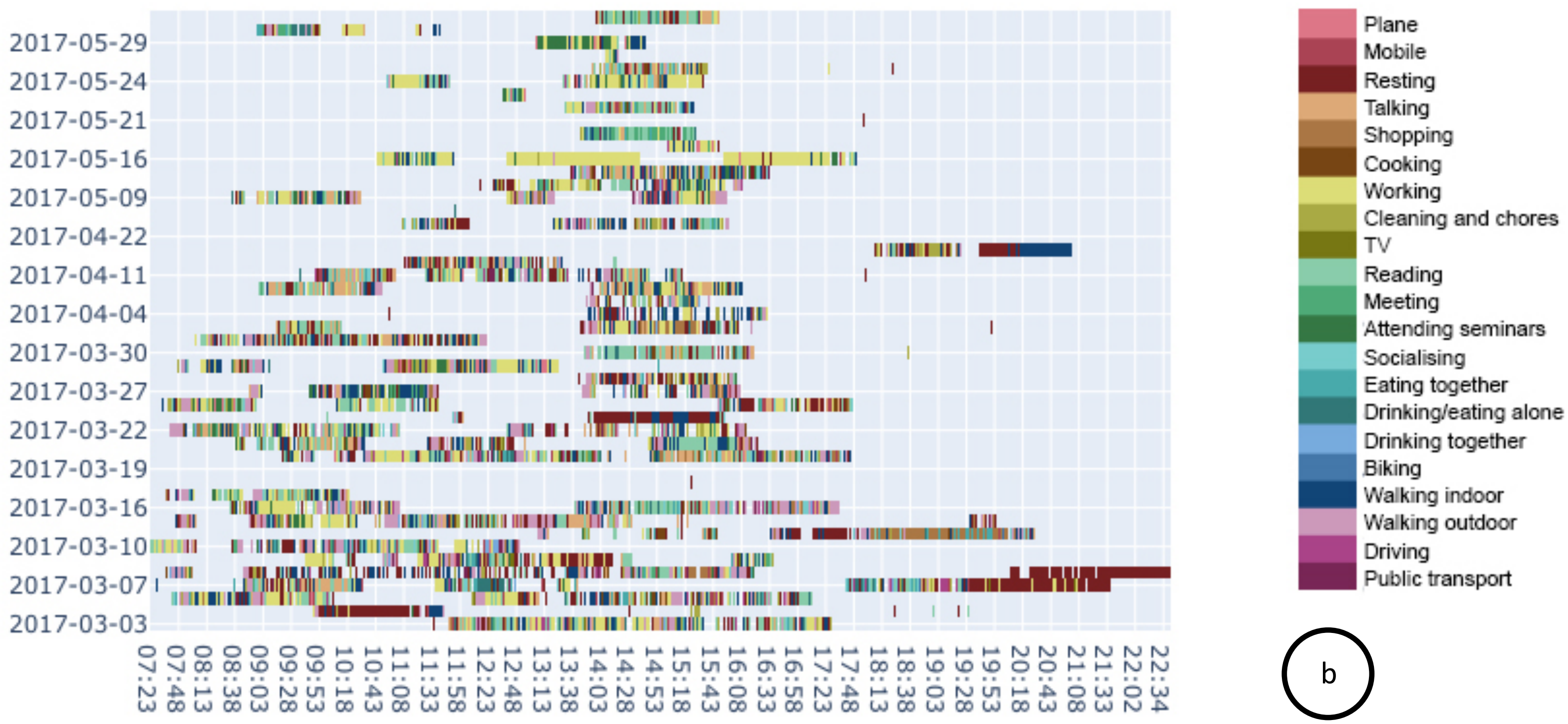
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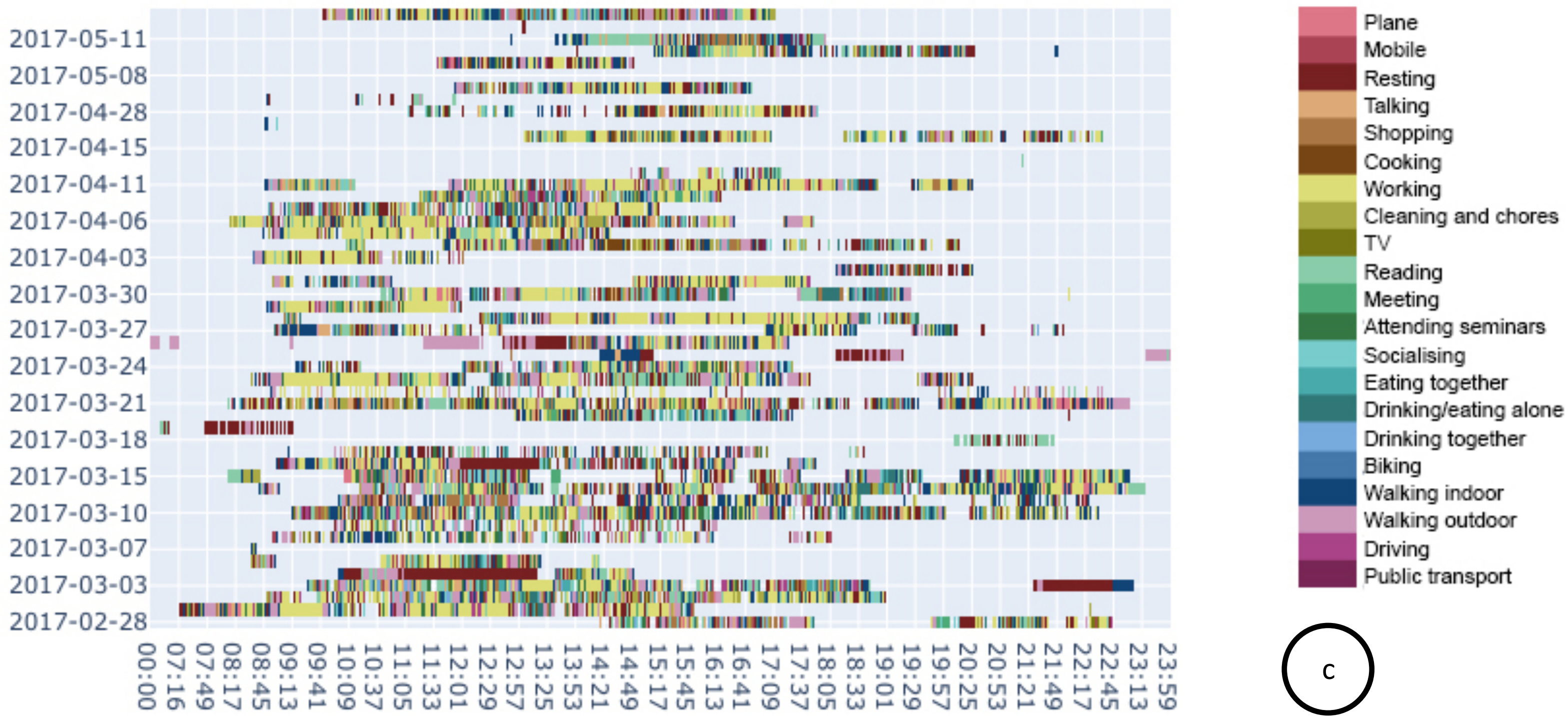
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Biking
Walking indoor
Walking outdoor
Driving
Public transport

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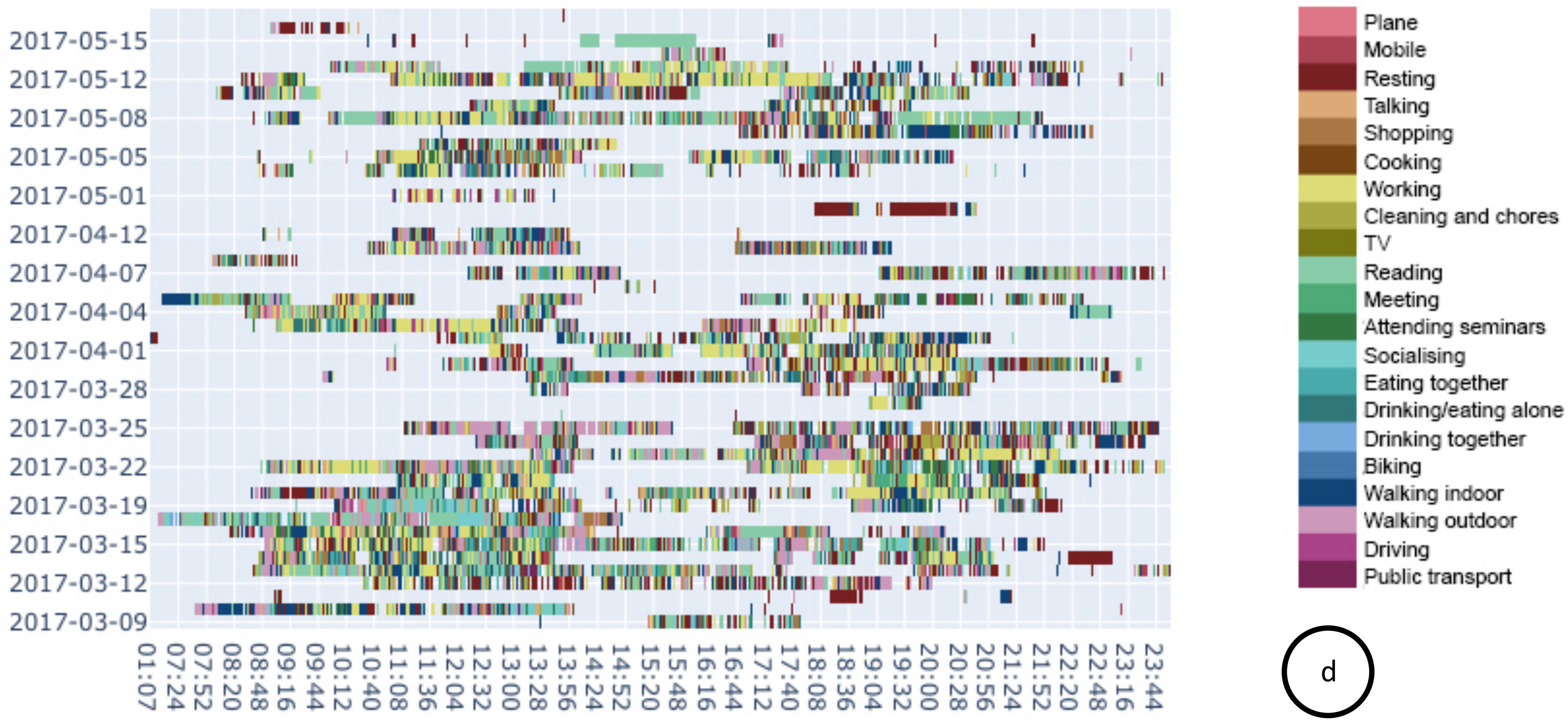
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Socialising
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Drinking together
Biking
Walking indoor
Walking outdoor
Driving
Public transport
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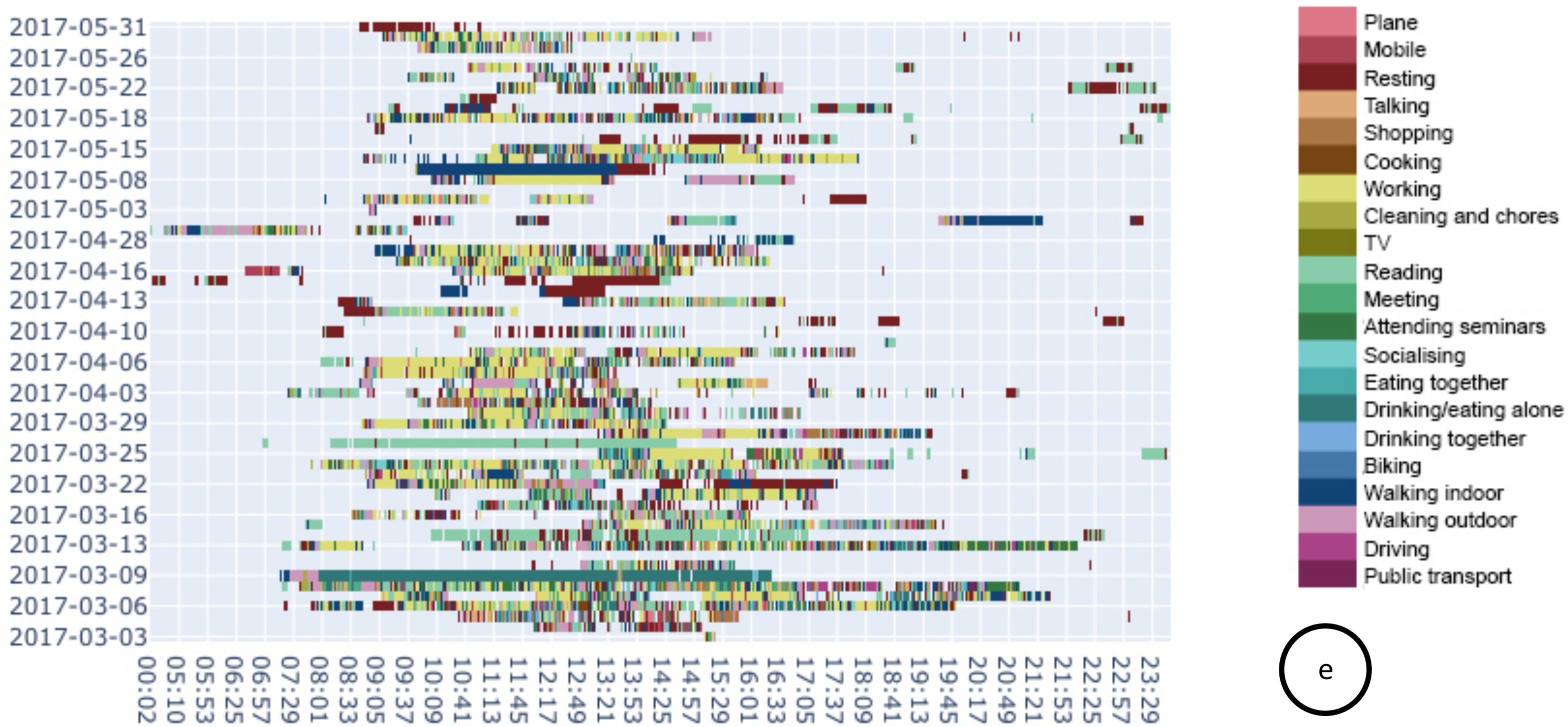
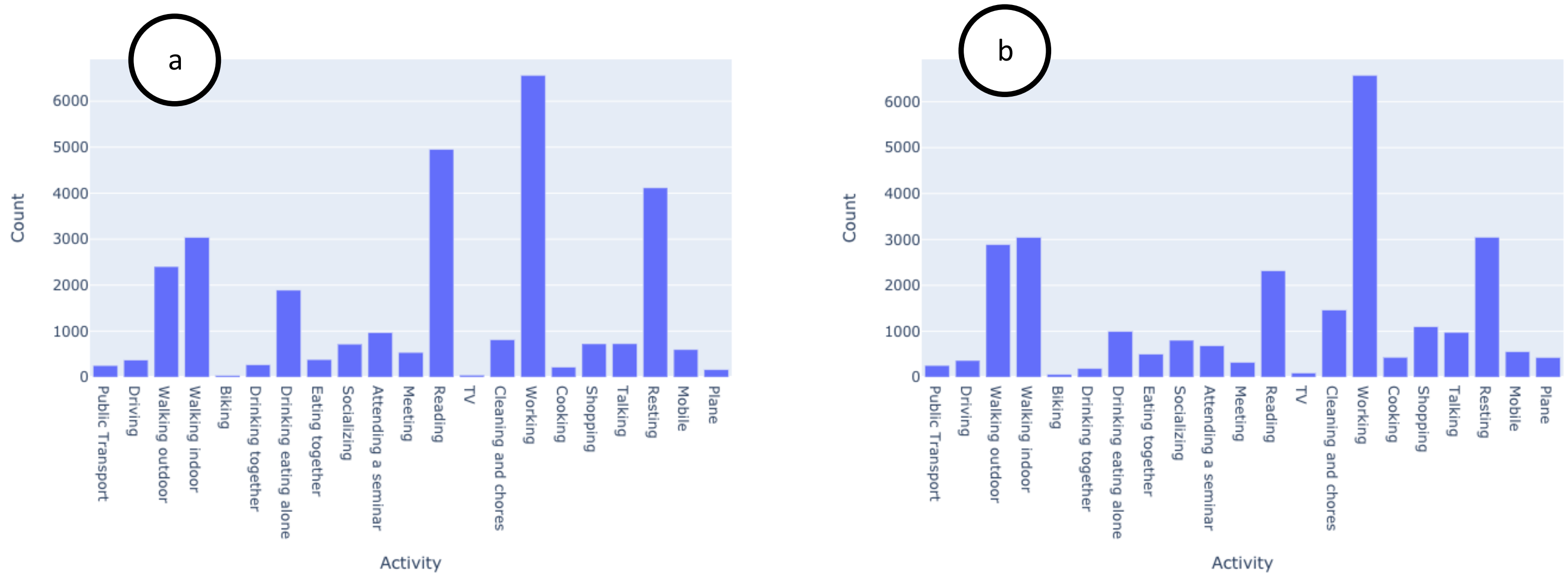


Figure 6.6 (a-e). Heatmaps of the five students' (14, 4, 10, 13 and 1) categorised activities throughout the semester. Each row represents a day, and each colour represents the respective activity labels per frame.


a
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Public Transport
Driving
Walking outdoor
Walking indoor
Biking
Drinking together
Drinking eating alone
Eating together
Socializing
Attending a seminar
Meeting
Reading
TV
Cleaning and chores
Working
Cooking
Shopping
Talking
Resting
Mobile
Plane
Activity

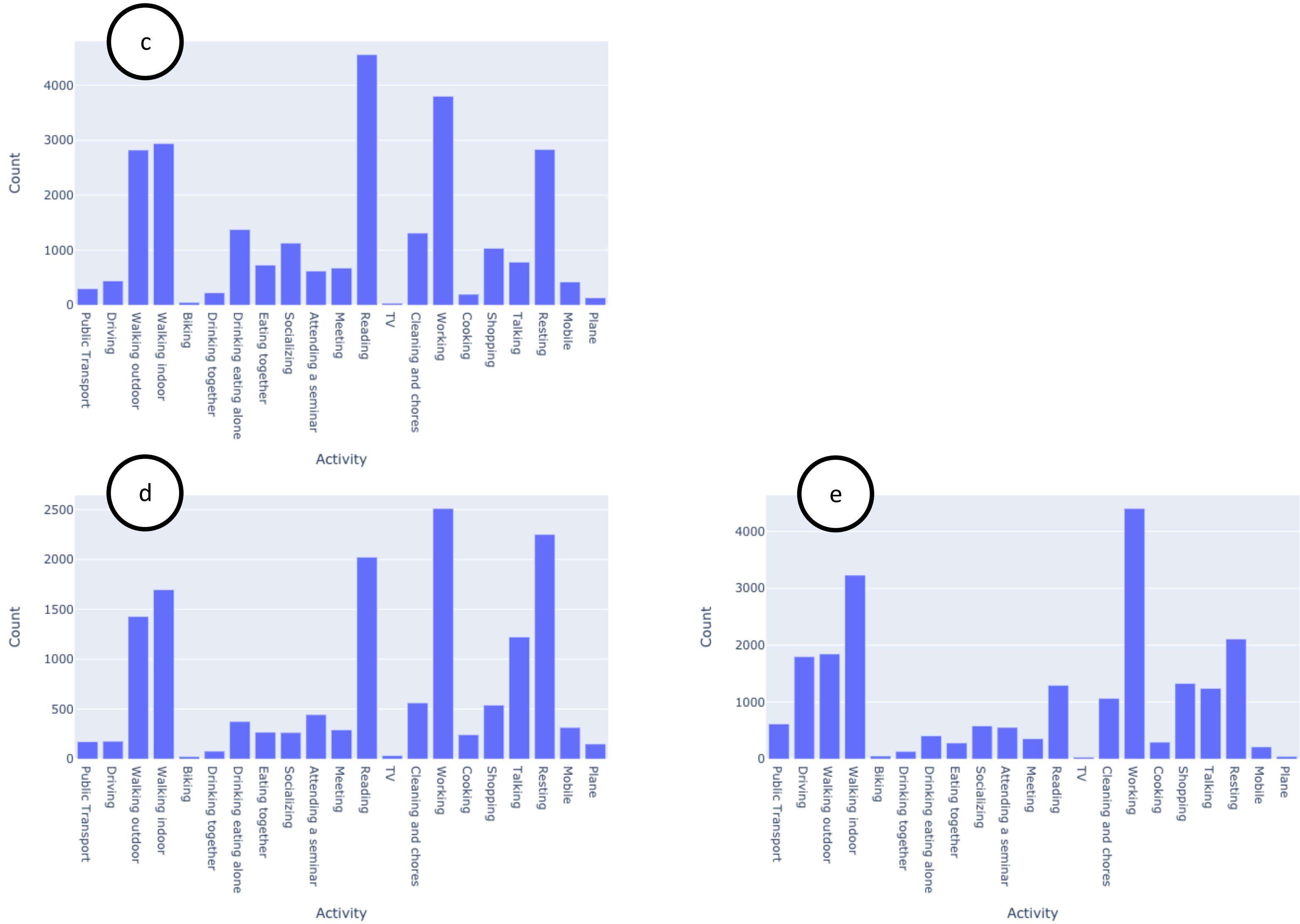


Figure 6.7 (a-e). A count of total activities captured from each students' (14, 4, 10, 13 and 1) photostream, over the semester.

Discussion and conclusions

In this chapter, I have reported on the use of small wearable auto-cameras to capture photographic data of students' day-to-day activities. Photographic data was gathered from 21 undergraduate students over a period of one semester (approximately four months), to identify different behaviours. The photos were analysed by categorising them under 21 different egocentric activities. The aim was to produce a richer and more holistic picture of students' lived experience.

The findings illustrate complex activity patterns in each of the students' lives, painting unique pictures of what it means to 'be a student'. When the activities were tallied across the entire dataset, some commonalities could be seen (such as *Working* being consistently among the most frequent activities). However, looking at the heatmaps, it became clear that these behaviours were being carried out in very different ways between students, most notably in terms of *when* these activities took place during a day, or whether they occurred in small, recurring patches or in a continuous block. This reinforces the importance of taking an idiographic view of student data; when we aggregated activity counts across the entire dataset, the complexity and nuances of individual students' behaviours were subsequently lost.

As mentioned, sometimes it was difficult to differentiate the egocentric categories as either clearly studying or socialising behaviours—often they were not mutually exclusive but dependent on the context in which they were taking place. One important takeaway from this research is the necessity of 'context' for any of the data being interpreted. In Chapter 8, I look deeper into the concept of the Quantified Self (Wolf & Kelly, 2014), which envisions the students themselves (not outside researchers) as the principal users of these type of data—in this scenario, the students are in possession of the necessary contextual information by which to interpret their own data, and subsequently, use it to inform their own personal development.

Using wearable cameras to capture student activity data does have some limitations. First, I was limited by the available devices at the time of this research. The device I chose was practical (e.g., small, lightweight and affordable), but did mean I was somewhat limited in how much I could customise it. I able to get the sampling interval to 30 seconds, which was deemed enough for this exploratory research; however, in some cases, it may be desirable to sample more frequently.

Also, there were limitations with the photographs themselves. First, some of the photos taken were affected by environmental factors such as movement (blurring) and available light. While the amount of data lost to these issues was minimal, nonetheless, it resulted in gaps in the data. Moreover, I had no control over what the camera actually captured. The point-of-view of the camera (straight forward from the chest of the wearer) means I did not capture any information about the environment surrounding the student. As such, there may have been other activities going on that were not captured by the camera. Finally, the students could choose to remove the camera at any time, which also means some activities would not have been captured.

To make use of the data, we had to consult experts in the field of Computer Vision. In other scenarios, this may not be possible and as such limits the usefulness of this method for general use. Also, the categorising of photostream data was based on previous investigations of daily activities in *generic* settings, which meant some of the categories did not readily apply to the university context or had to be redefined (e.g., *Working* to mean 'working on computer'). Additionally, categories were determined based on a 3-minute window, and again this may or may not be appropriate in different contexts.

Nevertheless, the findings offer valuable insights into the benefits of using photos to capture naturally occurring student activity data, to understand their actual day-to-day practices rather than relying on perception data. The continuous capture of photostream data as outlined in this chapter represents an extreme example of practices that are very much already ingrained in this generation's lives: that is, the constant documenting of one's life/activities through photographs. The prevalence of mobile phones (with high-definition cameras), the phenomenon of social media/selfie culture, and growing participation in ‘lifelogging’ activities by today’s youth point to a degree of ‘comfort’ with being ‘recorded’ and watched (Price et al., 2017). In my informal discussions with students, none of them seemed overly concerned sharing aspects of their lives (some of which could be considered quite ‘intimate’, for example, those behaviours exhibited in private, or not in the company of others); also, students would routinely talk about their friends and flatmates’ interest in the study, and lack of concern over being inadvertently captured in any of the photos. Perhaps one could argue that these students are being naïve with regards to their personal data/information being captured in such an overt manner; however, the fact remains that students exhibit a level of comfort being ‘on camera’, regardless of the reasons why.

THERE IS AS YET INSUFFICIENT DATA FOR A MEANINGFUL ANSWER.

—

Isaac Asimov, *The Last Question*
(Asimov, 1956, p. 7)

CHAPTER 7 : MAPPING THE VIRTUAL ACTIVITIES OF UNDERGRADUATE STUDENTS

Introduction

It is generally accepted that higher education today incorporates a great deal of computer technology and that students use digital devices in virtually all aspects of their academic life, from accessing their lectures online, to conducting research, to writing and publishing scholarly work. Most of the current undergraduate student cohort use multiple technologies on a daily basis; have had access to the internet since a young age; and are generally comfortable adopting new technologies and digital behaviours (e.g. interaction on social media) (Mohsen, Ismail, Parsaei & Karwowski, 2019; Ingle & Duckworth, 2013). However, the lines between academic and non-academic technology use are also becoming increasingly blurred for 21st century students. Conole, De Laat, Dillon, and Darby (2008) declared that students' use of technologies is intermingled with social or leisure activities and is almost indistinguishable from their academic use. Sim and Butson (2014) found that undergraduate students were typically unable to accurately judge how much of their technology use was for academic or non-academic purposes. Several studies have reported that students are likely to multitask with technology when studying, constantly switching between academic and non-academic activities (e.g. Weimer, 2012; Burak, 2012).

Today, it is still relatively unclear exactly how students are using computer devices in their day-to-day life, and to what extent academic and non-academic activities are intertwined in their digital practices. A decade ago, Conole et al. (2008) wrote that digital technologies were changing student academic practice, particularly in terms of 'anytime, anywhere' learning. However, other studies report on the negative impact that technology use can have on academic performance (see Wentworth & Middleton, 2014 for a review of the literature), suggesting that heavy Internet and social media use are correlated with lower-performing students. These conflicting pressures present challenges for teachers and educational designers who want to provide environments and experiences that effectively cater to students' digital educational needs.

The problem is that most studies related to student computer use are based on self-reports rather than measures of actual practice. For example, Wentworth and Middleton (2014) conducted a large-scale survey to determine the effects of technology on student performance, but concluded by saying:

> …measures of technology use may need to be refined. Student self-reports may have been biased, either positively or negatively, due to memory errors and lack of awareness of their actual frequency of using technology (p. 310).

As with the previous two chapters, we are faced with a challenge to capture accurate data about student activity—in this instance, computer usage. This has previously been done via post-event recollection data, but now we have access to technology that allows for the continuous logging of computer use. In this chapter, I explore the use of one such application, RescueTime (https://www.rescuetime.com). The exploration of students' virtual activities (events) represents an extension of the Space-Event-Movement (SEM, Tschumi, 1976) perspective, as virtual spaces and events were not originally considered as part of the framework (more on this extended SEM perspective in chapter 8). Auto logging computer activity is also a further example of Reality Mining (Eagle & Pentland, 2006).

The structure of this chapter is as follows: first, I discuss the characteristics of the 21st century student with regards to their technology use. I then build on a framework around New Ways of Working (Nijp, Beckers, van de Voorde, Geurts, & Kompier, 2016), and use this as a lens for interpreting students' computer use behaviour. Finally, I describe the work carried out as part of this doctoral study—I outline the methods of collecting computer usage data from a cohort of undergraduate students and present a range of examples of how this data can be analysed and presented.

The digital student

Andone, Boyne, Dron, and Pemberton (2005) defined the term ‘digital student’ to describe students who have grown up with active participation in technology as a common feature of their lives. Their research posits that the arrival and rapid dissemination of digital technology in the last decade of the 21st century has changed the way students think and process information. Many of the Millennial/Generation Y and Generation Z members are now part of the digital student cohort (Seemiller & Grace, 2017). Unlike the generations who have gone before, the current generational cohort of students were born into a world of the Internet, social media and mobile technologies. Their increased exposure to technology has changed the way they interact and respond to digital devices (Morgan, 2014). As they enter higher education, they are bringing their digital ways of thinking with them. Therefore, there is a need to deliberate about how this will affect higher education.

Although it is impossible to ‘define’ such a large group of unique individuals, Sutherland (2016) outlines four generational markers of the 21st century student:

1. They want prompt feedback: this generation of students grew up with technologies (e.g., texting, the Internet, and social media) that allow them to connect with the world instantaneously. Indeed, they expect the same instantaneity when it comes to their education.
2. They interact differently: social media has revolutionised how we connect. While students of the past valued face-to-face meetings, 21st century learners prefer to connect via digital devices.
3. They want to have a say in their education: technology has put digital learners in control of their lives. Consequently, they also expect to have a voice in their learning process.
4. They prefer an interdisciplinary approach: the 21st century student is keen for information and wants to gain knowledge beyond traditional subject boundaries. They view the world as one extensive network of connections and expect their education to mirrors that. Digital learners are more likely to undertake multiple degrees or take additional classes.

This change in practices has also influenced the way this generation understands and engages in work (Anderson, Baur, Griffith, & Buckley, 2017). The Millennials (Generation Y) have been the primary drivers behind movements that question how we engage in work, a movement known as 'New Ways of Working' (Nijp et al., 2016). Understanding the changes that drive 'New Ways of Working' offers an insight into the ways this generation of students are likely approaching their learning.

New Ways of Working

'New Ways of Working' is a transformative movement brought about by the blend of digitalisation of the workplace and millennial vitality for change (Nijp et al., 2016). It is an initiative looking to boost productivity and wellbeing, mainly by eliminating many of the obstacles and management styles of the past and bringing them into line with the new multigenerational lifestyles (Ruostela et al., 2015). The initiative is driven by the concept of independence and flexibility, enabling people to work anytime, and from anywhere.

Proponents of this movement question the traditional work-life balance idea—they expect to be able to communicate with their peers/colleagues wherever they are and whenever they choose (Nijp et al., 2016). They are not familiar with the traditional boundaries between home and work life and the need to be at a fixed desk/space to get work done (Nijp et al., 2016). They are querying the long hour's philosophy and the 'presenteeism' pattern of work that has been inherited from the previous 'industrial' orientated generation (Afif, 2019). And they value their personal freedom, expecting to be given some discretion over where/how they want to work in their lives (Afif, 2019).

Researchers have predicted that by 2020 Generation Y and Generation Z, the current student cohort, will make up about sixty percent of the workforce (Brown, 2017). Considering their powerful effect on trends, technological innovation, workplace culture and the way they communicate, higher education institutions may have to change their practices of teaching and learning to attract and retain the attention of these generations. According to Mayer (2006) it is these new transformations in work practice and ethics that institutions should proactively draw on to build more contemporary learning cultures.

New ways of learning

This combination of social change in attitudes towards work, combined with the freedom that comes with technology, is confronting traditional institutional practices head-on. In higher education, the idea that 'studying' for students has to take priority over the rest of life is now being challenged (Reay, Crozier, & Clayton, 2010; Mayer, 2006). Technology has always played an essential role in learning; however, the immense change in technology and the growing presence of the Internet have changed the nature of students' work. Students are no longer thinking and getting information as they may have had in the past, and this has given them a different set of behaviours and experiences than previous generations (Mishra & Henriksen, 2018). Their affinity for the digital has shaped the way they learn, get information, think and interact. They have become collaborative, autonomous, exploratory and connected learners (Mishra & Henriksen, 2018).

As noted by Sutherland (2016), for this generation, personal life is not separated from learning; instead, they view learning as personal life. For example, if students can view an informative video about the subject they are interested in from home, or on the move, at a time that suits them, why are they expected to attend a lecture at 9 am? Some of the current institutional processes were established during the industrial age of work that was preparing people to commit a fixed position of their lives to their employer and fit their leisure, holidays, and family life around it (Mitra, 2016). These new ways of learning are being considered beneficial for the future of this generation, as well as higher education itself (Afif, 2019; Gonzales, 2015).

This study aimed to explore the digital behaviours of undergraduate students to determine if they exhibit 'New Ways of Working'. The following section outlines the specific method employed in this study.

Method

Computer activity data was gathered from the personal computers (laptops) of 21 undergraduate health science students from the University of Otago, over one semester (approximately four months, from the end of February 2017 to the end of June 2017). For specific details on the participants, see Chapter 4. The data was gathered using a computer application called RescueTime. RescueTime is a personal time management application for logging and tracking digital activity hours. It sits in the background of the device without causing any interruptions to normal computer use and records the date, time, duration and type of computer programmes used, as well as the date, time and duration of websites visited. Table 7.1 shows an extract of a RescueTime dataset.

Table 7.1 Sample dataset of RescueTime activity collected by a student.

Date	**Time**	**Duration (mins)**	**Activity**
2017-02-24	16:25:00	1	iTunes
2017-02-24	16:30:00	266	microsoft onenote
2017-02-24	16:30:00	22	blackboard.otago.ac.nz
2017-02-24	16:30:00	4	stickies
2017-02-24	16:30:00	3	login.microsoftonline.com
2017-02-24	16:30:00	2	otago.ac.nz

Note that the software does not collect the content of documents or websites. RescueTime has been used to capture productivity measures of computer programmers (Meyer, Barton, Murphy, Zimmermann, & Fritz, 2017), and similar activity tracking software has been used before in higher education to compare students' perceptions of computer use with actual use data (Sim, 2016) and to track the computer usage of academics (Butson, 2019).

Participants were given full control over the software, including the ability to turn it on and off and to delete any data they did not want to be included in the study. As well as having access to the raw data throughout, participants were also emailed summary reports of their weekly activities. This was deemed an essential part of the research design—since data tracking at this level has 'Big Brother' overtones, I believed it was essential that students felt they were in control of their privacy and owned their data. I also wanted to encourage them to find utility in the data being generated and learn more about their own practices.

We performed a number of analyses on the data to generate different perspectives on student computer use, such as: graphing each students' computer use over time; analysing the frequency of application names to get a sense most common digital behaviours; and aggregating different application use within the same time period to gain insight into multitasking behaviours. The specific analyses undertaken are discussed alongside the findings in the following section. Note that all computer usage data was cleaned of any identifying features to ensure anonymity prior to inclusion in this thesis.

Findings

I will now report the general findings of the computer usage data capture from the students. Overall, 7,244 total data hours were captured from 20 students, with an average of 362 hours per student (note that student 6 had issues with their data capture which resulted in unreadable files; they have been excluded from further analysis). Table 7.2 shows the total number of hours captured by each student.

Table 7.2 The total number of computer usage hours captured by each student, ranked by the highest hours captured to the lowest.

Student	Number of hours captured	Student	Number of hours captured
1	727	**8**	329
7	660	**18**	328
4	644	**20**	280
13	553	**16**	276
2	503	**15**	260
21	474	**10**	222
14	444	**11**	175
12	403	**5**	110
17	347	**19**	87
9	342	**3**	80

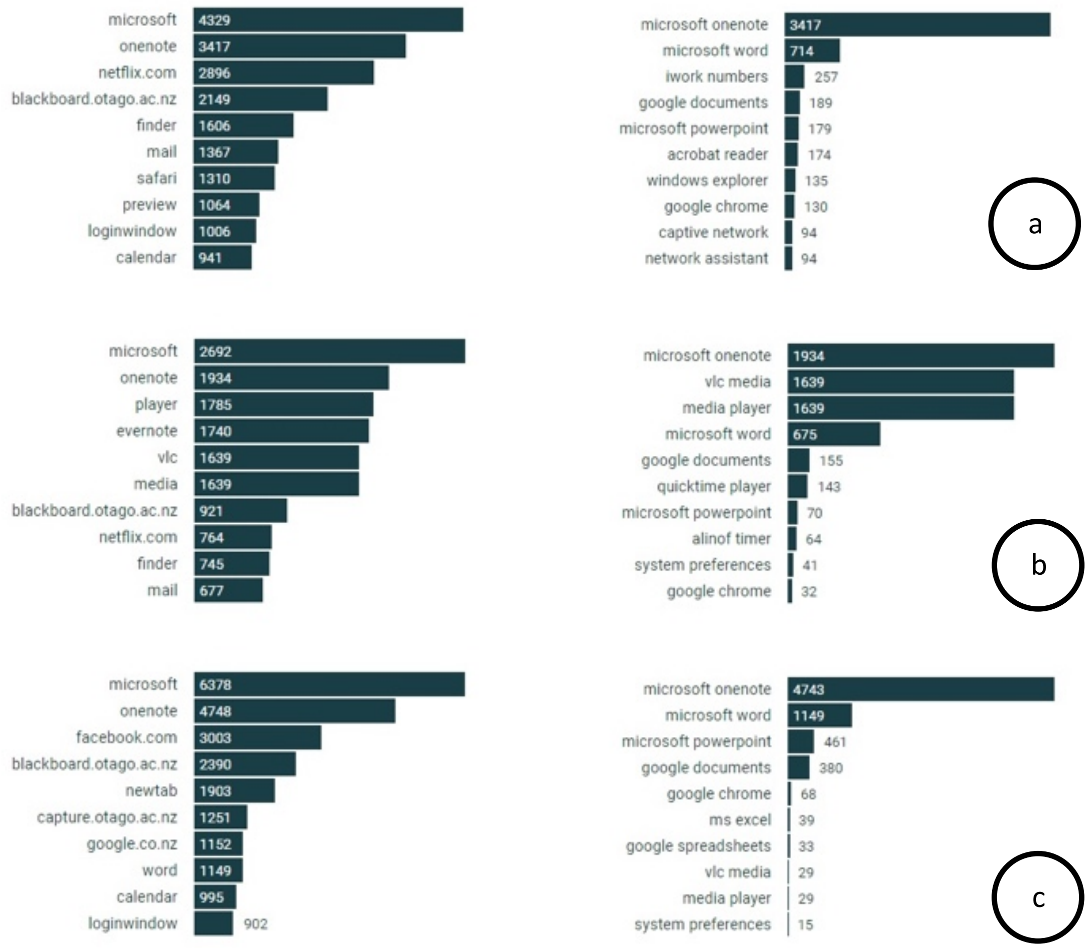
To illustrate the types of analyses possible with this data, I will use a subset of the student data; specifically, I will use the five students with the largest number of data capture hours (students 1, 7, 4, 13 and 2).

In the following sections, I first report on the students' application use, then present their computer use over time, following by multitasking and task-switching behaviours, and finally, the prevalence of anytime, anywhere technologies.

Application use

First, I wanted to gain an overall appreciation of undergraduate use of computer devices based on actual rather than reported data. In particular, I wanted to know: what applications do undergraduate students use over the course of a semester? I achieved this by undertaking a word frequency analysis of software application names, using the Quantext text analysis software (McDonald & Moskal, 2017)—Figure 7.1 (a-e) shows the top 10 most frequent words and bigrams (word pairs) from the full list of applications used by each student; the most recurring words/bigrams float to the top, and can give us an overview of the most commonly used computer applications.

As shown in Figure 7.1 (a-e), the students had different usage patterns; however, some common elements were noted. For instance, website URL addresses recurred often across all students' most frequent word lists, indicating that Internet use is high amongst these students (note that I am not making any distinctions here between the kinds of websites students were visiting, thus I cannot say whether these were for academic or non-academic purposes). Also, interestingly, there were repeated occurrences of 'OneNote' and 'Microsoft OneNote', which is highly likely to be associated with academic use. Microsoft OneNote is an ideal collaborative application for taking notes and organising information. Other frequently occurring applications included the traditional applications of email and media players, which suggest an intermingling of leisure (i.e. networking and entertainment) with study activities.


microsoft 4329
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netflix.com 2896
blackboard.otago.ac.nz 2149
finder 1606
mail 1367
safari 1310
preview 1064
loginwindow 1006
calendar 941
microsoft onenote 3417
microsoft word 714
iwork numbers 257
google documents 189
microsoft powerpoint 179
acrobat reader 174
windows explorer 135
google chrome 130
captive network 94
network assistant 94
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onenote 1934
player 1785
evernote 1740
vlc 1639
media 1639
blackboard.otago.ac.nz 921
netflix.com 764
finder 745
mail 677
microsoft onenote 1934
vlc media 1639
media player 1639
microsoft word 675
google documents 155
quicktime player 143
microsoft powerpoint 70
alinof timer 64
system preferences 41
google chrome 32
b
microsoft 6378
onenote 4748
facebook.com 3003
blackboard.otago.ac.nz 2390
newtab 1903
capture.otago.ac.nz 1251
google.co.nz 1152
word 1149
calendar 995
loginwindow 902
microsoft onenote 4743
microsoft word 1149
microsoft powerpoint 461
google documents 380
google chrome 68
ms excel 39
google spreadsheets 33
vlc media 29
media player 29
system preferences 15
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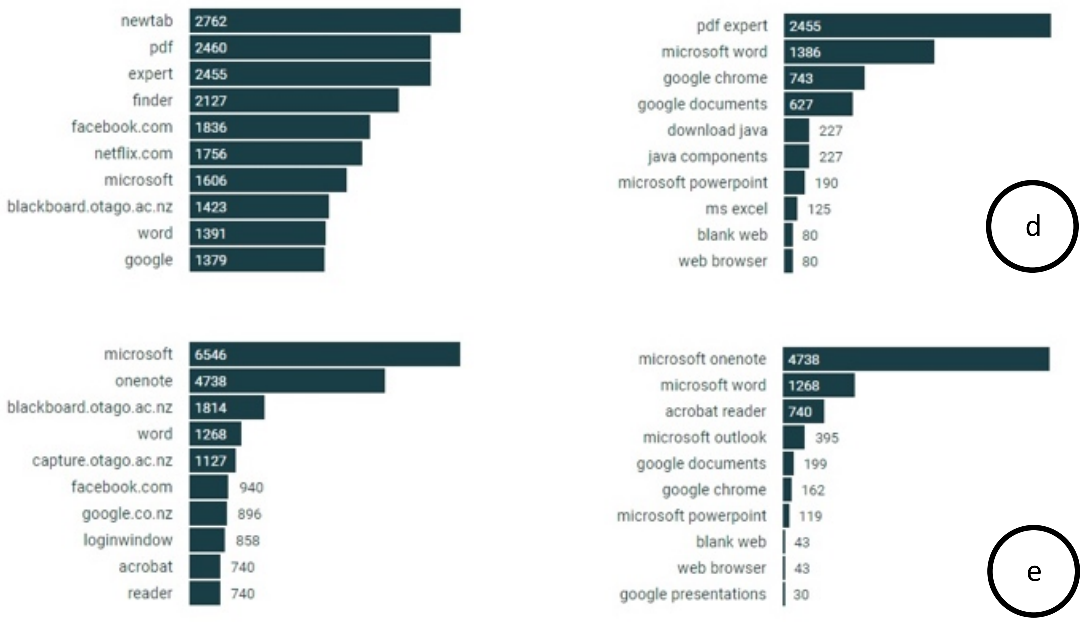


Figure 7.1 (a-e). The top 10 most frequent words/bigrams from the full list of students' application use (students 1, 7, 4, 13, and 2 respectively).

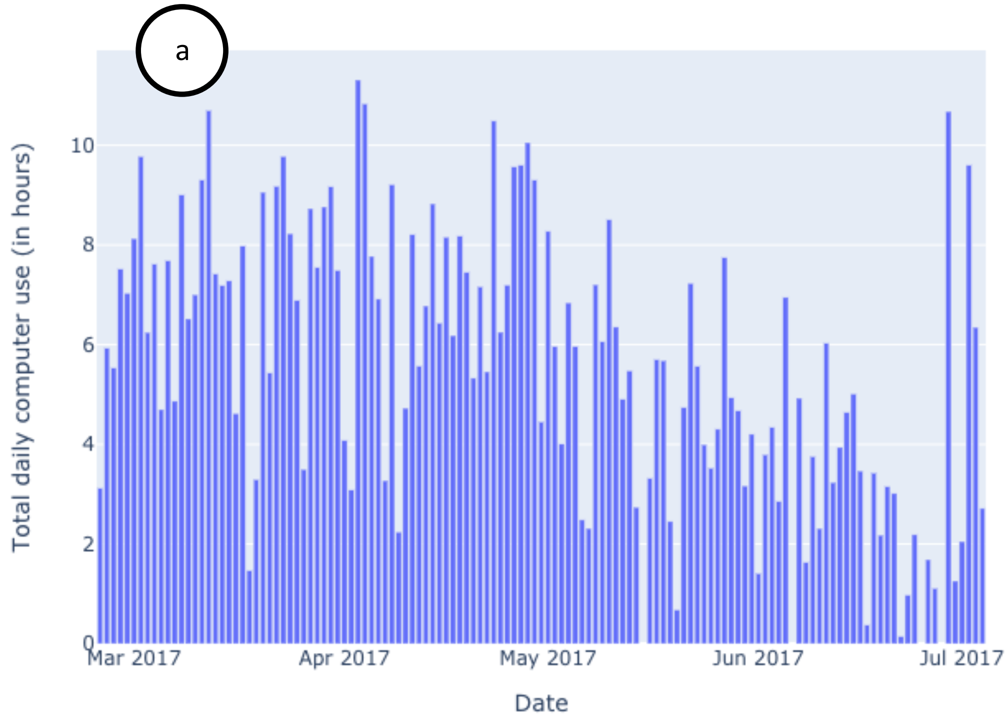
Higher education research often discusses the 21st century students' expectations for the use of technology in their learning environments. However, few efforts have been made directly to better understand how this generation defines technology. Flogie and Aberšek (2019, p. 43) suggest that "it is not just computers and the internet, but whatever digital devices or applications that help a student meet his or her needs". As my initial exploration shows, there is a multitude of applications being utilised by these students (it should be noted that this study only explored students' usage of their laptop devices; the students are likely to use multiple other digital devices, such as smartphones or campus computer labs, so their overall technology use is likely to be much higher than is reported here).

Computer use over time

The RescueTime data also provided an overview of how the students' computer usage changed over the semester. Figures 7.2 shows the five students and their daily computer use over the data capture period. The students exhibited different usage patterns: some appeared random, while others seemed to show trends over time. For example, student 1 (Figure. 7.2 a) shows a general decline in computer use as the semester progresses, but also a sharp spike in activity in the last few days of the data capture. By contrast, student 2 (Figure. 7.2 e) shows a gradual increase in computer use over the entire data capture period. The lack of generalisability in the data is again further evidence that an idiographic approach to researching student experiences is warranted.

Multitasking and task-switching behaviours

Junco and Cotten (2012, pp. 505-506) describe multitasking as “divided attention and non-sequential task-switching”. The digital student is continuously engaged in task-switching while in class and throughout the rest of their day. For example, Judd and Kennedy (2011), in a study of observing student computer use, noted that in more than twenty percent of the computer sessions they observed, students were involved in multiple activities and switched between them, on average, at least every two minutes. As Inayatullah (2002), argues, simplicity is a fallacy in this day and age when technology allows us the ability to layer [tasks]. However, some researchers (e.g., Jeong, & Hwang, 2016; Sana, Weston, & Cepeda, 2013) argue that multitasking decreases retention and attention, suggesting that doing less is better for productivity, and that the simpler a task is, the better the result will be.


a
Total daily computer use (in hours)
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6
8
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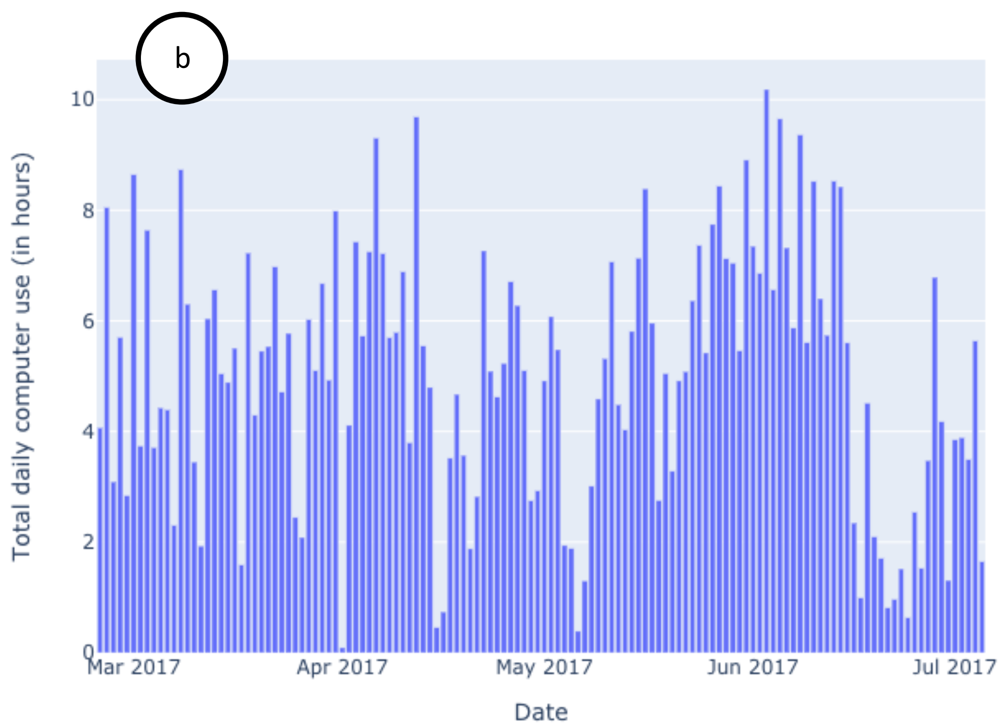
Mar 2017
Apr 2017
May 2017
Jun 2017
Jul 2017
Date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Total daily computer use (in hours)
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Mar 2017
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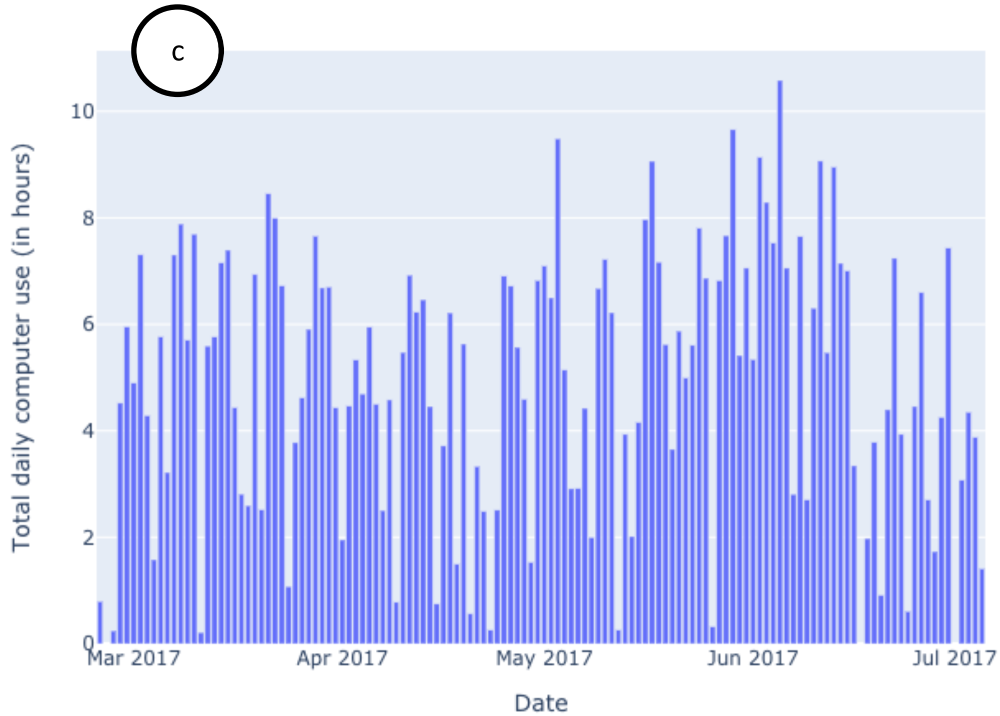
Jun 2017
Jul 2017
Date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Total daily computer use (in hours)
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10
Mar 2017
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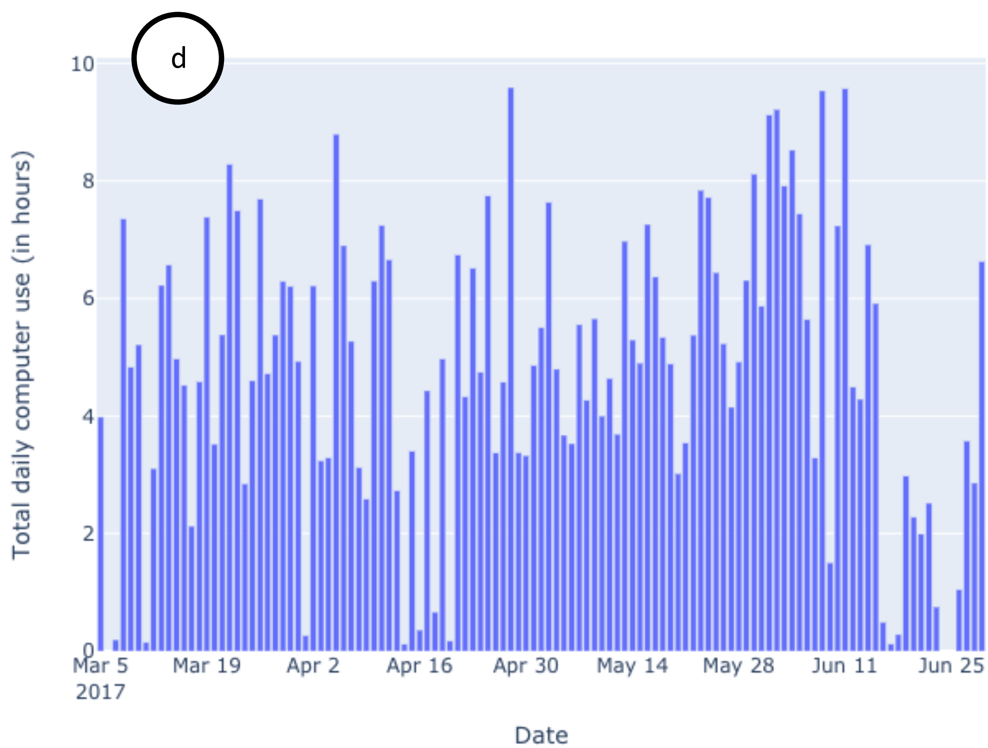
d
Total daily computer use (in hours)
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Jun 25
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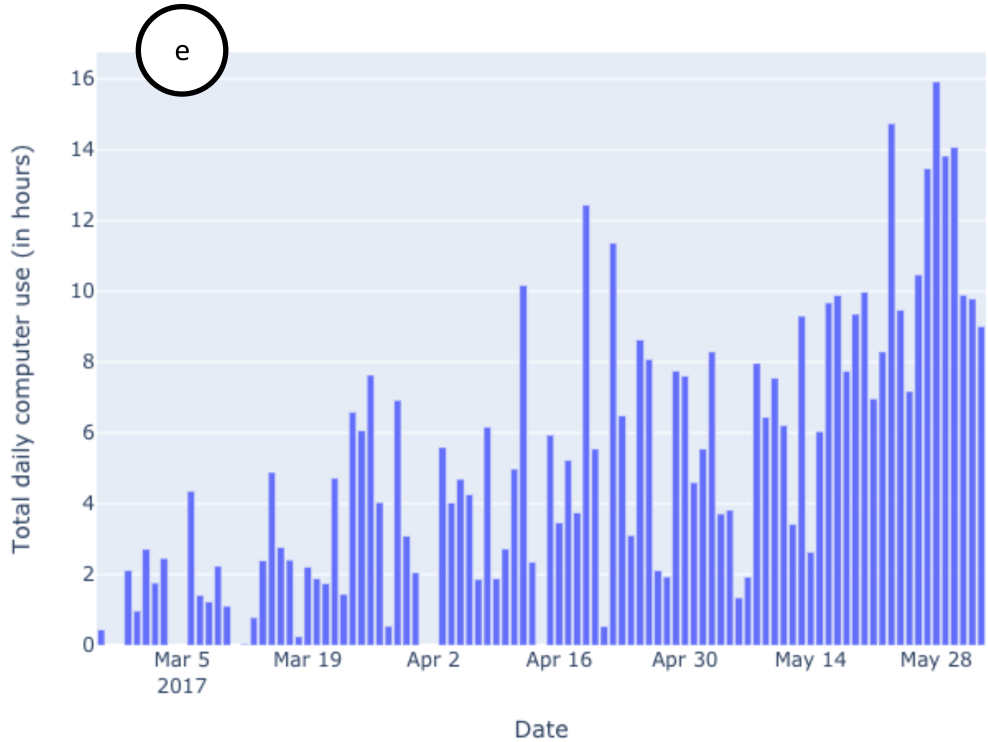


Figure 7.2 (a-e). Daily computer usage (in hours) over a semester for students: 1 (a), 7 (b), 4 (c), 13 (d) and 2 (e) (note the start of the semester is February, and the end is June and the time period captured differs between students).

Figure 7.3 (a-e) shows an example of task-switching behaviour observed from students 1, 7, 4, 13, and 2: the darker the band, the higher the number of different activities taking place in that hourly slot. All five students show many instances of task-switching behaviours. While there appears to be a slight increase in these behaviours in the evenings for most students, generally the behaviours appear again to be unique to each student.

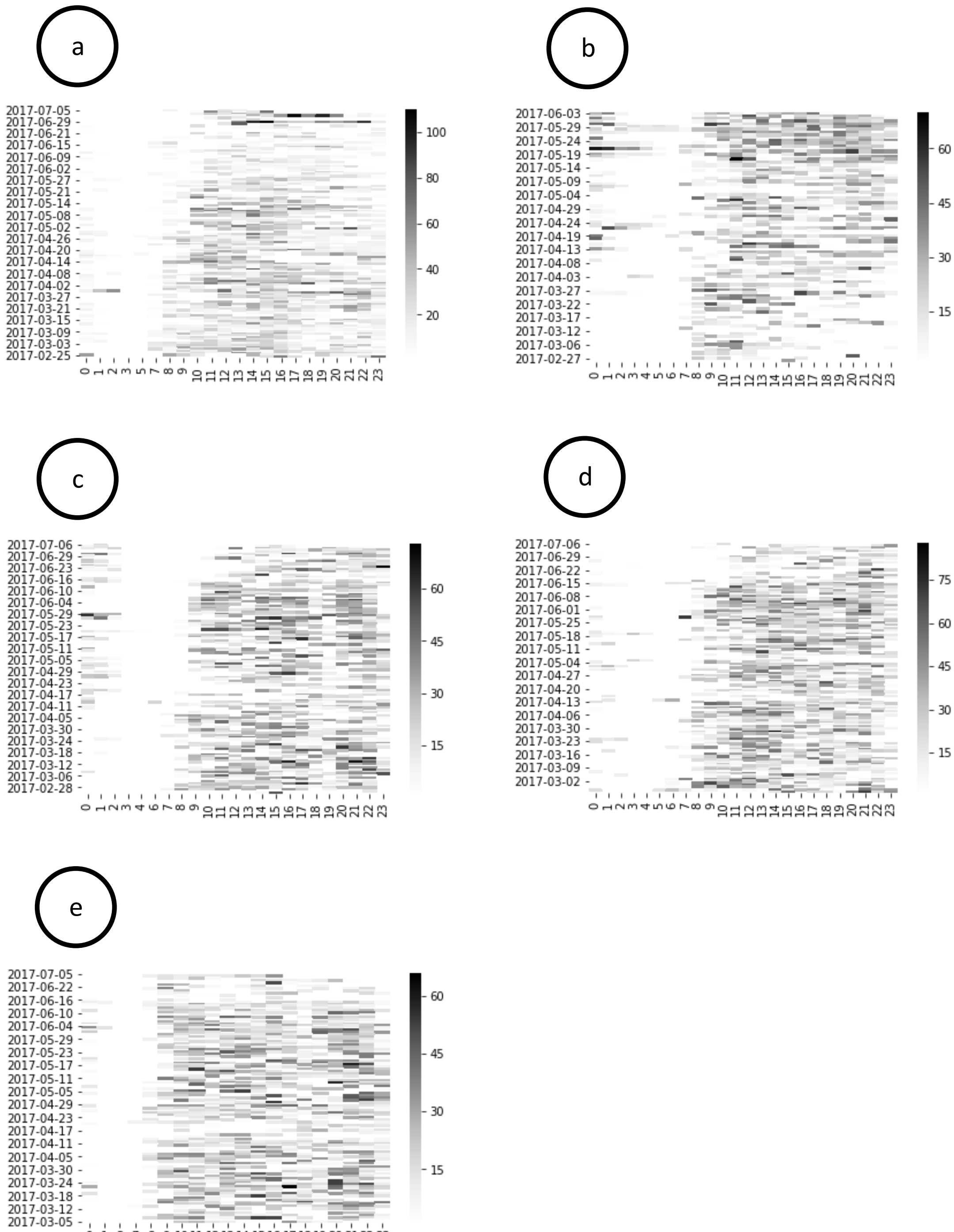
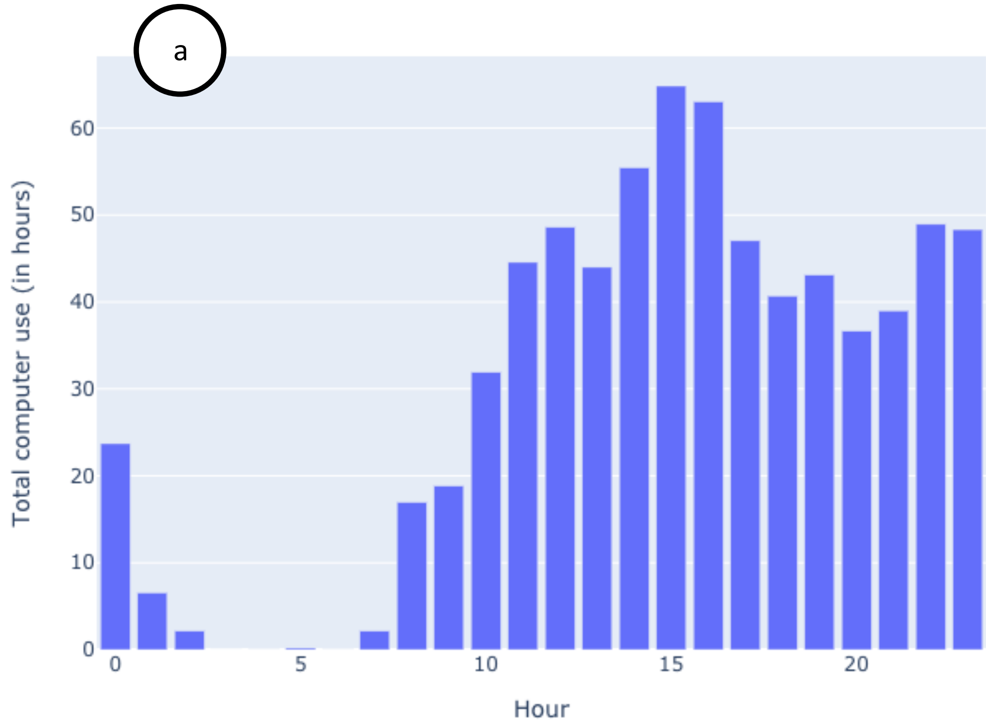


Figure 7.3 Heatmap of hourly computer usage from students 1 (a), 7 (b), 4 (c) 13 (d), and 2 (e) showing a high degree of multitasking or task-switching behaviour (note the start of the semester is February (bottom of the y-axis), and the end is June/July (top of the y-axis)).

Anytime, anywhere technologies

Analysis of the data can also reveal how much activity on their computers the students engage in throughout the day. Figure 7.4 (a-e) shows the aggregated hourly computer usage over the whole semester for the five students, broken down by hour.

From this, we can see whether particular hours are more heavily used than others. There were no discernible times that appeared to show significantly more use than others. Most students exhibited steady computer use through what could be considered ‘normal awake hours’ (e.g., 9 am to 10 pm), and relatively little use when expected to be sleeping. However, student 7 did show moderate use through these ‘sleeping hours’, illustrating that some students display ‘anytime, anywhere’ behaviours with regard to their technology use. It was notable that three of the students had peaks in the late evening (about 10 pm), with two having peaks during the daytime.


a
Total computer use (in hours)
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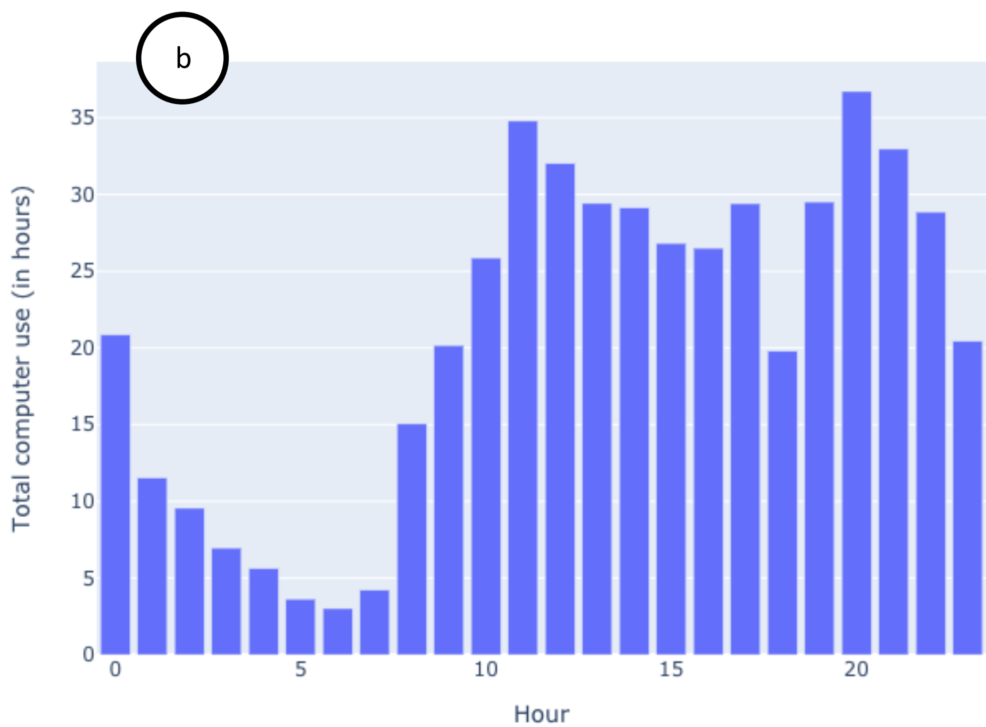
b
Total computer use (in hours)
0
5
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15
20
25
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35
0
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15
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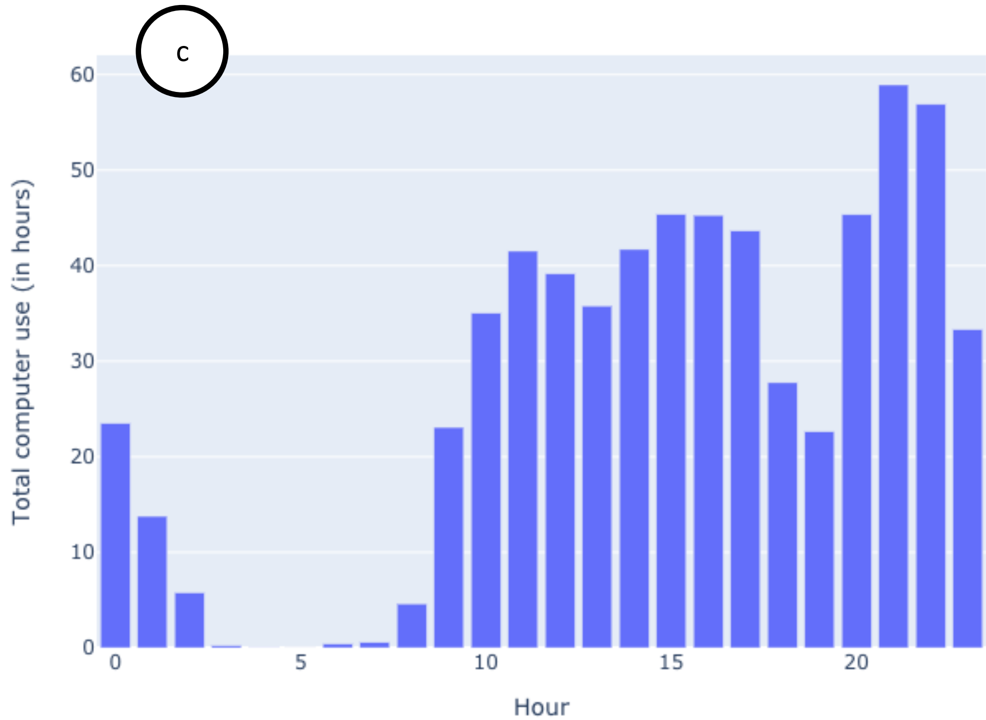
Hour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60
50
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10
0
Total computer use (in hours)
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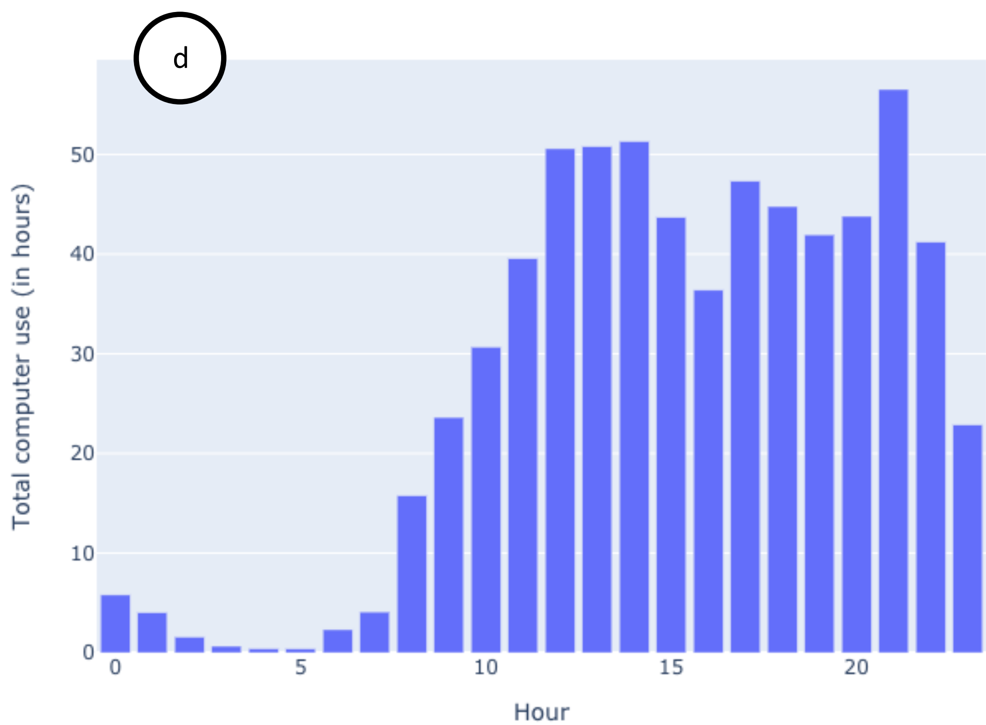
20
Hour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50
40
30
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10
0
Total computer use (in hours)
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5
10
15
20
Hour

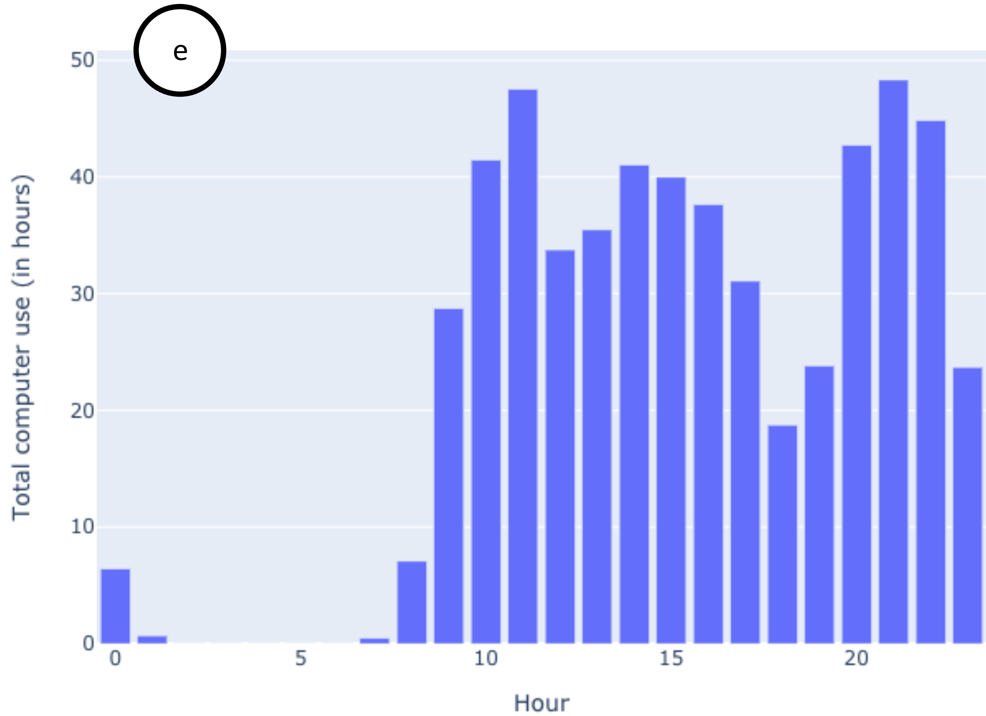


Figure 7.4 Aggregated hourly computer usage for one semester from students 1 (a), 7 (b), 4 (c), 13 (d), and 2 (e).

Discussion and conclusions

This chapter explored the computer usage behaviours of undergraduate students by using techniques to capture naturally occurring digital traces. Over 7,000 hours of computer usage data was harvested from 20 undergraduate student participants in this study, over one semester. The data analysis provides some insights into (1) what applications students use most frequently, (2) how much students use their computers during the semester, (3) the multitasking/task-switching behaviours of students, and (4) the times most common for students to use their computer devices. Many observations drawn from these data suggest that students are exhibiting characteristics in line with the 'New Ways of Working' phenomenon (Nijp et al., 2016). These results point to exciting areas for future research around the complexities of student digital behaviours and illustrate the potential of new research methods to capture data about student practices.

Overall, the extent to which this cohort of undergraduate students utilised their computers in their daily lives was extensive (keeping in mind that the data generated here was only from one of each student's personal computer devices; their overall technology use is expected to be much higher). Internet use was by far the most common computer activity of students, with also a high occurrence of 'academic' applications being utilised (e.g. Microsoft OneNote). Students also exhibited frequent multitasking/task-switching behaviours (Judd & Kennedy, 2011), and demonstrated a constant intermingling of both academic and non-academic applications (e.g. in keeping with the observations of Reay, Crozier, & Clayton, 2010; Mayer, 2006). The rest of the analyses did not produce any generalisable findings concerning student computer use, but this simply serves to reiterate the central theme of this thesis: namely, that student experience need be investigated from an idiographic perspective.

As with the other two methods, the software I chose for this study was readily available and easy to use but was somewhat limited by the amount that it could be customised. For example, the RescueTime app reported general application names, but not any information on what students were using those applications for. Also, while it was important that students were able to view and control their data throughout the study, the ability for students to remove entries from the app may have resulted in gaps in the data.

Finally, through this study, I again want to raise awareness of these methods in the higher education community. In particular, I believe students can benefit from using self-monitoring software such as RescueTime to learn more about their own behaviours and make changes where necessary. Ultimately, the tensions concerning the place of technology in 21st century education may be resolved by the students themselves. I elaborate on these self-monitoring behaviours as part of the Quantified Self movement in the following chapter (Chapter 8).

You will have to admit that times have changed.
Couldn't you please try these other more up-to-date activities?
Maybe they have some educational value after all?

—

J. Abner Peddiwell, *The Saber-tooth Curriculum*
(Peddiwell, 2004, p. 43)

CHAPTER 8 : DISCUSSION AND CONCLUSIONS

Introduction

Before discussing the broader implications of this research, it is useful to revisit the aims of this thesis—namely, (1) to implement three 'new' methods that have had little prior use in researching 'student experience', but have shown promise in researching lived experience in other contexts; and (2) to evaluate the usefulness of these new methods for providing insights into the experiences of 21st century undergraduate students. The new methods trialled here were in response to previous research calling for less reliance on self-reported data of student experience (e.g. from surveys) and were informed by the principles of Reality Mining (Eagle & Pentland, 2006), or the continuous capture of naturally occurring activity data. I employed wearable devices to accurately and unobtrusively collect data from a group of undergraduate students, looking at the spaces they occupy while at university, and their activities, both physical and virtual. The idea of looking at student spaces and activities (events) was informed by Tschumi's (1976) Space-Event-Movement (SEM) framework. The continuous data collection generated large datasets that demanded new means of analysing, visualising and, ultimately, conceptualising what it means to 'be a student' in the 21st century. In particular, I have argued for both a more holistic view of student experience—that is, that student experience be recognised as comprising a myriad of influences and factors that stretch beyond the consideration of academic practices only—and a more idiographic representation of each student's unique experiences.

This research was designed to be exploratory in nature. I began this journey with many ideas and a general direction of enquiry, but no explicit research questions. I wanted to answer the call for new methods in researching student experience and chose methods that were proven in other contexts, and which I could readily trial in a university setting. I aimed to capture 'new' data about student activities, but I did not know what I was looking for, or what I would find. As such, my analyses were equally exploratory and designed to illuminate the sorts of insights that *could* be teased out of such datasets.

Here, at the conclusion of my research journey, I recall Reiter (2017, p. 144), who felt a need to defend exploratory research:

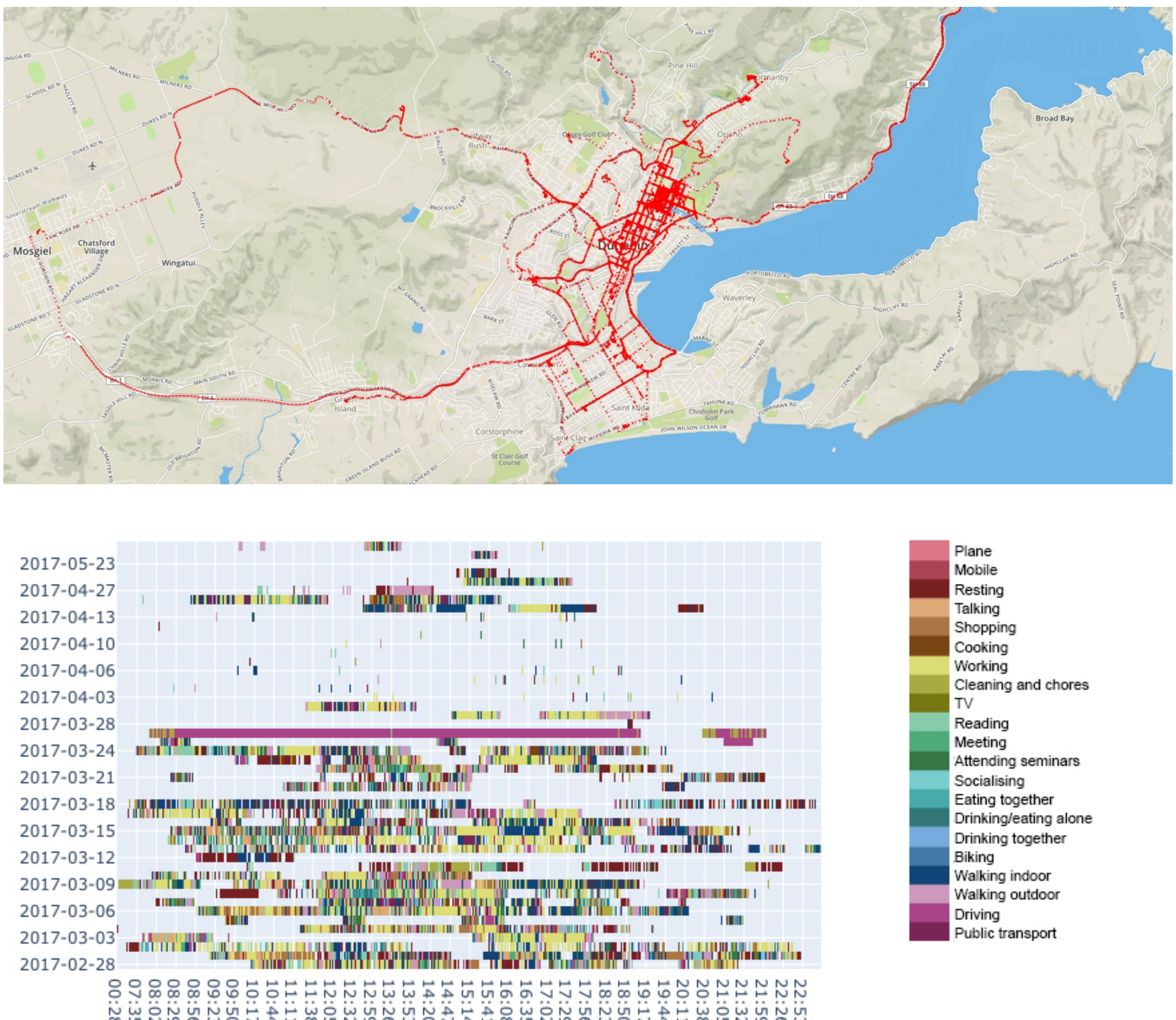
> As the process of "making sense" of a phenomenon is a gradual process that can be compared to a learning process, exploratory research is characterized by a process of reformulating and adapting explanations, theories, and initial hypotheses inductively. It begins, in other words similar to deductive research, with previously formulated theories - but it does not stop there. Instead, it uses empirical data to refine, adapt, or specify and reformulate theories and initial hypotheses to the point that the observed makes more sense to the observer and is thus explained better, i.e. in a more plausible and consistent way.

I have explored three novel and innovative methods for capturing student experience data, and was planning, initially, at this stage to tie the three datasets together under a unifying framework and derive actionable insights from my work. Instead, I have revised my original assumptions about the value of this work. I have, like Reiter (2017) comments, gradually reformulated my initial 'hypotheses' in the light of the empirical data I have collected. Here, in the final stages of my dissertation, I have taken a far more critical view of the utility of the data I have collected, and its value to the institution of higher education. In the discussion that follows, I attempt to deconstruct my research in light of my *learning from my research*, and provide what I hope are deeper considerations for the place of 'student analytics' in the future of higher education, beyond a naïve belief that collecting large enough datasets will invariably yield useful insights.

Contributions

In this research, I have demonstrated the potential of these new methods for capturing student data that was previously challenging (or impossible) to collect; in this way, I believe I have responded to the calls of authors such as Borden and Coates (2017) for new analytical methods to research the complexity of student experience (i.e., student analytics). However, beyond this, there is not a lot that can be utilised, in *these* datasets, by the university as a whole—not as they are. This is precisely because 'student experience' is specific to individuals, and not generalisable across the entire student body. The idiographic approach adopted here, throughout this research, invariably precludes the findings from being immediately relevant to others besides the participants.

Contemporary student life is complex; it does not fit neatly into categories of 'academic' and 'non-academic' activities; nor into delineations of 'on-campus' and 'off-campus'; nor into breakdowns of 'on task' and 'off task'. For example, in researching the student experience, I have created diagrams such as those shown in Figure 8.1.



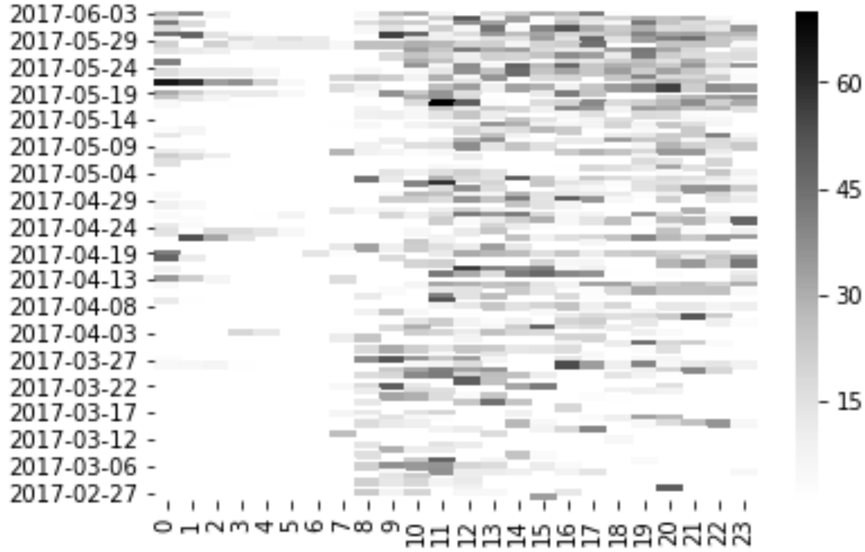


Figure 8.1 Example diagrams taken from preceding chapters in this thesis, used as exemplars of the chaotic nature of student life.

The diagrams shown in Figure 8.1, to the casual observer appear, chaotic, fragmented, and lacking obvious patterns. To a researcher, or to the institution, removed from the context of the individual who generated these data, these data reveal little beyond some 'surface-level' observations, and little that we did not already know (e.g. that students tend to spend a lot of time on campus, or at the mall; that students multitask; or that students do not tend to use their computers while they are sleeping).

Accepting that the raw data alone do not yield immediate insights into a generalisable student experience, we *can* attempt to derive a conceptual framework about the nature of the modern student experience from what we have observed thus far. Such a framework could help to contextualise different types of student behaviours, which in turn could help students to interpret their data, or even train algorithms to model and predict individual students' experiences.

As mentioned, Tschumi's Space-Event-Movement (SEM, Tschumi, 1976) framework pushed me initially to look at student spaces and their activities in these spaces, and thus provides an excellent starting point for formulating our conceptual model. To reorient the reader, SEM takes into consideration the spaces that people come to inhabit, the events (or activities) that they conduct in those spaces, and how they move between spaces or events. For my purposes, SEM provides a way of triangulating my three datasets, as each taken on their own cannot provide enough perspective on a student experience to be useful for further analysis. For example, tracking student movements with the GPS app (as described in chapter 5) can reveal spaces that are important to an individual student (e.g. the main campus library), but does not give us any insight into *how* the students are using that space, or *why* that space is significant (although we can make some assumptions based on the norms of 'accepted use' of spaces—that is, the library is typically used for studying, thus we could assume the student is using it for academic purposes). However, we already know from existing literature (e.g., Paretta & Catalano, 2013; Suarez, 2007) that students will use spaces such as the library for a variety of reasons, only some of which we would count as 'academic'. Therefore, while we can make some guesses about why students may frequent certain places or spaces during their day, we cannot say with any certainty what they are actually doing in them.

In a similar vein, using the auto-cameras to capture student activity (as described in chapter 6) can give us a breakdown of the various things students do throughout the day. However, again, we are only seeing part of the whole picture. For instance, an image depicting a group of friends talking could, on first glance, be construed as 'socialising'; upon contextualising that photo as having taken place within a university study room (as a hypothetical space) we might then re-evaluate the activity as 'academic'.

Considering these scenarios, there is a clear relationship here between spaces and events (for the sake of the conceptual model being developed, 'activities' or 'behaviours' will henceforth be referred to as 'events'). An event exists within a given space, and certain societal norms and expectations give rise to *certain* events within *certain* spaces. Likewise, events can influence or shape spaces in new and different ways than perhaps first envisioned (take, for example, a church that has been decommissioned and now serves as a private residence). We are also extending SEM beyond its original conception—that is, as an architectural construct to describe physical spaces—by incorporating virtual spaces and events into the model (as explored in chapter 7). As the digital world transcends the boundaries of the physical (i.e., students can access mobile digital devices such as laptops or smartphones anytime, anywhere), the virtual activities provide another qualifying data point to inform our judgements of what is happening in a given space. For example, if a student's GPS identifies them as being 'at the library' (space), and their photostream data suggests 'studying' behaviours (event), we might categorise their behaviour as 'academic'. However, if their RescueTime data simultaneously points to non-academic activities (e.g. 'online shopping' or 'watching a movie on the computer'), we would likely revise our initial assessment as predominantly 'non-academic' behaviour.

Thus, what becomes significant to us is the isolation and identification of certain 'space-events', or combinations of spaces and events that *together* reveal insights into their nature. By combining (triangulating) the three datasets, a number of student 'space-events' can be determined. Table 8.1 below shows a small subset of the combined datasets from Student 1, including the event category (as determined from the activity recognition processing of the captured image), a space (as determined from the GPS coordinates), and any virtual activities (as determined from the computer monitoring software).

Table 8.1 Subset of combined datasets for Student 1, denoting events, spaces and virtual activities from a single day.

Date	**Time**	**Event**	**Space**	**Virtual activities**
28/02/17	18:23:41	Working	University of Otago	['microsoft onenote', 'Finder', 'Preview', 'blackboard.otago.ac.nz']
28/02/17	18:24:14	Working	University of Otago	['microsoft onenote', 'Finder', 'Preview', 'blackboard.otago.ac.nz']
28/02/17	18:24:44	Working	University of Otago	['microsoft onenote', 'loginwindow']
28/02/17	18:25:14	Working	University of Otago	['microsoft onenote', 'loginwindow']
28/02/17	18:25:46	Working	University of Otago	['microsoft onenote', 'loginwindow']
28/02/17	18:26:16	Drinking/eating alone	University of Otago	['microsoft onenote', 'loginwindow']
28/02/17	18:26:46	Drinking/eating alone	University of Otago	['microsoft onenote', 'loginwindow']
28/02/17	18:27:19	Walking outside	University of Otago	['microsoft onenote', 'loginwindow']
28/02/17	18:27:49	Walking outside	University of Otago	['microsoft onenote', 'loginwindow']
28/02/17	18:28:19	Walking outside	University of Otago	['microsoft onenote', 'loginwindow']
…				
28/02/17	20:01:39	Resting	King Edward Court	[]
28/02/17	20:02:09	Resting	King Edward Court	[]
28/02/17	20:02:43	Resting	King Edward Court	[]
28/02/17	20:03:13	Mobile	King Edward Court	[]

By grouping adjacent rows in the table that illustrate identical spaces and events (both physical and virtual), we can isolate distinct student 'space-events'; Table 8.2 shows this 'space-event' grouping with the same subset of data for Student 1 ('space-event' groupings are denoted by the tag 'SE').

Table 8.2 Combined datasets from Student 1 grouped according to common 'space-events' (SE1, SE2, etc...).

	Date	Time	Event	Space	Virtual activities
SE1	28/02/17	18:23:41	Working	University of Otago	['microsoft onenote', 'Finder', 'Preview', 'blackboard.otago.ac.nz']
	28/02/17	18:24:14	Working	University of Otago	['microsoft onenote', 'Finder', 'Preview', 'blackboard.otago.ac.nz']
SE2	28/02/17	18:24:44	Working	University of Otago	['microsoft onenote', 'loginwindow']
	28/02/17	18:25:14	Working	University of Otago	['microsoft onenote', 'loginwindow']
	28/02/17	18:25:46	Working	University of Otago	['microsoft onenote', 'loginwindow']
SE3	28/02/17	18:26:16	Drinking/eating alone	University of Otago	['microsoft onenote', 'loginwindow']
	28/02/17	18:26:46	Drinking/eating alone	University of Otago	['microsoft onenote', 'loginwindow']
SE4	28/02/17	18:27:19	Walking outside	University of Otago	['microsoft onenote', 'loginwindow']
	28/02/17	18:27:49	Walking outside	University of Otago	['microsoft onenote', 'loginwindow']
	28/02/17	18:28:19	Walking outside	University of Otago	['microsoft onenote', 'loginwindow']
	…				
SE5	28/02/17	20:01:39	Resting	King Edward Court	[]
	28/02/17	20:02:09	Resting	King Edward Court	[]
	28/02/17	20:02:43	Resting	King Edward Court	[]
SE6	28/02/17	20:03:13	Mobile	King Edward Court	[]

We can now add meta-categorisation to these ‘space-events’, such as SE1 ‘studying at the university’ or SE5 ‘resting at King Edward Court’. The virtual activities help confirm assumed meta-categorisation; that is, having assumed SE1 ‘studying at the university’, we can look to the virtual activities and confirm from the presence of ‘microsoft onenote’ and ‘blackboard.otago.ac.nz’ that this student is indeed likely studying.

Having isolated distinct ‘space-events’ we can now conceptualise the *movement* component of the SEM framework as the transition between different ‘space-events’. The frequency of movement between ‘space-events’ gives some weighting to the importance of a given ‘space-event’; for example, in Table 8.2 we see Student 1 move from SE2 (‘studying at the university’) to SE3 (‘drinking/eating alone at the university’) and then to SE4 (‘walking outside the university’) within the space of a minute or two. As such, we can infer from multiple *movements* within such a short space of time that these are not particularly significant ‘space-events’ (e.g. ‘eating’ in this scenario is likely ‘snacking while studying’ as opposed to ‘sitting down to a meal’).

From this perspective, we can perform a further categorisation, grouping similar adjacent ‘space-events’, and non-significant ‘space-events’ (that is, those characterised by frequent *movements*) into ‘meta space-events’. A conceptual depiction of ‘meta space-events’ as an extended SEM model is shown in Figure XX. Table 8.3 provides an example of categorising ‘meta space-events’ from the sample student data.

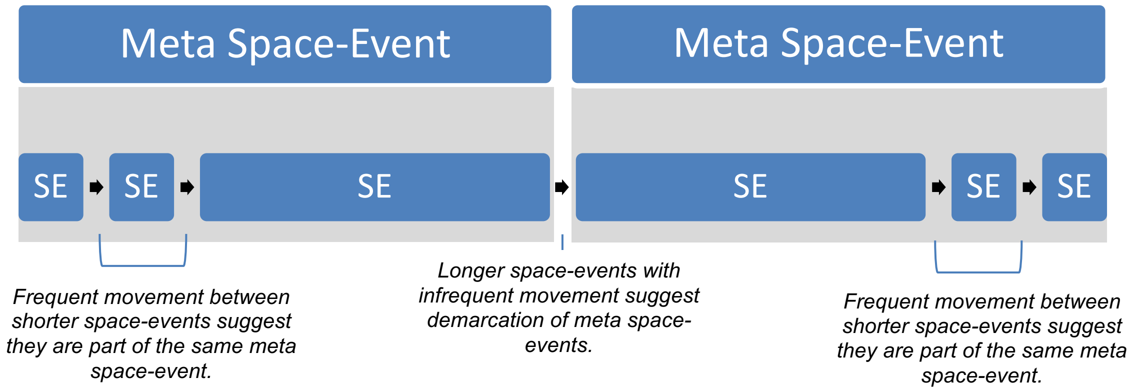


Figure 8.2 Extended SEM model showing 'space-events' (SE), and categorisation of adjacent 'space-events' with frequent movements in a short time as 'meta space-events'.

Table 8.3 Adjacent 'space-events' from Student 1's combined datasets grouped into 'meta space-events' (e.g., 'Studying', 'Travelling' and 'Leisure').

		Date	**Time**	**Event**	**Space**	**Virtual activities**
Studying	SE1	28/02/17	18:23:41	Working	University of Otago	['microsoft onenote', 'Finder', 'Preview', 'blackboard.otago.ac.nz']
		28/02/17	18:24:14	Working	University of Otago	['microsoft onenote', 'Finder', 'Preview', 'blackboard.otago.ac.nz']
	SE2	28/02/17	18:24:44	Working	University of Otago	['microsoft onenote', 'loginwindow']
		28/02/17	18:25:14	Working	University of Otago	['microsoft onenote', 'loginwindow']
		28/02/17	18:25:46	Working	University of Otago	['microsoft onenote', 'loginwindow']
	SE3	28/02/17	18:26:16	Drinking/eating alone	University of Otago	['microsoft onenote', 'loginwindow']
		28/02/17	18:26:46	Drinking/eating alone	University of Otago	['microsoft onenote', 'loginwindow']
Travelling	SE4	28/02/17	18:27:19	Walking outside	University of Otago	['microsoft onenote', 'loginwindow']
		28/02/17	18:27:49	Walking outside	University of Otago	['microsoft onenote', 'loginwindow']
		28/02/17	18:28:19	Walking outside	University of Otago	['microsoft onenote', 'loginwindow']
		…				
Leisure	SE5	28/02/17	20:01:39	Resting	King Edward Court	[]
		28/02/17	20:02:09	Resting	King Edward Court	[]
		28/02/17	20:02:43	Resting	King Edward Court	[]
	SE6	28/02/17	20:03:13	Mobile	King Edward Court	[]

In Table 8.3, we have grouped Student 1's 'space-events' into 'meta space-events': SE1, SE2 and SE3 as 'studying', SE4 as 'travelling', and SE5 and SE6 as 'leisure'.

Using the extended SEM model as a conceptual framework, we can group student 'space-events' across prolonged periods, and subsequently consolidate the three messy datasets of each student into a more relevant narrative of their lived experience according to dimensions of interest. For example, Figure 8.2 below shows one week's data from Student 1, consolidated into four possible 'meta space-events' that have previously been of interest to researchers of the student experience:

- 'studying'—academic activities alone or with peers, such as reading or using academic-oriented computer applications (e.g. Nonis & Hudson, 2006);
- 'travelling'—geospatial movement/relocation between spaces (e.g. Innis and Shaw, 1997);
- 'socialising'—non-academic activities with peers or family, including talking and eating (e.g. Gibney, Moore, Murphy & O'Sullivan, 2011); and
- 'leisure'—non-academic activities alone, including eating and using computer applications of a non-academic nature (e.g. Welker & Wadzuk, 2012).

Note that these are just a few examples of possible 'meta space-events', and is not intended to be an exhaustive inventory of all the potential activities of a student (as an example of other potential categories, Richardson, King, Olds, Parfitt and Chiera, 2019, investigated how long students engage in physical activity, how much sleep they get, and how much 'screen time' they have in a given day). The idea is that student spaces and events can be grouped according to whatever dimensions are relevant at a given time.

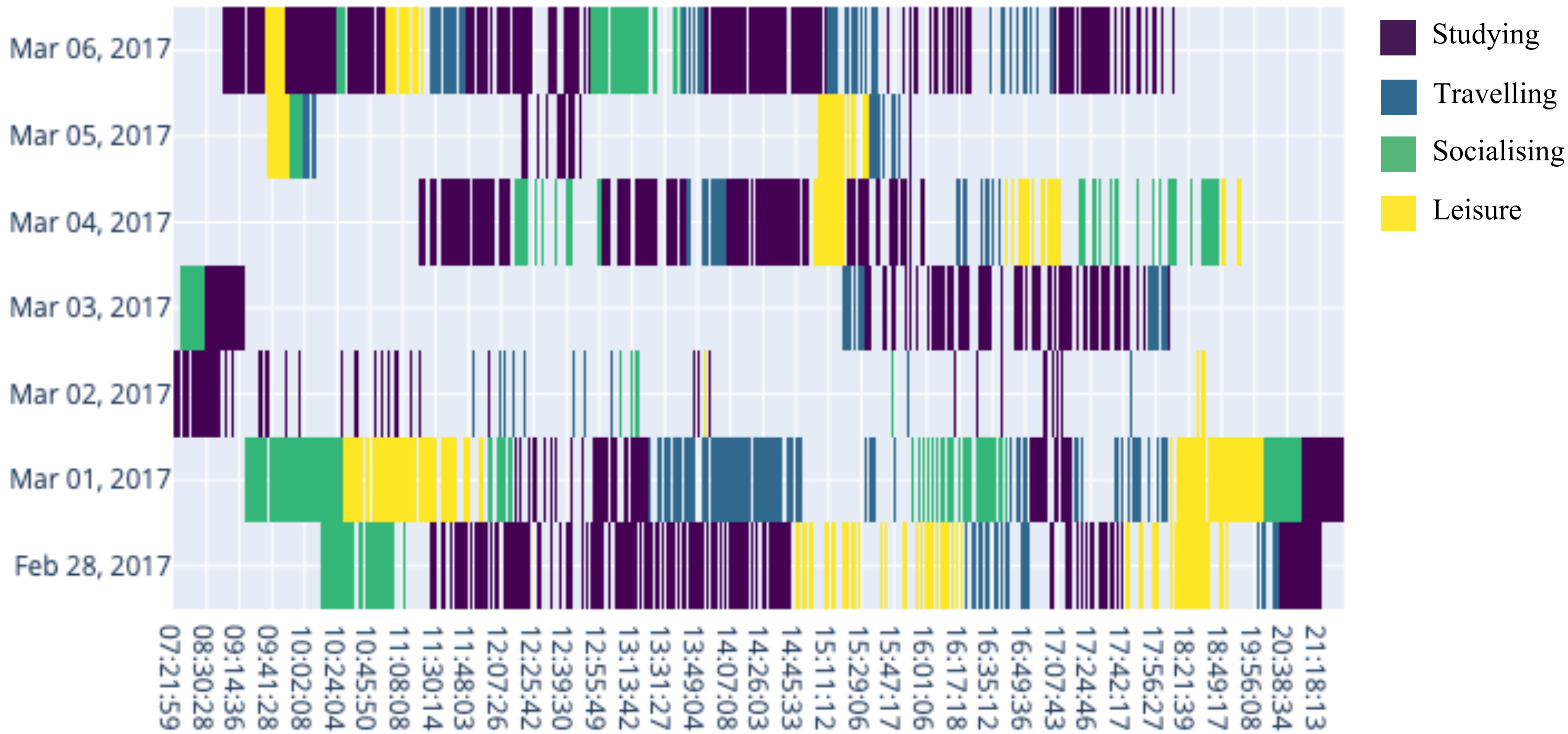


Figure 8.3 One week's worth of data from Student 1, grouped into four example 'meta space-events'-'Studying (purple)', 'Travelling (blue)', 'Socialising (green)', and ‘Leisure (yellow)'.

In this example week, Student 1 spends approximately 50.4% of their recorded time engaged in academic study, 15.2% of their recorded time travelling between spaces, 17% of their recorded time socialising and 17.4% of their recorded time resting or engaged in non-academic activities alone. As has been the case with the analyses in the preceding chapters, the goal is not to try and attribute any 'value' to these activity ratios; as external observers, we have no way of knowing, for example, whether this is a 'good' amount of time spent in academic study versus socialising. The patterns of the 'meta space-events' are still highly contextual and unique to each student.

Thinking back to Jones' (2018) conceptual model of a student ecosystem with different micro and macro influences on student experience, by analysing student activities in terms of 'meta space-events' we can begin to quantify the degree to which various dimensions influence the *overall* student experience. For example, Jones (2018) identifies seven microsystems with which a student interacts, and which subsequently play a role in shaping the student experience—social background, the degree programme, extra curricula activity, preparing for life after graduation, expectations pre-university, transition (settling into student life), and university peer and friendship groups. However, he goes on to say that his model "does not identify the extent of [those microsystem interactions]" and that the model "needs to be developed further to identify how each microsystem might influence an individual student according to his/her individual circumstances" (Jones, 2018, p1047). Similarly, Benckendorff, et al (2009) provide a (non-exhaustive) list of student influences including age, gender, participation in work, and peer and staff interactions, but also do not discuss whether any of these influences play a greater or lesser role in defining student experience.

Borden and Coates' (2017) model of student analytics does provide some quantification of different qualities of student experience in what they term 'student success reports'; these reports attribute weightings to different qualities of student experience (e.g. participation in noncurricular activities or engagement with staff). However, in generating their reports, they also note that most of the data needed to inform these reports are not readily available to institutions, or come from lagged sources such as national surveys. The benefit of the 'meta space-event' approach outlined in this thesis is the use of real-time data, that can be analysed quickly and continuously, and regularly reported back to students.

However, while this provides a conceptual framework to help examine what makes up a student's experience of higher education, we are still left with only part of the story. We can easily capture what students are doing (and where), and use this interpretation of SEM to generalise an individual student's spaces and events into more useful categories (e.g. 'studying' or 'socialising'), but we are still left without any insight into *why* students do the things they do (or *why* they do them in the spaces they do, or at the times that they do).

And herein lies the great irony of my research—that what began as a counter-argument to the heavy use of perception-based data in student experience, has come around to *depending on* that perception data to qualify the metrics. Specifically, the *why* is missing from this equation. I can gather countless hours of activity data to paint a rich picture of 'the student experience' for a given student, but without knowing the reasons behind those activities, there is little to act upon. The frameworks that I explored early in this thesis (e.g. Bronfenbrenner's EST or Tschumi's SEM) seemed useful for describing the relationships between different aspects of student life—for instance, the conception that students operate within a sort of 'ecological system', where different influences shape the overall experience; or the notion that spaces and places are *socially constructed*, and are given meaning only by the activities that take place within them. However, such perspectives are only helpful in describing the *what* of student experience; that is, students go to these places and do these things. But to provide any sort of meaningful feedback, or intervention, there needs the added insight of *why* they go to these places (and not others), and *why* they participate in these practices (and *why* in these specific locations). In the end, balancing the naturally-occurring activity data with perception-based data would result in an *even more holistic* picture of student experience. Of course, the methods to capture these perceptions are not as sophisticated as the methods to capture activity, and thus it remains impossible (at this point in time) to scale this sort of dual-perspective system.

Here, before continuing, I want to clarify my position. Do I think, then, that the idea of 'student analytics' is inherently not useful? Do I think that there are no insights that the institution can derive from gathering these types of student activity data (without corresponding perception data to provide the *why*)? No, of course not. I still believe there is a great deal of value in these data, to researchers and the institution in general. However, the value comes from asking specific questions, and collecting the appropriate data to answer those questions; in a sense, providing the context for the *why* from the beginning. I am not the university. I have no explicit questions about aspects of the student experience that I want answered. By collecting these data, I have demonstrated *how* one might employ a Reality Mining (Eagle & Pentland, 2006) approach in higher education, but not necessarily *why*. As I stated in my introductory chapter:

> I hope my investigation will act as a catalyst to promote interest in the exploration of new methods of research and promote a more contemporary understanding of student experience in higher education.

And I still do. It is my sincere hope that institutional researchers will see something of value in my explorations and take this approach further, applying these types of data capture methods and approaches to answering *real* questions. However, any attempt of mine to try and distil 'meaningful' insights from *these* datasets would ultimately be an exercise in apophenia.

But that is not to say that there is not value in these data that I have collected as they are; there is (currently) an inherent way to get at the *why*. As discussed in Chapter 3, I have embraced the notion of 'students as collaborators'—this has been clear in the informal discussions held with students, and the fact that they had full control over what data ultimately made it into my research. As such, this project has always been about the students, as participants, as researchers, and as the principal beneficiaries of the findings. Working with the undergraduate students, giving them the devices and control over their data, I realised the potential of agency to spark interest and excitement in wanting to learn more, and possibly change particular practices, as a result of actually seeing the representations of their everyday activities. In short, the students *themselves* provide their *own why*. We capture the activity data for them (which is otherwise hidden from their eye), and they carry with them the real-time perception data to readily qualify their metrics, thus completing the picture. I will outline now a growing trend known as the Quantified Self (Wolf & Kelly, 2014), which embodies the principles I am attempting to extol in this discussion.

Quantified Self

'Quantified Self' refers both to the cultural phenomenon of self-tracking with technology and to a community of individuals who share an interest in self-knowledge through numbers (Wolf & Kelly, 2014). The history of continuous data collection using wearable devices goes back decades (Riphagen, van Hout, Kritjnen, & Gootjes, 2013)—from early attempts of shoe company Nike to measure runners' steps in the 1970s (McClusky, 2009), to counter-surveillance ('sousveillance') experiments utilising miniature wearable cameras popularized by Steve Mann (Mann, Nolan, & Wellman, 2003; Mann, 1998). However, the self-tracking of personal metrics for personal development is more contemporary. Quantified Self practices intersect with the practice of lifelogging and other movements that integrate technology and data acquisition into daily life, generally with the aim to improve physical, mental, and/or emotional well-being. The extensive implementation in recent years of wearable trackers such as the Fitbit or the Apple Watch (Lamkin, 2018), combined with the increased presence of Internet of Things, have made self-tracking accessible to a large segment of the population. As Wolf (as cited in "Counting every moment", 2012) noted, "almost everything we do generates data".

Even though the idea of self-tracking is not new, recent technological advances are making it more accessible to the general population. Many people are regularly tracking what they eat or how much physical activity they get within a week. Technology has made it easy to collect and examine these types of personal data. Since these technologies have become smaller and cheaper to be added to smartphones or tablets, it is more straightforward to take the quantitative approaches used in science and business and apply them to the personal domain.

A major application of the Quantified Self movement has been in health and wellness improvement (Oliveira-Barra et al., 2019; Swinhoe, 2018; Hay, 2013). Several devices and services assist with tracking physical movement, caloric intake, sleep quality, posture, and other factors included in personal well-being. Quantified Self approaches are also being used to improve personal or professional productivity (e.g., Meyer et al., 2017) with tools and services being utilised to assist individuals with keeping track of what their daily activities, where they spend their time, and with whom they interact.

The Quantified Self movement is also demonstrating to be a major component of 'big data science', due to the volume of data that users are gathering daily. Although these dataset streams are not standard big data, they become interesting sites for data analysis studies, that could be applied to medical-related fields to foresee health patterns or aid in genomic projects. Examples of studies that have been done using Quantified Self data include projects such as the DIYgenomics studies (Kido & Swan, 2016), the American Gut microbiome project (Debelius et al., 2016), and the Harvard's Personal Genome Project (Ball et al., 2014).

Philosophers like Foucault (1988) are recognised as being a part of the foundations in the ideas of the quantified movement. Foucault's work focuses on the idea of 'care of the self', in which he emphasises the significance of self-knowledge for personal development. Foucault clarifies that it involves looking inside oneself and emphasises self-reflection, which is also associated with the Quantified Self movement. In the context of higher education, 'self-reflection' means critically assessing the ways in which we can improve upon a certain task or performance (Kolb, 1976).

Quantified Self for improving Student Experience—a 'thought experiment'

Thinking about the principles and foundations of the Quantified Self movement, we can theorise scenarios where personal data tracking could play an important role in improving the student experience. Like the work of Einstein that I alluded to in Chapter 3, I will attempt to employ abductive reasoning, with some creative leaps of imagination, in my theorising.

I will start by describing a practice of self-tracking that I engage in myself: personal fitness metrics collected by a wearable FitBit device. The FitBit (worn on the wrist, like a watch) continuously measures my heart rate, my location (via GPS), and the number of steps I take (inferred from an accelerometer sensor of my movement) every day; the corresponding smartphone app performs calculations on the measurements and reports back to me metrics for how 'active' I am each day, how many calories I burn, and even a score for how well I sleep each night. Here, I engage with two levels of personal data—the raw data (i.e., heart rate, GPS), and extrapolations based on aggregated analyses of the raw data (e.g. estimating calories burned from heart rate and movement data, which here are proxies for 'exercise').

The same levels of data capture and analysis are features in our theoretical student experience 'thought experiment'—for example, capturing activities from photostream data or computer usage data, along with location data, and extrapolating academic behaviours such as 'studying'. One could imagine a system similar to the FitBit app which reports back to students, in real-time, a breakdown of their daily activities, and quantifies various behaviours (and, in fact, the RescueTime software attempts to do just this, with a built-in measure of 'productivity', https://www.rescuetime.com).

Another important feature of the FitBit, which is equally applicable in our student experience scenario, is the ability to set personal goals and 'nudges' based on the incoming data. For example, every day I have a step goal which I can set according to my personal fitness requirements; there are also hourly reminders to 'get moving' if the device detects that I am not on track to meet my goal. These motivational features are also components in our student experience system—daily goals for 'work' or 'computer use' or 'socialising', coupled with regular 'nudges' to keep students working towards their personal goals.

Here we see a role for the higher education institution, to provide the necessary infrastructure to bring together various data sources, and report back to students the various metrics that they can use for personal development. And, it is not as if universities are not already doing this to some degree: the fields of 'learning analytics' and 'institutional analytics' are already dedicated to collecting, analysing and reporting on student-related data traces, usually for the purposes of early detection of 'at risk' students (e.g., see Arnold, & Pistilli, 2012, for a review of the Signals learning analytics platform developed at Purdue University). The system I am proposing here, though, is more aligned with the idiographic 'student analytics' concept put forth by Borden and Coates (2017), whereby data is used to enhance each student's personal 'experience' of higher education.

A critical perspective on 'student analytics' and the role of the institution

In this discussion I have questioned how much intrinsic value there is in these sorts of 'student analytics' for the institution; that is if these data are so highly individualised and context-dependent, what capacity is there for the institution to derive insights from them at scale? I have contended that potentially with the right questions, the institution could gather specific 'student analytics' that *could* provide insights in certain cases. However, taking a critical perspective, one question that should be asked is, morally, to what extent the institution should *even be involved* in the capture, analysis and application of these types of personal student data?

Taking a lead from the 'learning analytics' literature (which is a close cousin of the kinds of data capture approaches being discussed here), we see a number of growing concerns in recent years. For example, as learning analytics becomes more entrenched in higher education (and more tied to institutional economic imperatives), there is a danger that such metrics will end up being used less for improving student experiences, and more for progressing the interests of the institution as a political and financially competitive entity (Selwyn, 2019). Further, learning analytics has slipped beyond the walls of academia and is now also the domain of third-party vendors, becoming a billion-dollar industry and introducing new stakeholders into the mix who may not have the students' interests utmost in their priorities. If not approached thoughtfully and responsibly, the area of 'student analytics' could follow similar paths.

'Student analytics' as a primarily institutionally-focussed endeavour (as opposed to student-focussed) also runs the risk of being *perceived* in certain ways by students, simply due to the power dynamic between students and the university. As the 'authority' figure in this relationship, the actions of the institution may be viewed in a certain light by students, even if that view is inaccurate. As Selwyn (2019) notes, there is a danger that analytics gathered by the institution may be perceived as a form of surveillance, rather than as a support mechanism, regardless of actual intentions. Further, Selwyn (2019) also suggests that analytics collected by the institution could be susceptible to 'performativity' influence—that is, if students believe that analytics are being captured by the institution for 'evaluatory' purposes, they may be inclined to produce data that casts them in a particular (favourable) light.

There are also embedded sociotechnical factors in any technological-related endeavour, and these are often overlooked in discussions of the pragmatics or the usefulness of 'doing a thing'. Because these technologies are built and shaped by humans, they are inevitably imbued with the same cultural contexts, political influences, social inequalities, and perspectives and biases as their creators (Kop, Fournier, & Durand, 2017). As Perrotta and Williamson (2018, p. 8) write, "algorithms establish certain forms of 'order', 'pattern' and 'coordination' … and [have the potential] to reinforce, maintain or even reshape visions of the social world, knowledge and encounters with information.". Again, great caution is needed by those engaging with these new data sources, as the unintended 'influencing' of the end users is a distinct possibility.

Although my thesis is very contemporary and future-focussed, many of the ideas I find myself wrestling with in this discussion chapter are not new at all; this central tension between who should use these data/insights and how, relate firmly back to Marxist theories about the individual versus the institution. In particular, I find a number of resonating concepts in the political writings of Henri Lefebvre. For instance, Lefebvre (1969, pp140-141) writes:

> Self-management of all sources of production (to be understood in the broad sense of social production) implies self-management of learning – this is a particular but conspicuous case of self-management viewed as a pedagogy of the totality of social life. This is the only way in which it is possible to strike a decisive blow at the capitalist and bourgeois conception of knowledge as though it were a form of capital.

Here we see mention of the 'pedagogy of the totality of social life', its relation to the self-management of learning, and the rejection that knowledge (or education) should be exploited as a form of capital by the institution. It surprises me at this stage of writing that so many of the ideas that emerged organically from my research are summarised so succinctly in a paragraph from over fifty years ago.

Further, we find Lefebvre (2009, p151) cautioning about the transfer of power of the "electronic and cybernetic methods" of economic management "to the technocrats, machine programmers, serving them as a means for manipulating people." Obviously, Lefebvre was not writing about such modern computer technology or data analytics as I have described in this research; and yet, the fundamental concept about controlling technology in order to manipulate the masses has very modern overtones (below I refer to instances such as the Facebook-Cambridge Analytica data scandal (Persily, 2017) as an example of ethical issues in data capture and analytics research).

In the end, my critical stance represents an age-old struggle, between the individual and the institution. I advocate on the behalf of the student and seek to empower them because ultimately the institution has different goals, and its use of student analytics would invariably serve to drive its own imperatives. By situating the student at the centre of this research, not just as subject or collaborator but also as the primary recipient of the knowledge gained through this journey, my aim is not so much to advance the field of student experience forwards (that is, say something *new* about student experience), but rather sideways, targeting a new audience.

Key considerations for implementing methods using wearable devices

In the following section, I attempt to identify some known challenges around fieldwork, data analysis, and ethics and privacy, and use of data, and suggest actions aimed at mitigating them. This is not expected to be an exhaustive list, and more challenges are likely to come to light as these approaches become more entrenched in the higher education landscape.

Fieldwork

To effectively identify patterns and trends in behaviour, activity data needs to be collected over extended periods of established cycles (e.g. in the case of student behaviour, over a semester or year). While the actual collection of this type of continuously occurring data occurs automatically, considerable effort is required to set up the infrastructure and familiarise participants (and researchers) with the devices and applications involved. This can include up-front training in the use of the devices, and the adherence to daily routines of wearing the devices, charging the devices, and exporting data. The challenges here are around managing the unfamiliarity of these new devices and approaches. It is possible that the novelty of these devices, and newfound access to rich personal data, will act as catalysts for participant engagement and enthusiasm. However, more likely is that some participants will simply forget or neglect processes during the research because they are not familiar or entrenched in their everyday routines. As these devices become more commonplace, this should become less of a concern, but for the immediate researcher, this is something to consider.

Also, somewhat ironically, while the miniature nature of wearables is a benefit for unobtrusive data collection, it may also lead to issues with devices being lost or misplaced. In these situations, to help safeguard against privacy breaches of participant data, it is important to ensure all devices and applications are password protected. Regular meetings with participants are also encouraged to ensure devices are being cared for, and processes adhered to.

Keeping consistency in the data collected is crucial, and as such, this means continuous administration and organisation during fieldwork. The researcher must stay up-to-date with procedural operations and frequently review the incoming data to ensure the devices are functioning correctly. Again, having regular informal meetings with the participants to review their data and troubleshoot any technical issues can help in this regard. Having regular interaction with the participants has the added benefit of building rapport and establishing a trusting relationship, something which is important in overcoming any suspicions or concerns around data usage or privacy (i.e. alleviating surveillance concerns, described in more detail later).

Data storage and management

In general, the mining of continuous data will generate large and complex datasets. As such, traditional data processing applications and techniques may be inadequate, and specialist software or computer equipment may be needed. Using multiple devices for data capture may result in datasets of different formats (e.g. image data from cameras, movement data from GPS, etc.), and researchers may need new and innovative data management tools, and frameworks designed to support coupling these various datasets—the integration of huge datasets can become quite intricate, and researcher upskilling may be required. The amount of data coming in by continuous data capture may also quickly become overwhelming and unmanageable if appropriate management processes are not established and adhered to by researchers. And, with new data being generated at such a rapid pace, constant and careful monitoring is needed to identify and respond to issues quickly and effectively.

Analysis

As well as challenges in actually capturing and managing data from wearable devices, there are considerations for analysing, interpreting and representing such data. Traditionally, observational research has involved manual processes of assigning labels and descriptions to recorded data. However, the volumes of the data generated from Reality Mining approaches render manual analysis inadequate. Instead, automated computer techniques are required to handle identification and clustering of these massive datasets (such as the GPS algorithms or Computer Vision techniques described earlier).

While these types of analyses have proven useful at extracting information about the lived experience from Reality Mining datasets, the approaches are highly specialised and likely to be beyond the capacity of many researchers. As such, for this type of research to become more ingrained in higher education, researchers may be required to upskill in new areas of computer processing and machine learning or seek new collaborations with experts in these fields.

Finally, there are also challenges in collating and presenting the findings of such analyses; traditional tables and graphs are typically inadequate at effectively communicating patterns and differences in these large and complex datasets. Instead, new and innovative data visualisation techniques will need to be used, such as heatmaps and network diagrams, which can better illustrate the relationships in the data.

Ethics and privacy

This type of data collection brings with it a host of ethical and privacy concerns, both in terms of perceived surveillance and the capture of personal data. Today, social media and the pervasion of apps and sites that actively or passively capture behavioural data *en masse* can lead users to feel uneasy about practices that appear to be surveillance. The perception of personal data being constantly recorded and used, potentially without the awareness or consent of those involved (e.g. the ‘Big Brother’ or ‘information panopticon’ phenomenon, Zuboff, 1988), have stifled the progress of Reality Mining research being more widely applied (Oliver & Vayre, 2015). This is not helped by events such as the recent Facebook-Cambridge Analytica data scandal (Persily, 2017), which revealed that millions of Facebook users unwillingly had their personal data used to influence election results; or the recent reports of Google tracking users' locations even when they explicitly turn these features off (Gibbs, 2017). For higher education, such concerns have also been raised with learning analytics (Pardo & Siemens, 2014).

The Reality Mining approach I advocate through this thesis is different—my belief is that these data mining approaches open up possibilities for end users to own, use and see value in their own behavioural and activity data. In commercial applications, typically, such data mining is macroscopic; that is, companies are interested in large-scale capture of digital footprints or traces, mining social networks and consumer activities to uncover inherent patterns of behaviour. My approach is aimed at the individual, and predominantly seeks to empower students to own and use their data for self-edification.

The use of wearable devices such as cameras for Reality Mining research also raises a number of ethical and legal concerns around the capture of personal (and personally-identifying) information, specifically by those not directly involved in the research. Because these devices are continuously worn throughout the day, it is likely they will capture members of the public. However, it is impractical to obtain informed consent from every person within the study location. Usually, the privacy laws of the country dictate where or when photographs can be taken. For example, in New Zealand, it is generally lawful to take photographs of people in public places without their consent (New Zealand Police, 2020, https://www.police.govt.nz/faq/items/23297), so long as they are in a place where there is no expectation of privacy, such as beach, park or other public places. However, photographs cannot be taken in places where people would reasonably expect privacy (such as public toilets and changing areas), or if the taking of photographs could interfere with other people's use and enjoyment of the same place. While third parties are not the intended subject of the images, I nevertheless feel that the privacy of those who do not consent to be a part of the research must be protected. This can be done through actions such as de-identifying any materials (e.g. blurring photographs) prior to publishing or disseminating research findings.

Continually recording the wearer's environment also raises concerns for participant privacy, particularly in relation to the capture of potentially sensitive or inappropriate data (the inadvertent capture of a personal password, for instance). In these cases, the devices are under the control of the participant, who can view and remove or censor any data prior to its use by researchers. It is also incumbent for researchers to be vigilant and delete any personally identifiable information on behalf of the participant before allowing anyone else to view it.

Use of data

As mentioned, one of the emergent benefits of this study was that students could utilise their own data for self-improvement; however, this only became apparent as a principal 'takeaway' from this research *after* primary data collection had ended. As such, I did not follow-up with this cohort of students on this particular angle in any formal way (that is, do they actually find these types of data useful for informing their daily practices).

If institutions want to utilise such data, they need to be mindful of the limitations. For example, while the data can reveal where students go and what they do, they cannot tell us *why* they are behaving in this way. Thus, if wanting to find out *why* students behave in certain ways, researchers need to couple these new methods with more traditional methods that ask students why.

The future of higher education

As I write this discussion, an article has been published in the New York Times about the future of higher education (Marcus, 2020); and it occurs to me that my thesis may be written for an institution that does not yet exist. The New York Times article talks about a very different model of higher education, where students 'subscribe' to courses rather than enrol in semesters, and have their questions answered by AI chatbots. It may sound somewhat far-fetched, but the truth is that some universities are already playing around with these new ideas. And we have already seen rapid evolution (and in some cases, revolution) in several other industries—streaming media replacing music and video stores (Te, 2019; Yap, 2017); online shopping disrupting the postal service (Ramstad, 2019; Lierow, Janssen, & D'Incà, 2016); and companies such as Uber, Lime and AirBnB turning traditional taxi and hotel industries on their heads (Alton, 2016).

Universities will not be able to cling to traditional notions of what their role is, or what the student's role is, in the wake of such changes. As the technologies that allow for 'anytime/anywhere' experiences become ever-pervasive in our society, the next generations of students will demand more from their 'student experience'. And their data will be key in making this a success. The other aforementioned industries are already using customer data to personalise experiences, providing dashboards and insights into behaviour that feed into future decision-making. And so, too could higher education.

In the end, my research is about possibilities, and a call to action for universities to re-examine their practices in the light of a new era. As Jones (as cited in Marcus, 2020, para. 7) states, "Universities may be at the cutting edge of research into almost every other field … but when it comes to reconsidering the structure of their own … they've been very risk-averse." I have taken a number of new technologies, methodologies and ideas and shown what is possible for the future of student experience. The fact that I have few 'answers' at this stage is not the point; indeed, these case studies may not prove useful to anyone outside of the original participants. The methods I have tried out here made sense to me, and were convenient to trial; there are many other cutting-edge approaches that could provide insights into aspects of the student experience from wearable devices capable of measuring the 'body voice', such as sleep patterns (Sano, Taylor, Jaques, Chen, & Martinez, 2018; de Zambotti et al., 2016), stress through Heart Rate Variability (HRV) and Electrodermal Activity (EDA) (Lima, Osório, & Gamboa, 2019; Posada-Quintero, Dimitrov, Moutran, Park, & Chon, 2019), or cognitive load through fNIRS and EEG (Morales, Ruiz-Rabelo, Diaz-Piedra, & Di Stasi, 2019; Tan, Kerr, Sullivan, & Peake, 2019). But again, it is not so much about urging universities to simply implement these technologies, or adopt these approaches, but rather rethink their purpose, their goals, and their relationship with their students in light of new innovations.

What then is the role of the institution in this ‘futuristic’ scenario? Much in the same way that the university provides advising on what courses to take, or provides pastoral care for students, there is a need for guidance on interpreting and acting on this type of data. For instance, I can collect data on my FitBit about my daily exercise habits and set my own goals for how many minutes to be active or how many steps to take in a day, but I still need some guidance on what those goals should be.

This all seems very forward-thinking and ‘creative’ but reflecting on the current state of affairs across the world (the novel coronavirus) it would seem more pertinent than ever to be thinking about how the future might look. So, if I must end with recommendations for the institution, let it be these: look forward, and be creative! Redefine student experience. Embrace new technologies and new possibilities. Ultimately, be open to re-envisioning the structure and role of the institution. The ‘university’ as we know it is changing; perhaps not as fast it should, but quicker than we might realise. In much the same way as our students change each generation and bring with them a unique set of behaviours and expectations into the campus environment. Note that I am not advocating to ‘throw out’ the entirety of the old system in favour of something radically new; there is scope to integrate the types of methods outlined in this thesis into existing structures. As such, there is much need for further research into the methodologies and approaches I have experimented with here. Mine were the first exploratory steps (or in the words of Lefebvre (1991), “tentative sketches for these future techniques”) into a brave new world of holistic, idiographic ‘student analytics’; I wanted to know what was possible, and to test the limits of the technology, the readiness of the participants, and myself as a researcher. I did not know what was going to be useful when I started, and truth be told, I am unsure how much of what I have done is useful now at the other end. But I have taken the first steps; I have shown that there is something worth looking at, and it is now up to others in the higher education research community to follow in my footsteps and explore the bounties that this new frontier has to offer.

Conclusion

As higher education evolves, so too must its methods of interrogation. Whether or not the students of today are fundamentally ‘different’ than previous generations is a matter of scholarly debate; however, what is different is the type of data they now generate, and the means by which it can be collected and studied. With wearable devices becoming increasingly popular in society, particularly among younger generations, we can now collect data about spaces visited, events undertaken, habits of study, eating and fitness, and even biometric data such as stress levels at unprecedented scale and fidelity.

By employing new methods, we, as researchers, find ourselves in a new position to start interrogating some of these ‘other’ aspects of student life, not previously available to us. New methods of capturing data of a person’s ‘lived experience’ (and, equally, new ways of thinking about what data is, and how it can be used) mean we can look into aspects of students’ lives not previously considered in higher education research. We can now capture continuous naturally occurring activity data that is: objective (as compared to perception-based data, such as that from surveys or interviews); unobtrusively collected; and easily quantified for analysis and reporting. What was once a time-consuming and laborious process of observation for gathering behaviour and activity data, now happens automatically and passively, opening up a new world of discovery.

Moreover, higher education can empower students to track and analyse their own activity, helping them to potentially uncover useful insights from their daily student life. Analysed data by the institution can be presented back to students in the form of dashboards that are based on personal targets, thresholds and long-term behavioural goals. By providing accurate representations of activity (rather than leaving students to rely on their perceptions of their activity), it is possible students may identify undesirable patterns of behaviour and make changes. This already happens in other contexts, for example, the movement known as the Quantified Self.

In higher education, we know this process of self-evaluation for improvement as reflective learning: the act of learning by returning to and evaluating past performances and personal experiences to promote continuous learning and improve future experiences (Kolb, 1976). The difficulty has been the reliance on self-discipline to activate these feedback loops. The power of Reality Mining, however, lies in its ability to furnish evaluative data on-the-fly over extended periods without the need for diligence and discipline. This highly dynamic state means students are engaged in a rapid closed-loop feedback model that can be viewed by the minute, hour, day or week. The result is students actively involved in understanding their own habits, behaviours and activities to ultimately become better at what they do.

This thesis looked at the student experience using new and innovative research methods. While the ultimate ‘findings’ were more philosophical than originally anticipated, this research nonetheless prompted a great deal of reflection on the use and usefulness of these new methods for higher education. It is hoped that the ideas explored here will stimulate an interest in reviewing the dominant methods of research in higher education and encourage researchers to trial new research approaches to provide a more holistic representation of the lived experience of students. There is still a great deal to be explored here; mine are but the first steps into a brave new world. But I truly believe it is a matter of *when* and not *if* higher education will be forced to revise its traditional notions of students, data, and ultimately, its purpose in our society.

She's so self-conscious
She has no idea what she's doing in college
That major that she majored in don't make no money
But she won't drop out, her parents will look at her funny
Now, tell me that ain't insecure
The concept of school seems so secure
Sophomore three years ain't picked a career.

—

Kanye West, *All Falls Down*
(West, 2004, track 4)

POSTSCRIPT : RESEARCH JOURNAL

In an effort to remain transparent and honest in my research in this section of the PhD I describe my personal journey through formulating the research project, conducting it and seeing it in action, as well as making inferences from the data by letting the data speak to me.

Developing the area of inquiry

To begin the process of framing a research question, detailed research was required to successfully write and gather the material to recognize the gaps in the current research. This required plenty of hard work and dedication to stay focused and on task.

The topic of my PhD project involves understanding what it means to 'be a student' for undergraduate health science students studying at the University of Otago. The fundamental enquiry underpinning my project is the exploration of the 21st century student experience. I chose this particular topic based on my experiences/findings from my Master's research project. I noticed how most of the literature around student experience is based on perception-based data rather than actual practice data. This realisation encouraged me to understand student experience through the use of digital devices, to be able to capture naturally occurring, continuous student data, and a PhD project was the perfect opportunity to explore this concept.

Establishing a relationship with supervisors

Russell – Having worked with Russell during my Master's studies made my transition into the PhD easier. During the development of my research topic, I had his constant guidance and support. He and I would meet regularly to discuss the progress of my project. Having someone experienced to understand and guide me through my project has been very beneficial for me.

Rachel – I did not really know Rachel before starting my PhD; she is the Dean of the Graduate Research School (GRS), so I was a little intimidated in the beginning. But now I have established a good working relationship with her, and I feel more comfortable discussing issues and ideas with her.

Both my supervisors have been closely involved in helping me design concepts for the research and the process of narrowing down my research topic.

Device testing including camera, GPS device and phone apps, and RescueTime software

To make sure I had the basic idea of how the devices and data capture techniques work, it was essential for me to carry out some device testing. This took place over a one-week period, and it gave me the chance to experience and record the process/methods as well as develop some themes around the spatiotemporal patterns of students' daily movements.

Trial data capture from three undergraduate health science students

Before gathering the data, I thought it would be prudent to do preliminary diagnostic explorations. Good data gathering depends on data that is collected using viable and reliable measures, and these, in turn, depend on developing concepts based on empirical research. In this instance, I needed to know (1) the students' opinions of the functioning of the digital capture devices; and (2) something about student activity/behaviours as observed/captured by these digital capture devices. A trial data capture from three undergraduate students, over a one-week period, allowed me to do so.

Doctoral visit to the Universitat de Barcelona

During the final stage of data collection, I got the opportunity to visit the Universitat de Barcelona. I was invited by Dr Petia Radeva from the Department of Mathematics and Computer Science, to work alongside her and her team as a visiting doctoral student for one month in July. I was based in the Computer Science Faculty while at the university. I used this opportunity to analyse some of my data in their image analysis lab. I have since continued to work closely with Petia and her team on the detailed analysis of the images from the student participants and on papers for publication regarding the use of convolutional neural networks for image analysis. During my time in Barcelona, I also presented at the EDULearn (International Conference on Education and New Learning Technologies) conference.

Continuing a relationship with the participants

Due to the sensitive nature of the data collected from the participants, I believe that it is truly important for me to keep them informed of all the different activities (e.g., analysis, publications and conference presentations as well as involving other collaborators) that occur during the project.

One goal of the project is to give back to the students in terms of student awareness of their own identity/life, and it has been especially rewarding for me to see the students' continued willingness to be involved in and their curiosity to learn about the project.

I have set up an online platform (SharePoint) for the project called SEM, where students can view exactly what is happening with their data and can benefit from learning more about themselves. We also have regular coffee catch-ups to see how everyone is feeling about the use of their data in the study so far.

My understanding

During my time at the university, I learned a lot about how students learn both in the classroom and in their independent study time, and gained a broader understanding of the student experience, both through my own research and working with colleagues from across the institution. My Master's degree was specifically focused on student study habits, and particularly about the connection between different study strategies and learning theories. My PhD topic takes this research one step further and examines the extracurricular influences on a student's time at university, and how these can affect academic performance and well-being. I believe my experiences working with students, as well as in-depth research into their study habits, give me unique insights into the challenges facing students today. I am enthusiastic and passionate about education, and want to use my knowledge and skills to improve the experiences of all students; I know first-hand how difficult tertiary study can be, and how important it is to have strong support structures available.

REFERENCES

Acker, S. R., & Miller, M. D. (2005). Campus learning spaces: Investing in how students learn. *EDUCAUSE Center for Applied Research Bulletin*, 2005(8), 1.

Adjei, S. A., Botelho, A. F., & Heffernan, N. T. (2016, April). Predicting student performance on post-requisite skills using prerequisite skill data: an alternative method for refining prerequisite skill structures. In *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge* (pp. 469-473).

Afif, M. R. (2019, March). Millennials Engagement: Work-Life Balance VS Work-Life Integration. In *Social and Humaniora Research Symposium (SoRes)*. Atlantis Press.

Aghaei, M. (2017, November). Social signal extraction from egocentric photo-streams. In *Proceedings of the 19th ACM International Conference on Multimodal Interaction* (pp. 656-659).

Aghaei, M., Dimiccoli, M., & Radeva, P. (2016). Multi-face tracking by extended bag-of-tracklets in egocentric photo-streams. *Computer Vision and Image Understanding*, 149, 146-156.

Ainley, P. (2008). The varieties of student experience–an open research question and some ways to answer it. *Studies in Higher Education*, 33(5), 615-624.

Altbach, P. G., Reisberg, L., & Rumbley, L. E. (2019). *Trends in global higher education: Tracking an academic revolution*. Brill.

Alton, L. (2016, April 11). *How Purple, Uber and Airbnb Are Disrupting and Redefining Old Industries*. Retrieved from https://www.entrepreneur.com/article/273650

Andersen, C. K., Wittrup-Jensen, K. U., Lolk, A., Andersen, K., & Kragh-Sørensen, P. (2004). Ability to perform activities of daily living is the main factor affecting quality of life in patients with dementia. *Health and quality of life outcomes*, 2(1), 52.

Anderson, H. J., Baur, J. E., Griffith, J. A., & Buckley, M. R. (2017). What works for you may not work for (Gen) Me: Limitations of present leadership theories for the new generation. *The Leadership Quarterly*, 28(1), 245-260.

Andone, D., Boyne, C. W., Dron, J., & Pemberton, L. (2005). Digital students and their use of e-learning environments. 302-306. In *Proceedings of the IADIS International Conference.*

Arksey, H., & Knight, P. T. (1999). *Interviewing for social scientists: An introductory resource with examples*. Sage.

Arnold, K. E., & Pistilli, M. D. (2012, April). Course signals at Purdue: Using learning analytics to increase student success. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 267-270).

Arnstein, S. R. (1969). A ladder of citizen participation. *Journal of the American Institute of planners*, 35(4), 216-224.

Asimov, I. (1956). The last question. *Science Fiction and Philosophy*, 279-289.

Baghramian, M., & Carter, J. A. (2015). Relativism. *Stanford Encyclopedia of Philosophy*, pp. 1-60.

Bagnoli, A. (2009). Beyond the standard interview: The use of graphic elicitation and arts-based methods. *Qualitative research*, 9(5), 547-570.

Ball, M. P., Bobe, J. R., Chou, M. F., Clegg, T., Estep, P. W., Lunshof, J. E., Vandewege, W., Zaranek, A. W., & Church, G. M. (2014). Harvard Personal Genome Project: lessons from participatory public research. *Genome medicine*, 6(2), 10.

Barnum, C. M. (2011). *Usability testing essentials: ready, set--test*. Burlington, MA: Morgan Kaufmann Publishers.

Behadili, S. (2016). *Adaptive Modeling of Urban Dynamics with Mobile Phone Database* (Doctoral dissertation).

Benckendorff, P., Ruhanen, L., & Scott, N. (2009). Deconstructing the student experience: A conceptual framework. *Journal of Hospitality and Tourism Management*, 16(1), 84-93.

Benckendorff, P., & Zehrer, A. (2017). *The future of teaching and learning in tourism. In Handbook of teaching and learning in tourism*. Edward Elgar Publishing.

Berger, D., & Wild, C. (2016). The Teaching Excellence Framework: would you tell me, please, which way I ought to go from here. *Higher Education Review*, 48(3).

Bergold, J., & Thomas, S. (2012). Participatory research methods: A methodological approach in motion. *Historical Social Research/Historische Sozialforschung*, 191-222.

Bernstein, R. J. (2011). *Beyond objectivism and relativism: Science, hermeneutics, and praxis*. University of Pennsylvania Press.

Birenboim, A., Anton-Clavé, S., Russo, A. P., & Shoval, N. (2013). Temporal activity patterns of theme park visitors. *Tourism Geographies*, 15(4), 601-619.

Bliuc, A. M., Goodyear, P., & Ellis, R. A. (2017). The role of students' social identities in fostering high-quality learning in higher education. In K. I. Mavor, M. J. Platow, & B. Bizumic (Eds.), *Self and Social Identity in Educational Contexts* (pp. 211-222). Routledge.

Bloch, R., & Mitterle, A. (2017). On stratification in changing higher education: the “analysis of status” revisited. *Higher Education*, 73(6), 929-946.

Bolanos, M., Dimiccoli, M., & Radeva, P. (2016). Toward storytelling from visual lifelogging: An overview. *IEEE Transactions on Human-Machine Systems*, 47(1), 77-90.

Booth, M. (2012). Learning Analytics: the new black. *Educause Review*, *47*(4), 52-53.

Borden, V. M., & Coates, H. (2017). Learning analytics as a counterpart to surveys of student experience. *New Directions for Higher Education*, 2017(179), 89-102.

Brayton, J., Ollivier, M., & Robbins, W. (2014). *Introduction to feminist research*. Retrieved from https://www2.unb.ca/parl/research.htm

Brewer, J., & Hunter, A. (1989). *Multimethod research: A synthesis of styles*. Sage Publications, Inc.

Bronfenbrenner, U. (1977). Toward an experimental ecology of human development. *American psychologist*, 32(7), 513.

Bronfenbrenner, U. (1994). Ecological models of human development. *Readings on the development of children*, 2(1), 37-43.

Bronfenbrenner, U. (1999). Environments in developmental perspective: Theoretical and operational models. In S. L. Friedman & T. D. Wachs (Eds.), *Measuring* *environment across the life span: Emerging methods and concepts* (pp. 3– 28). Washington, DC: American Psychological Association.

Brooks, A. (2007). *Reconceptualizing representation and identity: Issues of transculturalism and transnationalism in the intersection of feminism and cultural sociology*. Sage Publishing/Sage Publications.

Brown, S. (2017). How generations x, y and z may change the academic workplace. *Chronicle of Higher Education*, 64, 19-19.

Buissink-Smith, N., Spronken-Smith, R., & Grigg, G. (2008). Understanding the Millennial Generation: Can the Literature Go Down Under?. *New Zealand Journal of Educational Studies*, 43(1), 127.

Burak L. (2012). Multitasking in the university classroom. *International Journal for the Scholarship of Teaching and Learning*, 6(2), 1–12.

Burnore, N. (2013). *Social Media Application for Unconventional Warfare*. Master's thesis, Command and General Staff College, Fort Leavenworth, KS.

Busari, A. A., Osuolale, O., Omole, D. O., Ojo, A. A., & Jayeola, B. (2015). Travel behaviour of university enviroment: inter-relationship between trip distance and travel mode choice in south-western Nigeria. *International Journal of Applied Engineering Research*, 10(21), 42362-42366.

Butson, R. (2019). *The Office: The impact of the digital revolution on the office practices of early career academics* (Doctoral dissertation, University of Otago).

Buzwell, S., Bates, G.W., McKenzie, J., Alexander, S., Williams, J.S, Farrugia, M.M., & Crosby, A. (2016). *Valuing student voices when exploring, creating and planning for the future of Australian higher education*. Office for Learning and Teaching. Department of Education. Melbourne, Australia.

Calabrese, F., Smoreda, Z., Blondel, V. D., & Ratti, C. (2011). Interplay between telecommunications and face-to-face interactions: A study using mobile phone data. *PloS one*, 6(7).

Cameron, M. P., & Siameja, S. (2017). An experimental evaluation of a proactive pastoral care initiative within an introductory university course. *Applied Economics*, 49(18), 1808-1820.

Chandler, L., & Potter, A. (2012). Failure as Opportunity-reflection and Retention: Approaches to Supporting First Year University Students Experiencing Early Assessment Failure. *International Journal of Learning*, 18(7).

Caplan, S. (1990). Using focus group methodology for ergonomic design. *Ergonomics*, 33(5), 527-533.

Cartas, A., Marín, J., Radeva, P., & Dimiccoli, M. (2017, June). Recognizing activities of daily living from egocentric images. In *Proceedings of the Iberian Conference on Pattern Recognition and Image Analysis* (pp. 87-95). Springer, Cham.

Chatti, M. A., Dyckhoff, A. L., Schroeder, U., & Thüs, H. (2013). A reference model for learning analytics. *International Journal of Technology Enhanced Learning*, 4(5-6), 318-331.

Cheng, M. W., & Chan, C. K. (2020). Do university residential experiences contribute to holistic education?. *Journal of Higher Education Policy and Management*, 42(1), 31-48.

Cheung, Y. K., Hsueh, P. Y. S., Qian, M., Yoon, S., Meli, L., Diaz, K. M., Schwartz, J. E., Kronish, I. M. & Davidson, K. W. (2017). Are Nomothetic or Ideographic Approaches Superior in Predicting Daily Exercise Behaviors?. *Methods of information in medicine*, 56(06), 452-460.

Coates, H., Kelly, P., Naylor, R., & Borden, V. (2016). Innovative approaches for enhancing the 21st century student experience. *Alternation Journal*, 23(1), 62-89.

Cohen, L., Manion, L., Morrison, K., & Morrison, R. B. (2007). *Research methods in education*. Routledge.

Compagnat, M., Mandigout, S., David, R., Lacroix, J., Daviet, J. C., & Salle, J. Y. (2019). Compendium of physical activities strongly underestimates the oxygen cost during activities of daily living in stroke patients. *American Journal of Physical Medicine & Rehabilitation*, 98(4), 299-302.

Cone, J. D. (1986). Idiographic, nomothetic, and related perspectives in behavioral assessment. *Conceptual foundations of behavioral assessment*, 111-128.

Conner, T. S., Tennen, H., Fleeson, W., & Barrett, L. F. (2009). Experience sampling methods: A modern idiographic approach to personality research. *Social and personality psychology compass*, 3(3), 292-313.

Conole, G., De Laat, M., Dillon, T., & Darby, J. (2008). 'Disruptive technologies', 'pedagogical innovation': What's new? Findings from an in-depth study of students' use and perception of technology. *Computers & Education*, 50(2), 511-524.

Cooper, A. (2012). What is analytics? Definition and essential characteristics. *CETIS Analytics Series*, 1(5), 1-10.

Cotton, D. R., Stokes, A., & Cotton, P. A. (2010). Using observational methods to research the student experience. *Journal of Geography in Higher Education*, 34(3), 463-473.

Coulson, J., Roberts, P., & Taylor, I. (2015). *University planning and architecture: The search for perfection*. Routledge.

Counting every moment. (2012, March 3). Retrieved from https://www.economist.com/technology-quarterly/2012/03/03/counting-every-moment

Crane, L., Kinash, S., Bannatyne, A., Judd, M.-M., Eckersley, B., Hamlin, G., Partridge, H., Richardson, S., Rolf, H., Udas, K., & Stark, A. (2016). *Engaging postgraduate students and supporting higher education to enhance the 21st century student experience.* Final report prepared for Australian Government Office for Learning and Teaching.

Daniel, B. K., & Bird, R. (2019). Attention! Student Voice: Providing Students with Digital Learning Materials before Scheduled Lectures Improves Learning Experience. *Turkish Online Journal of Educational Technology-TOJET*, 18(3), 1-9.

Davies, R. (1968). People Take Pictures of Each Other. [Recorded by The Kinks]. On *The Kinks Are The Village Green Preservation Society* [CD]. USA: Reprise Records.

Debelius, J. W., Vázquez-Baeza, Y., McDonald, D., Xu, Z., Wolfe, E., & Knight, R. (2016). Turning participatory microbiome research into usable data: lessons from the American Gut Project. *Journal of microbiology & biology education*, 17(1), 46.

Debes, C., Merentitis, A., Sukhanov, S., Niessen, M., Frangiadakis, N., & Bauer, A. (2016). Monitoring activities of daily living in smart homes: Understanding human behavior. *IEEE Signal Processing Magazine*, 33(2), 81-94.

Deed, C., & Alterator, S. (2017). Informal learning spaces and their impact on learning in tertiary education: Framing new narratives of participation. *Journal of Learning Spaces*, 6(3).

De Groot, M., Drangsholt, M., Martin-Sanchez, F. J., & Wolf, G. (2017). Single subject (N-of-1) research design, data processing, and personal science. *Methods of information in medicine*, 56(06), 416-418.

de Montjoye, Y. A., Quoidbach, J., Robic, F., & Pentland, A. S. (2013, April). Predicting personality using novel mobile phone-based metrics. In *Proceedings of the International Conference on Social Computing, Behavioral-cultural Modeling, and Prediction* (pp. 48-55). Springer, Berlin, Heidelberg.

de Zambotti, M., Baker, F. C., Willoughby, A. R., Godino, J. G., Wing, D., Patrick, K., & Colrain, I. M. (2016). Measures of sleep and cardiac functioning during sleep using a multi-sensory commercially-available wristband in adolescents. *Physiology & behavior*, 158, 143-149.

Dimiccoli, M. (2018). Computer Vision for Egocentric (First-Person) Vision. In L. Marco, & G. M. Farinella (Eds.), *Computer Vision for Assistive Healthcare* (pp. 183-210). Academic Press.

Dimiccoli, M., Cartas, A., & Radeva, P. (2019). Activity recognition from visual lifelogs: State of the art and future challenges. In X. Alameda-Pineda, E. Ricci, & N. Sebe, (Eds.), *Multimodal Behavior Analysis in the Wild* (pp. 121-134). Academic Press.

Ding, F. (2017). "Free in time, not free in mind": First-year university students becoming more independent. *Journal of College Student Development*, 58(4), 601-617.

Duit, R., & Treagust, D. F. (2012). How can conceptual change contribute to theory and practice in science education?. In B. Fraser, K. Tobin, & C. J. McRobbie, (Eds.), *Second international handbook of science education* (pp. 107-118). Springer, Dordrecht.

Eagle, N., & Pentland, A. S. (2006). Reality mining: sensing complex social systems. *Personal and ubiquitous computing*, 10(4), 255-268.

East, D., Osborne, P., Kemp, S., & Woodfine, T. (2017). Combining GPS & survey data improves understanding of visitor behaviour. *Tourism Management*, 61, 307-320.

Edwards, D., & Griffin, T. (2013). Understanding tourists' spatial behaviour: GPS tracking as an aid to sustainable destination management. *Journal of Sustainable Tourism*, 21(4), 580-595.

Farrugia, D. (2015). Space and place in studies of childhood and youth. In J. Wyn & H. Cahill (Eds.), *Handbook of children and youth studies*. Singapore: Springer, 609–624.

Ferdous, M. S., Chowdhury, S., & Jose, J. M. (2017). Analysing privacy in visual lifelogging. *Pervasive and Mobile Computing*, 40, 430-449.

Ferguson, R. (2012). Learning analytics: drivers, developments and challenges. *International Journal of Technology Enhanced Learning*, 4(5/6), 304-317.

Ferguson, R., & Clow, D. (2015, March). Examining engagement: analysing learner subpopulations in massive open online courses (MOOCs). In *Proceedings of the Fifth International Conference on Learning Analytics and Knowledge* (pp. 51-58).

Fitzgibbon, K., & Prior, J. (2010). The changing nature of students' social experience within university. *Journal of Applied Research in Higher Education*, 2(1), 25-32.

Flogie, A., & Aberšek, B. (2019). *The Impact of Innovative ICT Education and AI on the Pedagogical Paradigm*. Cambridge Scholars Publishing.

Foucault, M. (1988). *Technologies of the self: A seminar with Michel Foucault*. University of Massachusetts Press.

Framingham, M. (2019). *IDC Reports Strong Growth in the Worldwide Wearables Market, Led by Holiday Shipments of Smartwatches, Wrist Bands, and Ear-Worn Devices*. Retrieved from https://www.idc.com/getdoc.jsp?containerId=prUS44901819

Frith, H., Riley, S., Archer, L. and Gleeson, K. (2005). Editorial: imagining visual methodologies. *Qualitative Research in Psychology*, 2: 187–198.

Fuentes-García, A. (2014). Katz activities of daily living scale. *Encyclopedia of quality of life and well-being research*, 3465-3468.

Fulford, A., & Mahon, A. (2018). *A philosophical defence of the traditional lecture*. Times Higher Education.

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends*, 59(1), 64-71.

Gibbs, S. (2017). *Google has been tracking Android users even with location services turned off*. Retrieved from https://www.theguardian.com/technology/2017/nov/22/google-track-android-users-location-services-turned-off-sim

Gibney, A., Moore, N., Murphy, F., & O'Sullivan, S. (2011). The first semester of university life;'will I be able to manage it at all?'. *Higher Education*, *62*(3), 351-366.

Goffman, E. (1959). *The Presentation of Self in Everyday Life*. United States: Doubleday.

Gonzales, F. (2015). *Reinventing the company in the digital age*. Turner.

Greller, W., & Drachsler, H. (2012). Translating learning into numbers: A generic framework for learning analytics. *Journal of Educational Technology & Society*, 15(3), 42-57.

Gravina, R., Alinia, P., Ghasemzadeh, H., & Fortino, G. (2017). Multi-sensor fusion in body sensor networks: State-of-the-art and research challenges. *Information Fusion*, 35, 68-80.

Grov, E. K., Fosså, S. D., & Dahl, A. A. (2017). A controlled study of the influence of comorbidity on activities of daily living in elderly cancer survivors (the HUNT-3 survey). *Journal of geriatric oncology*, 8(5), 328-335.

Guillemin, M. (2004). Understanding illness: Using drawings as a research method. *Qualitative health research*, 14(2), 272-289.

Hanewicz, C. (2009, August). Identifying student retention patterns using GIS technology. In *Proceedings of the Portland International Conference on Management of Engineering & Technology* (pp. 2231-2239). IEEE.

Haque, M., Sa, B., Majumder, M. A. A., Islam, M. Z., Othman, N. S. A. B., Lutfi, S. N. N. B., Kibria, G. M., Salam, A., Ismail, M. H., & Abdullah, S. L. (2018). Empathy among undergraduate medical students: A cross-sectional study in one Malaysian public medical school. *Annals of African medicine*, 17(4), 183.

Hardy, A., Hyslop, S., Booth, K., Robards, B., Aryal, J., Gretzel, U., & Eccleston, R. (2017). Tracking tourists' travel with smartphone-based GPS technology: a methodological discussion. *Information Technology & Tourism*, 17(3), 255-274.

Harper, D. (2002). Talking about pictures: A case for photo elicitation. *Visual studies*, 17(1), 13-26.

Harrison, S., Villano, R., Lynch, G., & Chen, G. (2015, March). Likelihood analysis of student enrollment outcomes using learning environment variables: A case study approach. In *Proceedings of the Fifth International Conference on Learning Analytics And Knowledge* (pp. 141-145).

Harvey, L., Burrows, A., & Green, D. (1992). *Total Student Experience: A first report of the QHE national survey of staff and students' views of the important criteria for assessing the quality of higher education*. Quality in Higher Education Project.

Harwell, D. (2019). *Colleges are turning students' phones into surveillance machines, tracking the locations of hundreds of thousands*. Washington Post.

Hay, T. (2013). *The rise of the 'quantified self' in health care*. Wall Street Journal.

Henderson, M., Selwyn, N., & Aston, R. (2017). What works and why? Student perceptions of 'useful' digital technology in university teaching and learning. *Studies in Higher Education*, 42(8), 1567-1579.

Hesse-Biber, S. J., Hesse-Biber, S. N., & Leavy, P. (Eds.). (2006). *Emergent methods in social research*. Sage.

Holton, M. (2016). The geographies of UK university halls of residence: examining students' embodiment of social capital. *Children's Geographies*, 14(1), 63-76.

Homan, A. (2015). *Z is for Generation Z.* Retrieved from https://tiie.w3.uvm.edu/blog/who-are-generation-z/#.Xo1Wq9NLiF0

Hopman-Rock, M., van Hirtum, H., de Vreede, P., & Freiberger, E. (2018). Activities of daily living in older community-dwelling persons: a systematic review of psychometric properties of instruments. *Aging clinical and experimental research*, 1-9.

Hornsby, K. S., & Yuan, M. (Eds.). (2008). *Understanding dynamics of geographic domains. CRC Press*.

Howe, N., & Strauss, W. (2000). *Millennials rising: The next great generation*. Vintage.

Howell, K. E. (2012). *An introduction to the philosophy of methodology*. Sage.

Inayatullah, S. (2002). Reductionism or layered complexity? The futures of futures studies. *Futures*, 34(3-4), 295-302.

Ingle, S., & Duckworth, V. (2013). *Enhancing Learning through technology in lifelong learning: Fresh ideas: Innovative Strategies: Fresh ideas; innovative strategies*. McGraw-Hill Education (UK).

Innis, K., & Shaw, M. (1997). How do students spend their time?. *Quality assurance in Education*.

Irvin, M., & Longmire, J. (2016). Motivating and supporting faculty in new technology based student success initiatives: An exploration of case studies on technology acceptance. *Journal of Student Success and Retention*, 3(1).

Ivory, V. C., Russell, M., Witten, K., Hooper, C. M., Pearce, J., & Blakely, T. (2015). What shape is your neighbourhood? Investigating the micro geographies of physical activity. *Social Science & Medicine*, 133, 313-321.

Jameson, M., & Smith, J. (2011). *Voices of students in competition: Health science first year at the University of Otago, Dunedin*. Clinical Correspondence.

Jeong, S. H., & Hwang, Y. (2016). Media multitasking effects on cognitive vs. attitudinal outcomes: A meta-analysis. *Human Communication Research*, 42(4), 599-618.

Johnson, L., Becker, S. A., Cummins, M., Estrada, V., Freeman, A., & Hall, C. (2016). *NMC horizon report: 2016 higher education edition* (pp. 1-50). The New Media Consortium.

Jones, R. (2018). The student experience of undergraduate students: towards a conceptual framework. *Journal of Further and Higher Education*, 42(8), 1040-1054.

Judd, T., & Kennedy, G. (2011). Measurement and evidence of computer-based task switching and multitasking by 'Net Generation' students. *Computers & Education*, 56(3), 625-631.

Junco, R., & Cotten, S. R. (2012). No A 4 U: The relationship between multitasking and academic performance. *Computers & Education*, 59(2), 505-514.

Katz, S., Ford, A. B., Moskowitz, R. W., Jackson, B. A., & Jaffe, M. W. (1963). Studies of illness in the aged: the index of ADL: a standardized measure of biological and psychosocial function. *Jama*, *185*(12), 914-919.

Kaufman, K. J. (2013). 21 ways to 21st century skills: why students need them and ideas for practical implementation. *Kappa Delta Pi Record*, 49(2), 78-83.

Keijzer-Broers, W., Nikayin, F., & De Reuver, M. (2014). *Main requirements of a Health and Wellbeing Platform: findings from four focus group discussions*. ACIS.

Kellehear A. (1993). Rethinking the survey. In D. Colquhoun and A. Kellehear (Eds.), *Health research in practice: political, ethical and methodological issues* (p. 126-137), London, Chapman Hall.

Kellner, L. & Egger, R. (2016). Tracking tourist Spatial-Temporal behavior in urban places, a methodological overview and GPS case study. In *Proceedings of the International Conference of Information and Communication Technologies in Tourism*, Bilbao, pp. 481-494.

Kelly, F., & Brailsford, I. (2013). The Role of the Disciplines: Alternative Methodologies in Higher Education. *Higher Education Research* & *Development* 32 (1): 1–4.

Khan, S., Rahmani, H., Shah, S. A. A., & Bennamoun, M. (2018). A guide to convolutional neural networks for computer vision. *Synthesis Lectures on Computer Vision*, 8(1), 1-207.

Khetarpaul, S., Chauhan, R., Gupta, S. K., Subramaniam, L. V., & Nambiar, U. (2011, March). Mining GPS data to determine interesting locations. In *Proceedings of the 8th International Workshop on Information Integration on the Web: in conjunction with WWW*, pp. 1-6.

Khosla, A., Raju, A. S., Torralba, A., & Oliva, A. (2015). Understanding and predicting image memorability at a large scale. In *Proceedings of the IEEE International Conference on Computer Vision,* pp. 2390-2398.

Kido, T., & Swan, M. (2016, March). Machine learning and personal genome informatics contribute to happiness Sciences and wellbeing computing. In *AAAI Spring Symposium Series*.

Kim, D. Y., & Song, H. Y. (2018). Method of predicting human mobility patterns using deep learning. *Neurocomputing*, 280, 56-64.

Kinosian, B., Wieland, D., Gu, X., Stallard, E., Phibbs, C. S., & Intrator, O. (2018). Validation of the JEN frailty index in the National Long-Term Care Survey community population: identifying functionally impaired older adults from claims data. *BMC health services research*, 18(1), 908.

Kolb, D. A. (1976). *Learning style inventory technical manual*. Boston: McBer.

Kompridis, N. (2006). *The Idea of a New Beginning: A romantic source of normativity and freedom*. In N. Kompridis (Eds.), Philosophical Romanticism (pp. 32-59). Routledge.

Kop, R., Fournier, H., & Durand, G. (2017). A critical perspective on learning analytics and educational data mining. *Handbook of Learning Analytics*, 319.

Korpilo, S., Virtanen, T., & Lehvävirta, S. (2017). Smartphone GPS tracking—Inexpensive and efficient data collection on recreational movement. *Landscape and Urban Planning*, 157, 608-617.

Kortegast, C., McCann, K., Branch, K., Latz, A. O., Kelly, B. T., & Linder, C. (2019). Enhancing ways of knowing: The case for utilizing participant-generated visual methods in higher education research. *The Review of Higher Education*, 42(2), 485-510.

Kotler, P., & Armstrong, G. (2010). *Principles of marketing*. Pearson education.

Kramer, M. W. (2017). Sensemaking. *The International Encyclopedia of Organizational communication*, 1-10.

Krause, K. (2005, September). The changing student experience: Who's driving it and where is it going. In *Proceedings of the Student Experience Conference: good practice in practice*, pp. 5-7.

Krause, K. L. (2017). The Australian higher education student experience: A personal reflection on 15 years of research. *HERDSA Review of Higher Education*, 4, 53-78.

Krause, K. L., & Coates, H. (2008). Students' engagement in first-year university. *Assessment & Evaluation in Higher Education*, 33(5), 493-505.

Krueger, R. A., & Casey, M. A. (2014). *Focus Groups: A Practical Guide for Applied Research*. Thousand Oaks: Sage publications Inc., 4.

Kruger, J. L., & Doherty, S. (2016). Measuring cognitive load in the presence of educational video: Towards a multimodal methodology. *Australasian Journal of Educational Technology*, 32(6).

Kwan, M. P., & Schwanen, T. (2016). Geographies of mobility. *Annals of the American Association of Geographers* 106: 243–256.

Lam, B. H., & Kwan, K. P. (1999). Students' expectations of university education. *Evaluation of the student experience project*, 3, 11-20.

Lamkin, P. (2018). *Smart wearables market to double by 2022: $27 billion industry forecast*. Forbes. Retrieved from https://www.forbes.com/sites/paullamkin/2018/10/23/smart-wearables-market-to-double-by-2022-27-billion-industry-forecast/#32e592426569

Laranjeiro, P. F., Merchán, D., Godoy, L. A., Giannotti, M., Yoshizaki, H. T., Winkenbach, M., & Cunha, C. B. (2019). Using GPS data to explore speed patterns and temporal fluctuations in urban logistics: The case of São Paulo, Brazil. *Journal of Transport Geography*, 76, 114-129.

Larson, L. C., & Miller, T. N. (2011). 21st century skills: Prepare students for the future. *Kappa Delta Pi Record*, 47(3), 121-123.

Lau, G., & McKercher, B. (2006). Understanding tourist movement patterns in a destination: A GIS approach. *Tourism and hospitality research*, 7(1), 39-49.

Laurillard, D. (2016). Learning number sense through digital games with intrinsic feedback. *Australasian Journal of Educational Technology*, 32(6).

Layer, G. (2016). Influencing change through a strategic approach to student attainment. In G. Steventon, D. Cureton, & L. Clouder, (Eds.), *Student Attainment in Higher Education* (pp. 23-39). Routledge

Lefebvre, H. (1969). *The explosion: Marxism and the French upheaval* (Vol. 12). NYU Press.

Lefebvre, H. (1991). *Critique of everyday life: Foundations for a sociology of the everyday* (Vol. 2). Verso.

Lefebvre, H. (2004). *Rhythmanalysis: Space, time and everyday life*. A&C Black.

Lefebvre, H. (2009). *State, space, world: Selected essays*. U of Minnesota Press.

Lefebvre, H., & Nicholson-Smith, D. (1991). *The production of space* (Vol. 142). Blackwell: Oxford.

Letherby, G. (2003). *Feminist research in theory and practice*. McGraw-Hill Education (UK).

Lierow, M., Janssen, S., & D'Incà, J. (2016). *Amazon is using logistics to lead a retail revolution*. Forbes. Retrieved from https://www.forbes.com/sites/oliverwyman/2016/02/18/amazon-is-using-logistics-to-lead-a-retail-revolution/#1894fda04e43

Lima, R., Osório, D., & Gamboa, H. (2019). Heart Rate Variability and Electrodermal Activity in Mental Stress Aloud: Predicting the Outcome. *BIOSTEC 2019*, 31(11), 42.

Liu, O. P., & Tee, O. P. (2014). Teaching Students of Today: The Buddha's Way. *International Journal of Progressive Education*, 10(2), 43-55.

Lowe, H., & Cook, A. (2003). Mind the gap: are students prepared for higher education?. *Journal of further and higher education*, 27(1), 53-76.

Macaskill, A., & Denovan, A. (2013). Developing autonomous learning in first year university students using perspectives from positive psychology. *Studies in Higher Education*, 38(1), 124-142.

MacIntyre, A. (2013). Relativism, power, and philosophy. *The American Philosophical Association Centennial Series*, 313-333.

Maddox, A., Lingham, B., & Bates, C. (2017). *Designing library learning space: an evaluation of the student experience*. Deakin University Library.

Magnusson, M. S., Burgoon, J. K., & Casarrubea, M. (2016). Discovering Hidden Temporal Patterns in Behavior and Interaction. *Neuromethods*, 111.

Mann, S. (1998, May). Wearable computing as means for personal empowerment. In *Proceedings of the 3rd International Conference on Wearable Computing (ICWC),* pp. 51-59.

Mann, S., Nolan, J., & Wellman, B. (2003). Sousveillance: Inventing and using wearable computing devices for data collection in surveillance environments. *Surveillance & society*, 1(3), 331-355.

Marcus, J. (2020). *How Technology Is Changing the Future of Higher Education*. Retrieved from https://www.nytimes.com/2020/02/20/education/learning/education-technology.html

Maslow, A. H. (1981). *Motivation and personality*. Prabhat Prakashan.

Matthews, H., Limb, M., & Percy-Smith, B. (1998). Changing worlds: the microgeographies of young teenagers. *Tijdschrift voor economische en sociale geografie*, 89(2), 193-202.

Mayer, D. (2006). The changing face of the Australian teaching profession: New generations and new ways of working and learning. *Asia-Pacific Journal of Teacher Education*, 34(1), 57-71.

McClusky, M. (2009). The Nike experiment: how the shoe giant unleashed the power of personal metrics. *Wired*, June, 22, 17-07.

McDonald, J. & Moskal A.C.M. (2017). Quantext: analysing student responses to short-answer questions. In H. Partridge, K. Davis, & J. Thomas. (Eds.), *Me, Us, IT! Proceedings ASCILITE2017: 34th International Conference on Innovation, Practice and Research in the Use of Educational Technologies in Tertiary Education* (pp. 133-137).

Méndez, G., Ochoa, X., & Chiluiza, K. (2014, March). Techniques for data-driven curriculum analysis. In *Proceedings of the Fourth International Conference on Learning Analytics and Knowledge,* pp. 148-157.

Metcalfe, A. (2015). Visual methods in higher education. *Research in the college context: Approaches and methods,* 111-127.

Meyer, A. N., Barton, L. E., Murphy, G. C., Zimmermann, T., & Fritz, T. (2017). The work life of developers: Activities, switches and perceived productivity. *IEEE Transactions on Software Engineering*, 43(12), 1178-1193.

Miller, H. J., & Wu, Y. H. (2000). GIS software for measuring space-time accessibility in transportation planning and analysis. *GeoInformatica*, 4(2), 141-159.

Mishra, P., & Henriksen, D. (2018). The Architecture of Creative Learning Environments. In *Creativity, Technology & Education: Exploring their Convergence* (pp. 103-109). Springer, Cham.

Mitra, S. (2016, April). The future of learning. *In Proceedings of the Third (2016) ACM Conference on Learning@ Scale,* pp. 61-62.

Mohareb, N., & Omar, O. (2018). Monitoring daily mobility patterns for university students using GPS tracking: Tripoli as a case study. *BAU Journal: Health & Well-Being, special edition,* 15-23.

Mohsen, J. P., Ismail, M. Y., Parsaei, H. R., & Karwowski, W. (Eds.). (2019). *Global Advances in Engineering Education*. CRC Press.

Morales, J. M., Ruiz-Rabelo, J. F., Diaz-Piedra, C., & Di Stasi, L. L. (2019). Detecting mental workload in surgical teams using a wearable single-channel electroencephalographic device. *Journal of surgical education*, 76(4), 1107-1115.

Morgan, J. (2014). *3 Reasons Why You Shouldn't Freak Out About Millennials In The Workplace*. Forbes. Retrieved from https://www.forbes.com/sites/jacobmorgan/2014/01/29/3-reasons-why-you-shouldnt-freak-out-about-millennials-in-the-workplace/#68eaa9262610

Morieson, L., Murray, G., Wilson, R., Clarke, B., & Lukas, K. (2018). Belonging in space: Informal learning spaces and the student experience. *Journal of Learning Spaces*, 7(2).

Moussouri, T., & Roussos, G. (2015). Conducting visitor studies using smartphone-based location sensing. *Journal on Computing and Cultural Heritage (JOCCH)*, 8(3), 1-16.

Mukherjee, M., & Bhattacharya, A. B. (2018). RSSI Based Indoor human activity Recognition System. *Techno International Journal of Health, Engineering, Management and Science (TIJHEMS)*.

Muller, D. A. (2008). *Designing effective multimedia for physics education*. Sydney: University of Sydney.

New Zealand Police. (2020). *What are the rules around taking photos or filming in a public place?*. Retrieved from https://www.police.govt.nz/faq/items/23297

New Zealand Productivity Commission. (2017). *New models of tertiary education: Final Report*. New Zealand Government, Wellington.

Nijp, H. H., Beckers, D. G., van de Voorde, K., Geurts, S. A., & Kompier, M. A. (2016). Effects of new ways of working on work hours and work location, health and job-related outcomes. *Chronobiology International*, 33(6), 604-618.

Noe, R. A., Hollenbeck, J. R., Gerhart, B., & Wright, P. M. (2017). *Human Resource Management: Gaining A Competitive Advantage, 10e*. Boston: McGraw-Hill/Irwin.

Noelker, L. S., Browdie, R., & Sidney Katz, M. D. (2013). A new paradigm for chronic illness and long-term care. *Gerontologist*, 8(6), 1-8.

Nonis, S. A., & Hudson, G. I. (2006). Academic performance of college students: Influence of time spent studying and working. *Journal of education for business*, *81*(3), 151-159.

Noulas, A., Scellato, S., Lathia, N., & Mascolo, C. (2012, December). Mining user mobility features for next place prediction in location-based services. In *Proceedings of the IEEE 12th International Conference on Data Mining* (pp. 1038-1043).

Oliveira-Barra, G., Bolaños, M., Talavera, E., Gelonch, O., Garolera, M., & Radeva, P. (2019). Lifelog retrieval for memory stimulation of people with memory impairment. In X. Alameda-Pineda, E. Ricci, & N. Sebe, (Eds.), *Multimodal Behavior Analysis in the Wild* (pp. 135-158). Academic Press.

Oliver, M. A., & Vayre, J. S. (2015). Big data and the future of knowledge production in marketing research: Ethics, digital traces, and abductive reasoning. *Journal of Marketing Analytics*, 3(1), 5-13.

Orwell, G. (1984). *Nineteen Eighty-Four.* Middlesex, England: Penguin Books Ltd..

Pachman, M., Arguel, A., Lockyer, L., Kennedy, G., & Lodge, J. (2016). Eye tracking and early detection of confusion in digital learning environments: Proof of concept. *Australasian Journal of Educational Technology*, 32(6).

Pardo, A., & Siemens, G. (2014). Ethical and privacy principles for learning analytics. *British Journal of Educational Technology*, 45(3), 438-450.

Paretta, L. T., & Catalano, A. (2013). What students really do in the library: An observational study. *The Reference Librarian*, 54(2), 157-167.

Pascarella, E. T., & Terenzini, P. T. (1991). *How college affects students: Findings and insights from twenty years of research*. Jossey-Bass Inc., Publishers, PO Box 44305, San Francisco, CA 94144-4305 (ISBN-1-55542-304-3--$75.00, hardcover).

Peddiwell, A. J. (2004). *The saber-tooth curriculum*. McGraw Hill Professional.

Peláez, A. D. (2017). *Egocentric rich images detection in a serious game for Alzheimer's patients*. Treballs Finals de Grau d'Enginyeria Informàtica, Facultat de Matemàtiques, Universitat de Barcelona. Retrieved from http://hdl.handle.net/2445/120329

Pepper, C. (2017). Informal learning spaces: A facilities management perspective. In G. Walton, & G. Matthews, (Eds.), *Exploring Informal Learning Space in the University* (pp. 125-140). Routledge.

Perrotta, C., & Williamson, B. (2018). The social life of Learning Analytics: cluster analysis and the 'performance'of algorithmic education. *Learning, Media and Technology*, 43(1), 3-16.

Persily, N. (2017). The 2016 US Election: Can democracy survive the internet?. *Journal of democracy*, 28(2), 63-76.

Phithakkitnukoon, S., Horanont, T., Di Lorenzo, G., Shibasaki, R., & Ratti, C. (2010, August). Activity-aware map: Identifying human daily activity pattern using mobile phone data. In *International Workshop on Human Behavior Understanding* (pp. 14-25). Springer, Berlin, Heidelberg.

Picciano, A. G. (2012). The evolution of big data and learning analytics in American higher education. *Journal of asynchronous learning networks*, 16(3), 9-20.

Pickett, J. P. (2018). *The American heritage dictionary of the English language*. Houghton Mifflin Harcourt.

Posada-Quintero, H. F., Dimitrov, T., Moutran, A., Park, S., & Chon, K. H. (2019). Analysis of Reproducibility of Noninvasive Measures of Sympathetic Autonomic Control Based on Electrodermal Activity and Heart Rate Variability. *IEEE Access*, 7, 22523-22531.

Powell, S., & MacNeil, S. (2012). Institutional readiness for analytics: A briefing paper. CETIS Analytics Series. *JISC Center for Educational Technology and Interoperability Standards*, *1*(8).

Prensky, M. (2001). Digital natives, digital immigrants. *On the horizon*, *9*(5).

Price, B. A., Stuart, A., Calikli, G., Mccormick, C., Mehta, V., Hutton, L., Bandara, A. K., Levine, M., & Nuseibeh, B. (2017). Logging you, logging me: A replicable study of privacy and sharing behaviour in groups of visual lifeloggers. In *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 1(2), 1-18.

Ramsden, P. (2008). The future of higher education teaching and the student experience. *The Higher Education Academy*, 30, 1.

Ramstad, K. F. (2019). *4 business models that are disrupting the parcel delivery industry*. Retrieved from https://www.mixmove.io/blog/4-business-models-that-are-disrupting-the-parcel-delivery-industry

Rand, A. (1943). *The Fountainhead*. Indianapolis: Bobbs-Merrill Co.

Rand, A. (1957). *Atlas Shrugged*. New American Library.

Rand, A., & Peikoff, L. (1999). *The Journals of Ayn Rand*. Penguin.

Randhawa, G. S., & Lomotan, E. A. (2018). Harnessing Big Data-Based Technologies Cancer Care to Improve. *Advancing the Science of Implementation across the Cancer Continuum*, 283.

Reay, D., Crozier, G., & Clayton, J. (2010). ‘Fitting in’ or ‘standing out’: Working-class students in UK higher education. *British Educational Research Journal*, 36(1), 107-124.

Reeves, C., Kiteley, R., Spall, K., & Flint, L. (2019). Working with Students as Partners: Developing Peer Mentoring to Enhance the Undergraduate Student Experience. In M. Snowden, (Eds.), *Mentorship, Leadership, and Research* (pp. 27-45). Springer, Cham.

Reiter, B. (2017). Theory and methodology of exploratory social science research. *International Journal of Science and Research Methodology*, 5(4), 129.

Richardson, A., King, S., Olds, T., Parfitt, G., & Chiera, B. (2019). Study and life: How first year university students use their time. *Student Success*, 10(1), 17-32.

Rios-Aguilar, C. (2014). The Changing Context of Critical Quantitative Inquiry. *New directions for institutional research*, 158, 95-107.

Riphagen, M., van Hout, M., Kritjnen, D., & Gootjes, G. (2013). *Learning tomorrow: visualising student and staff's daily activities and reflect on it*. Retrieved from http://medialabamsterdam.com/wp-content/uploads/2013/11/ICERIE2013_ Paper_M_Riphagen_AUAS. pdf.

Robinson, K. (2011). *Out of our minds*. London: Capstone.

Roy, E. A., (2020). *New Zealand student death: calls for welfare overhaul after body lay in room for month*. Retrieved from https://www.theguardian.com/world/2020/jan/10/new-zealand-student-death-calls-for-welfare-overhaul-after-body-lay-in-room-for-month

Ruostela, J., Lönnqvist, A., Palvalin, M., Vuolle, M., Patjas, M., & Raij, A. L. (2015). ‘New Ways of Working’as a tool for improving the performance of a knowledge-intensive company. *Knowledge Management Research & Practice*, 13(4), 382-390.

Sabri, D. (2011). What's wrong with ‘the student experience’?. *Discourse: Studies in the Cultural Politics of Education*, 32(5), 657-667.

Salas-Olmedo, M. H., Moya-Gómez, B., García-Palomares, J. C., & Gutiérrez, J. (2018). Tourists' digital footprint in cities: Comparing Big Data sources. *Tourism Management*, 66, 13-25.

Sana, F., Weston, T., & Cepeda, N. J. (2013). Laptop multitasking hinders classroom learning for both users and nearby peers. *Computers & Education*, 62, 24-31.

Sandars, J., & Morrison, C. (2007). What is the Net Generation? The challenge for future medical education. *Medical teacher*, *29*(2-3), 85-88.

Sandford, S. (2015). Contradiction of terms: Feminist theory, philosophy and transdisciplinarity. *Theory, Culture & Society*, 32(5-6), 159-182.

Sano, A., Taylor, S., Jaques, N., Chen, W., & Martinez, D. L. (2018). Mood, Stress and Sleep Sensing with Wearable Sensors and Mobile Phone. In *Proceedings of the 40th International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. Piscataway: IEEE.

Saunders, M., Lewis, P., & Thornhill, A. (2012). *Research methods for business students* (6. utg.). Harlow: Pearson.

Schautz, A. M., van Dijk, E. M., & Meisert, A. (2016). The use of audio guides to collect individualized timing and tracking data in a science center exhibition. *Visitor Studies*, 19(1), 96-116.

Scotland, J. (2012). Exploring the philosophical underpinnings of research: Relating ontology and epistemology to the methodology and methods of the scientific, interpretive, and critical research paradigms. *English language teaching*, 5(9), 9-16.

Scutt, C., & Hobson, J. (2013). The stories we need: Anthropology, philosophy, narrative and higher education research. *Higher Education Research & Development*, 32(1), 17-29.

Seemiller, C., & Grace, M. (2017). Generation Z: Educating and engaging the next generation of students. *About Campus*, 22(3), 21-26.

Selwyn, N. (2013). *Distrusting educational technology: Critical questions for changing times*. Routledge.

Selwyn, N. (2019). What's the Problem with Learning Analytics?. *Journal of Learning Analytics*, 6(3), 11-19.

Sevtsuk, A., & Ratti, C. (2010). Does urban mobility have a daily routine? Learning from the aggregate data of mobile networks. *Journal of Urban Technology*, 17(1), 41-60.

Sharkey, M. (2011, February). Academic analytics landscape at the University of Phoenix. In *Proceedings of the 1st International Conference on Learning Analytics and Knowledge,* pp. 122-126.

Shoval, N., Wahl, H. W., Auslander, G., Isaacson, M., Oswald, F., Edry, T., Landau, R., & Heinik, J. (2011). Use of the global positioning system to measure the out-of-home mobility of older adults with differing cognitive functioning. *Ageing & Society*, 31(5), 849-869.

Shoval, N., & Ahas, R. (2016). The use of tracking technologies in tourism research: the first decade. *Tourism Geographies*, 18(5), 587-606.

Siemens, G. (2010, August). Learning Analytics Google Group Discussion. Retrieved from https://groups.google.com/forum/#!msg/learninganalytics/HdEvcl6_2MA/sb43vonnLhsJ

Siemens, G. (2012, April). Learning analytics: envisioning a research discipline and a domain of practice. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge*, pp. 4-8.

Sim, K. N. (2016). *An investigation into the way PhD students utilise ICT to support their doctoral research process* (Doctoral dissertation, University of Otago).

Sim, K., & Butson, R. (2014). To What Degree Are Undergraduate Students Using Their Personal Computers to Support Their Daily Study Practices?. *IAFOR Journal of Education*, 2(1), 158-171.

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

Singh, K. (2007). *Quantitative social research methods*. Sage.

Slade, S., & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas. *American Behavioral Scientist*, 57(10), 1510-1529.

Smith, E., & White, P. (2015). What makes a successful undergraduate? The relationship between student characteristics, degree subject and academic success at university. *British Educational Research Journal*, 41(4), 686-708.

Sobolevsky, S., Bojic, I., Belyi, A., Sitko, I., Hawelka, B., Arias, J. M., & Ratti, C. (2015, June). Scaling of city attractiveness for foreign visitors through big data of human economical and social media activity. In the *IEEE International Congress on Big Data*, pp. 600-607.

Soja, E. W. (1989). *Postmodern geographies: The reassertion of space in critical social theory*. Verso.

Song, H. Y. (2016). Probabilistic space-time analysis of human mobility patterns. *Network*, 12(13), 14.

Spangenberg, T. (2014). Development of a mobile toolkit to support research on human mobility behavior using GPS trajectories. *Information Technology & Tourism*, 14(4), 317-346.

Stephenson, A., McDonough, S. M., Murphy, M. H., Nugent, C. D., & Mair, J. L. (2017). Using computer, mobile and wearable technology enhanced interventions to reduce sedentary behaviour: a systematic review and meta-analysis. *International Journal of Behavioral Nutrition and Physical Activity*, 14(1), 105.

Sun, L., & Axhausen, K. W. (2016). Understanding urban mobility patterns with a probabilistic tensor factorization framework. *Transportation Research Part B: Methodological*, 91, 511-524.

Sutherland, C. M. (2016). *Digital Natives: 4 Ways Technology Has Changed 'the' Student.* Retrieved from https://explorance.com/blog/digital-natives-4-ways-technology-changed-student/

Swinhoe, D. (2018). *The role of the Quantified Self in a corporate environment and what it means for IT*. Retrieved from https://www.cio.com/article/3268967/the-role-of-the-quantified-self-in-a-corporate-environment-and-what-it-means-for-it.html

Talavera, E., Radeva, P., & Petkov, N. (2017, February). Towards egocentric sentiment analysis. In the *International Conference on Computer Aided Systems Theory*, pp. 297-305. Springer, Cham.

Tan, S. J., Kerr, G., Sullivan, J. P., & Peake, J. M. (2019). A brief review of the application of neuroergonomics in skilled cognition during expert sports performance. *Frontiers in Human Neuroscience*, 13, 278.

Tan, A. H. T., Muskat, B., & Zehrer, A. (2016). A systematic review of quality of student experience in higher education. *International Journal of Quality and Service Sciences*.

Taylor, M. G., Lynch, S. M., & Ureña, S. (2018). Race Differences in ADL Disability Decline 1984-2004: Evidence From the National Long-Term Care Survey. *Journal of Aging and Health*, 30(2), 167-189.

Te, M. (2019). *What next after the end of video stores?* Retrieved from https://www.stuff.co.nz/entertainment/film/111263862/what-next-after-the-end-of-video-stores

Temple, P., Callender, C., Grove, L., & Kersh, N. (2016). Managing the student experience in English higher education: Differing responses to market pressures. *London Review of Education*, 14(1), 33-46.

Thagard, P., & Shelley, C. (1997). Abductive reasoning: Logic, visual thinking, and coherence. In M. L. Dalla Chiara, K. Doets, D. Mundici, & J. van Benthem, (Eds.), *Logic and scientific methods* (pp. 413-427). Springer, Dordrecht.

Thimm, T., & Seepold, R. (2016). Past, present and future of tourist tracking. *Journal of Tourism Futures*, 2(1), 43–55.

Thomas, L. K., Harden-Thew, K., Delahunty, J., & Dean, B. A. (2016). A vision of You-topia: Personalising professional development of teaching in a diverse academic workforce. *Journal of University Teaching & Learning Practice,* 13 (4): 1–13.

Tight, M. (2012). *Researching higher education*. McGraw-Hill Education (UK).

Tight, M. (2013). Discipline and methodology in higher education research. *Higher Education Research & Development*, 32(1), 136-151.

Toha, M. A. M., & Ismail, H. N. (2015). A heritage tourism and tourist flow pattern: A perspective on traditional versus modern technologies in tracking the tourists. *International Journal of Built Environment and Sustainability*, 2(2).

Tono, A., Tono, H., & Zani, A. (2020). Encoded Memory: Artificial Intelligence and Deep Learning in Architecture. In *Impact of Industry 4.0 on Architecture and Cultural Heritage* (pp. 283-305). IGI Global.

Tschumi, B. (1976). Architecture and transgression. *Oppositions*, 7(57), 5.

Tschumi, B. (1996). *Architecture and disjunction*. MIT press.

Van den Herik, K. W., & de Vreede, G. J. (2000). Experiences with facilitating policy meetings with group support systems. *International Journal of Technology Management*, 19(3/5), 246-268.

Vozniuk, A., Holzer, A., & Gillet, D. (2014, March). Peer assessment based on ratings in a social media course. In *Proceedings of the Fourth International Conference on Learning Analytics And Knowledge* (pp. 133-137).

Walters, A. (2010). *Bringing the market 'back into' supermarket: creating a social hub for local communities.* A thesis presented in partial fulfillment of the requirements for the degree of Master of Design at Massey University, Wellington, New Zealand (Doctoral dissertation, Massey University).

Wang, Y., Huang, C., & Shan, J. (2015, June). An initial study on college students' daily activities using GPS trajectories. In *Proceedings of the 23rd International Conference on Geoinformatics*, pp. 1-6.

Warren, S. (2002). Show me how it feels to work here: using photography to research organizational aesthetics. *Ephemera*, 2(3), 224-245.

Weick, K. E., Sutcliffe, K. M., & Obstfeld, D. (2005). Organizing and the process of sensemaking. *Organization Science*, 16(4), 409-421.

Weimer, M. (2012). *Students think they can multitask. Here's proof they can't*. Retrieved from https://www.teachingprofessor.com/topics/for-those-who-teach/multitasking-confronting-students-with-the-facts/

Welker, A. L., & Wadzuk, B. (2012). How students spend their time. *Journal of professional issues in engineering education and practice*, *138*(3), 198-206.

Wells, R. S., Kolek, E. A., Williams, E. A., & Saunders, D. B. (2015). "How we know what we know": A systematic comparison of research methods employed in higher education journals, 1996—2000 v. 2006—2010. *The Journal of Higher Education*, 86(2), 171-198.

Wentworth, D. K., & Middleton, J. H. (2014). Technology use and academic performance. *Computers & Education*, 78, 306-311.

West, K. & Hill, L. (2004). All Falls Down [Recorded by K. West]. On *The College Dropout* [CD]. USA: Def Jam Recordings.

Whelan, E., Teigland, R., Vaast, E., & Butler, B. (2016). Expanding the horizons of digital social networks: Mixing big trace datasets with qualitative approaches. *Information and Organization*, 26(1-2), 1-12.

Wolf, G., & Kelly, K. (2014). Quantified self: Self knowledge through numbers. *Accessed*, 2, 16.

Wood, E. M. (1972). *Mind and politics: An approach to the meaning of liberal and socialist individualism*. University of California Press.

Wood, Z. R. (2015). *The benefits of intellectual open-mindedness*. Retrieved from https://www.timeshighereducation.com/student/blogs/student-blog-benefits-intellectual-open-mindedness

Yalowitz, S. S., & Bronnenkant, K. (2009). *Timing and tracking: Unlocking visitor behavior*. Visitor Studies, 12(1), 47-64.

Yamanishi, Y., Tabei, Y., & Kotera, M. (2016, November). Statistical Machine Learning for Agriculture and Human Health Care Based on Biomedical Big Data. In *Forum "Math-for-Industry"* (pp. 111-123). Springer, Singapore.

Yap, A. (2017). *The last video stores*. Retrieved from https://thespinoff.co.nz/media/06-08-2017/the-last-video-stores/

Yoshimura, Y., Sobolevsky, S., Ratti, C., Girardin, F., Carrascal, J. P., Blat, J., & Sinatra, R. (2014). An analysis of visitors' behavior in the Louvre Museum: A study using Bluetooth data. *Environment and Planning B: Planning and Design*, 41(6), 1113-1131.

Yu, C. H. (1994). *Abduction? Deduction? Induction? Is There a Logic of Exploratory Data Analysis?*. Paper presented at the Annual meeting of the American Educational Research Association, New Orleans.

Yun, H. J., & Park, M. H. (2015). Time–space movement of festival visitors in rural areas using a smart phone application. *Asia Pacific Journal of Tourism Research*, 20(11), 1246-1265.

Zajda, J., & Rust, V. (2016). *Research in globalisation and higher education reforms. In Globalisation and higher education reforms* (pp. 179-187). Springer, Cham.

Zheng, W., Huang, X., & Li, Y. (2017). Understanding the tourist mobility using GPS: Where is the next place?. *Tourism Management*, 59, 267-280.

Zuboff, S. (1988). *In the age of the smart machine*. Basic Book, NY.

APPENDIX A : EMAIL FOR RECRUITMENT

Hi,

I'm Senorita John, a PhD student at the Higher Education Development Centre, University of Otago. I am seeking 15-20 participants for my PhD project, which is on 'Mining reality: detecting behavioural patterns in student spatiotemporal data'. My project explores what undergraduate students do at university, both in and out of class, where they spend their time and what activities they get up to.

I am seeking:

- On-campus full time undergraduate health science students regardless of the stage of your undergraduate degree, aged between 18-25.
- Students who have an apple or android smart phone.

The project entails monitoring student behaviour during the first semester using a range of mobile devices. Providing you give your consent, daily movement will be captured by a GPS phone app, and the spaces you spend time in will be recorded by a small clip-on camera that automatically takes a photo every 30secs. I also hope to record your mood via a mood phone app. I will keep in touch with you via weekly meetings to ensure the results being generated are consistent with your experiences.

Data collection will take place from February to June 2017. You have access to your data at all times, and can review and delete any data you do not wish to share with the researchers. There will be a small compensation (up to $200) for your time.

If you interested in participating and would like to know more, please send me an email at senorita.john@postgrad.otago.ac.nz and I will provide you with further information. This study has been approved by the University of Otago Human Ethics Committee (Ref No: 16/160).

Thank you for considering this request and I do hope you think about participating.

Kind regards,
Senorita John (Supervised by Professor Rachel Spronken-Smith and Russell Butson)

APPENDIX B : INFORMATION SHEET FOR PARTICIPANTS

[Reference Number: 16/160] [09/12/16]

UNIVERSITY of OTAGO

SAPERE AUDE

Te Whare Wānanga o Otāgo

NEW ZEALAND

MINING REALITY: DETECTING BEHAVIOURAL PATTERNS IN STUDENT SPATIOTEMPORAL DATA

INFORMATION SHEET FOR PARTICIPANTS

Thank you for showing an interest in this project. Please read this information sheet carefully before deciding whether or not to participate. If you decide to participate we thank you. If you decide not to take part there will be no disadvantage to you and we thank you for considering our request.

What is the Aim of the Project?

The aim of this study is to explore an individual's experiences as episodes of spaces, events and movements that reflect patterns and relationships across these dimensions. A GPS phone app will be used to capture daily movement traces of students, the places they visit and spend time in which will be used to understand the patterns of movement of undergraduate students. A second small clip-on camera that automatically takes a photo every 30secs will capture continuous context data which will be mapped against the GPS measures to identify core spaces that the students are spending their time in. Regular interactions with the participants will be incorporated as a feedback technique to ensure the results being generated are consistent with the student's experiences.

What Type of Participants are being sought?

Up to 15 undergraduate health science students are being sought for the study.
Selection will depend on you meeting the following criteria:

1. Full-time University of Otago undergraduate health science student aged between 1825 and based at the Otago campus.
2. In possession of an apple or android smart phone.

What will Participants be Asked to Do?

Should you be selected to take part in this project, you will be asked to:

Download and use a GPS and mood app on your cell phone. The apps will need to be turned on each day for a training period of 3-6 weeks training (Feb 2017) and over the formal period of semester 1, 2017 (Mar-Apr-Jun 2017) which will be designated as the 'study'. The hours of having the apps turned on will be from 'waking up' to 'bedtime', but may vary due to particular circumstances. You will also need to export the data collected, via the emails provided, each night. You will be responsible to (a) charge your cell phones each night; (b) charge the back-up battery packs provided; and (c) export that day's data via emails provided. Training will be offered in all aspects of the procedures you will need to follow.

Attach a small camera unit to the front of your body (clothing) each day for a training period of 3-6 weeks training (Feb 2017) and over the formal period of semester 1, 2017 (Mar-Apr-Jun 2017) which will be designated as the 'study'. The hours of wearing the device will be from 'breakfast' to 'bedtime', but may vary due to particular circumstances. You will be responsible to dock the unit in the charger each night. This will remove the data and recharge the battery. Training will be offered in all aspects of the procedures you will need to follow.

You will be invited to attend an informal discussion each week, which will last from 30-50 minutes. These sessions will give you a chance to comment on the data collected and discuss any logistical issues. Digital notes will be generated from these meetings.

What Data or Information will be Collected and What Use will be Made of it?

Five datasets will be generated: Movement data (GPS traces), Context data (clip-on camera unit), Computer usage data (RescueTime software), Mood data (mood app) and Participant discussion data. The following is a detailed discussion of each dataset.

Movement data (GPS traces): GPS (global positioning system) data will be used to determine your daily movement traces, the places you visit and spend time in. The applications being used—GeoTracker and EasyTrials—are space-based navigation application systems that provide high quality location and time information. You will have access to this data at all times on your cell phone devices.

Context Dataset: A photograph will be taken every 30sec during waking hours from the small clip-on camera. These photographs will be used to contextualise your daily events. At the completion of the project, you will receive a copy of these photos.

Computer Usage Dataset: Software will be installed on your computer that will record the date, time, duration and type of computer programmes used as well as the date, time and duration of the websites visited over a six-month period. The software does not collect the content of the documents or websites. An orientation session will be offered at the start of the study to inform and train you in the purpose of using the software. You will be instructed on how to control the software, including the ability to turn it on and off and to delete any material. At the completion of the project, you will be given copies of your data (records of computer activity) and the computer usage software will be completely removed from your computers. Computer usage data will be cleaned of any identifying features to ensure anonymity. You will have access to anonymised outputs to verify anonymity before disclosure.

Mood data: This data set includes the use of technology for tracking and representing emotions through user-initiated approaches. The focus of this study is to understand emotion and mood as affective reactions to an event, typically short-lived and directed at a specific object. To be able to do so applications will be installed on your cell phones to track and record your mood. Mood tracker applications will allow the logging and tracking of moods periodically through the day. The application (Moodlytics) will allow the analysis of your mood journals through charts and graphs. You will have access to this data at all times on your cell phone devices.

Discussions Dataset: The purpose of these sessions is to hear your thoughts/perceptions regarding the data being captured. Your views and descriptions will be used to qualify the data from the other data sets. These sessions will also allow you an opportunity to raise any questions or technical concerns relating to the study.

The following inducement will be given to you as participants in this project:

- Phone applications being used for the research have been paid for and you are able to keep these and continue using them.
- Up to $200 per participant.

Outline of data management and security procedures.

Only the three members of the research team will have access to the datasets. You will also be able to request copies of the information you provide. Requests for this information can be raised at any time and will be discussed at the regular discussion sessions. On completion of the study you will be presented with both a complete and an abridged version of the GPS and camera data.

Please note that the data obtained as a result of this study will be retained for **at least 5 years** in secure storage. Any personal information held on you will be destroyed at the completion of the study and the data derived from the research will be kept for much longer or possibly indefinitely.

The results of the project may be published and will be available in the University of Otago Library (Dunedin, New Zealand) but every attempt will be made to preserve your anonymity.

On the Consent Form you will be given options regarding your anonymity. Please be aware that should you wish we will make every attempt to preserve your anonymity. However, with your consent, there are some cases where it would be preferable to attribute contributions made to individual participants. In these cases your decision will be sought.

This study will involve informal discussions where the general line of inquiry will be concerned with your weekly activities. The precise nature of the interaction has not be determined in advance, but will depend on the way in which the discussion develops and that in the event that the discussion develops in such a way that you feel hesitant or uncomfortable you may decline to answer any particular question(s) and/or may withdraw from the project without any disadvantage of any kind.

Can Participants Change their Mind and Withdraw from the Project?

You may withdraw from participation in the project at any time and without any disadvantage to yourself of any kind.

What if Participants have any Questions?

If you have any questions about our project, either now or in the future, please feel free to contact:

Senorita John *or* Russell Butson

Higher Education Development Centre Higher Education Development Centre

P: +64 3 479 8415 P: +64 3 479 5789

E: senorita.john@postgrad.otago.ac.nz E: russell.butson@otago.ac.nz

This study has been approved by the University of Otago Human Ethics Committee. If you have any concerns about the ethical conduct of the research you may contact the Committee through the Human Ethics Committee Administrator (ph +643 479 8256 or email gary.witte@otago.ac.nz). Any issues you raise will be treated in confidence and investigated and you will be informed of the outcome.

APPENDIX C : CONSENT FORM

[Reference Number: 16/160] [09/12/16]

MINING REALITY: DETECTING BEHAVIOURAL PATTERNS IN STUDENT SPATIOTEMPORAL DATA

CONSENT FORM FOR PARTICIPANTS

I have read the Information Sheet concerning this project and understand what it is about. All my questions have been answered to my satisfaction. I understand that I am free to request further information at any stage.

I know that:-

1. My participation in the project is entirely voluntary and that I am free to withdraw from the project at any time without any disadvantage;
2. Requests from researchers to use my photographs must be approved by me using a Media Release form prior to their publication/use.
3. The raw data on which the results of the project depend will be retained in secure storage for at least five years;

4. The study will require me to maintain a high level of care over the devices and be vigilant in daily charging and data uploading. And that I must contact the PI if I believe the device has malfunctioned, been damaged, or lost.
5. I am aware that regular discussions will involve an open-discussion approach where the general line of inquiry will be concerned with my daily office activities. I have been informed that the precise nature of the questions which will be asked have not been determined in advance, but will depend on the way in which the discussions develop and that in the event that the line of questioning develops in such a way that I feel hesitant or uncomfortable I may decline to answer any particular question(s) and/or may withdraw from the project without any disadvantage of any kind.
6. The results of the project may be published and will be available in the University of Otago Library (Dunedin, New Zealand).

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7. I, as the participant: a) agree to being named in the research, ☐

OR; b) would rather remain anonymous ☐

I agree to take part in this project.

....

(Signature of participant) (Date)

....

(Printed Name)

…………………………………………………………..

Name of person taking consent

This study has been approved by the University of Otago Human Ethics Committee. If you have any concerns about the ethical conduct of the research you may contact the Committee through the Human Ethics Committee Administrator (ph +643 479 8256 or email gary.witte@otago.ac.nz). Any issues you raise will be treated in confidence and investigated and you will be informed of the outcome.

APPENDIX D : ETHICS APPLICATION

UNIVERSITY OF OTAGO HUMAN ETHICS COMMITTEE APPLICATION FORM: CATEGORY A

1. **University of Otago staff member responsible for project:**

   Professor Rachel Spronken-Smith

2. **Department/School:**

   Graduate Research School (GRS)

3. **Contact details of staff member responsible:**

   email: rachel.spronken-smith@otago.ac.nz
   phone: +64 3 479 5655

4. **Title of project:** MINING REALITY: DETECTING BEHAVIOURAL PATTERNS IN STUDENT SPATIOTEMPORAL DATA

5. **Indicate project type and names of other investigators and students**:

   Staff Co-investigators X **Names:** Mr Russell Butson

   Student Researchers X **Names:** Senorita John

   Level of Study (PhD, Masters, Hons): PhD

Institute/Company: University of Otago

6. Is this a repeated class teaching activity?

NO

7. Fast-Track procedure

NO

8. When will recruitment and data collection commence?

January 2017

When will data collection be completed?

December 2017

9. Funding of project

Is the project to be funded by an external grant?

NO

10. Brief description <u>in lay terms</u> of the purpose of the project (approx. 75 words)**:**

The life of an undergraduate student is typically characterised as one of studying, attending classes, and socialising. While all three areas have been extensively researched, most studies are based on students' perceptions (what they say they do) rather than practice (what they actually do) (John & Butson, 2016; Sim & Butson, 2014; Paretta & Catalano, 2013). We believe that in order to fully understand the experience of learning, we must look beyond the classroom. Specifically, we argue that student's every day experiences, while appearing repetitive and even mundane at first glance, all contribute to what it means to 'be a student', and impacts on the student overall ecosystem. New advances in digital data capture methods now allow us to explore these seemingly insignificant aspects of what we call the student's ecosystem.

11. Aim and description of project:

This study focuses on spatiotemporal patterns of students' daily movements and is based on Tschumi's (1976) space-event-movement (SEM) framework. The aim of this study is to explore an individual's experiences as episodes of spaces, events and movements that reflect patterns and relationships across these dimensions. Employing a variety of digital capturing devices, we will map a) the spaces in which students spend their time, b) their activities (events) within these spaces, and c) their movements between these spaces.

This research employs a constructivist approach within an individual case design. We draw on methods from Reality Mining (collection and analysis of machine-sensed data pertaining to human social behaviour), Spatiotemporal Analytics (analysis of relationships and patterns among spatially and temporally scattered events), and

Spatiotemporal Visualisation (visualisation of changes in information over space and time). It is our intention to focus on four continuous contextual data sets:

- Photographs from wearable auto-cameras to generate a photographic record of the student's contextual environment.
- Movement data from phone GPS to determine daily movement traces of students and the places they visit and spend time in.
- Computer usage from desktop application to capture virtual activities/events.
- Person profiling from participant profile modelling schema to provide a distinctive profile of each student.

12. Researcher/instructor experience and qualifications in this research area:

Senorita John completed her Masters in Higher Education with a focus on the study practices of health science students. This project required Senorita to reflect critically on the various research methodologies and methods in order to address the questions she was asking and understand the richness of the area under inquiry. As a result, she has become familiar with many emerging approaches for investigating ill-structured, complex phenomena. While still new to the academic space, Senorita has already presented her research at a national conference and submitted a paper for publication in an international peer-reviewed journal.

Russell Butson is a senior lecturer in Higher Education with HEDC and PhD candidate. His research is centred on 'reality mining' (the use of sensors to capture naturally occurring human data) to understand elements of' academic practice', as it pertains to the quantified-self (data acquisition on aspects of a person's daily life in terms of inputs and states), particularly where behaviours/activities can be aligned to aspects of change/development/learning captured within academic life (undergraduates, postgraduate and faculty). He has publications that have employed a variety of data types and methods: virtual space, video, photographs, computer logs, and diagrams.

The primary supervisor (Rachel Spronken-Smith) is a professor in higher education and geography. She has extensive higher education research experience as well as being an experienced supervisor.

13. Participants

13**(a) Population from which participants are drawn:** Undergraduate Health Science students will be recruited from the University of Otago, Dunedin campus.

13**(b) Inclusion and exclusion criteria:**

- Expression of interest in participating in the study.
- University of Otago campus based full-time undergraduate health science student aged between 18-25.
- Provision of written consent & conditions of device use/maintenance.
- Commitment to attend weekly discussion sessions.

13**(c) Estimated number of participants:** up to 15

13**(d) Age range of participants:** 18 - 25

13**(e) Method of recruitment:** A description of the study and invitation to participate will be sent via an email to all full time undergraduate health science students at the University of Otago, through the Division of Health Sciences. The invitation will link interested participants to an online questionnaire comprising 20 questions (appendix A). The responses to these questions will be used to generate a short-list of possible participants (n=30). Each person on the shortlist will be invited to attend a brief interview where the project will be outlined in more detail. On completion of these interviews the final cohort will be selected.

13**(f) Specify and justify any payment or reward to be offered** *(Refer to 13f of the Filling In Your Application document):*

The following inducement will be given to participants in this project:

- Phone applications being used for the research have been paid for and the students are able to keep these and continue using them.
- Up to $200 per participant.

14. Methods and Procedures:

The aim is to recruit up to 15 undergraduate students (mix of years) for a period of one semester. Each participant will be provided with an auto-camera, GPS unit and software for computer usage tracking. They will also be expected to meet for 30mins each week to review the data gather. These sessions will also be used to develop student profiles data. Data will be collected over a 5-month semester period (Mar 2017 – July 2017). Four forms of data have been identified as applicable to address the themes and questions. A brief overview of each dataset is presented below.

Movement data (GPS traces): GPS (global positioning system) data will be used to determine daily movement traces of students, with the places they visit and spend time in. The applications being used—GeoTracker and EasyTrials—are space-based navigation application systems that provide high quality location and time information. The hours of having the apps turned on will be from 'waking up' to 'bedtime', but may vary due to particular circumstances.

Context Dataset: Participants will be asked to wear a small clip-on unit that has a builtin camera (measuring 36x36x9 mm and weighting only 20 grams). The purpose of this device is to add context to the data streams generated by the GPS data captured through the GPS device. Once on, the camera will take a photo every 30sec. These photos are essential in order to map context. Participants will be required to plug the device into their computers each evening to charge and transfer photos to a secure data store. At this stage they also have the ability to delete any of the photographs that they do not want to be stored. At the completion of the project, participants will be given copies of their photos.

Computer Usage Dataset: Software will be installed on participant's computers that will record the date, time, duration and type of computer programmes used as well as the date, time and duration of the websites visited over the study period. The software does not collect the content of the documents or websites. An orientation session will be offered at the start of the study to inform and train participants in the use of this software. They will be instructed on how to control the software, including the ability to turn it on and off and to delete any data. At the completion of the project, participants will be given copies of their data (records of computer activity) and the recording software will be completely removed from their computers. Computer usage data will be cleaned of any identifying features to ensure anonymity. Participants will have access to outputs to verify anonymity before disclosure (information sheet).

Mood data: This data set includes the use of technology for tracking and representing emotions through user-initiated approaches. The focus of this part of the study is to understand emotion and mood as affective reactions to an event, typically short-lived and directed at a specific object. To be able to do so applications will be installed on the student's cell phones to track and record their mood. Mood tracker applications will allow the logging and tracking of moods periodically through the day. The application (Moodlytics) will allow the analysis of your mood journals through charts and graphs. The hours of having the app turned on will be from 'waking up' to 'bedtime', but may vary due to particular circumstances.

Discussions Dataset: Informal discussions with the participants are expected to occur weekly. The primary point of these sessions will be to hear participant's perceptions of their activities in order to qualify what is being captured from the camera and GPS tracker. They will also give the participants the opportunity to address any general questions or technical problems relating to the study. Digital notes from these sessions will be assembled to form the third data set.

15. Compliance with The Privacy Act 1993 and the Health Information Privacy Code 1994 imposes strict requirements concerning the collection, use and disclosure of personal information. The questions below allow the Committee to assess compliance.

15(a) Are you collecting and storing personal information (e.g.name, contact details, designation, position etc) directly from the individual concerned that could identify the individual?

YES

15(b) Are you collecting information about individuals from another source? NO

If YES, explain:

15(c) Collecting Personal Information:

- Will you be collecting personal information (e.g. name, contact details, position, company, anything that could identify the individual)?

  YES

- Will you inform participants of the purpose for which you are collecting the information and the uses you propose to make of it?

  YES

- Will you inform participants of who will receive the information?

  YES

- Will you inform participants of the consequences, if any, of not supplying the information?

  YES

- Will you inform participants of their rights of access to and correction of personal information?

  YES

15(d) Outline your data storage, security procedures and length of time data will be kept:

Visual, GPS & Mood data: Data captured from both the device and the mobile apps will be temporarily stored in the device and the participants cell phones. Participants will sync data nightly to a secure web application. The data will then be downloaded to the primary researcher's computer for collaborative analysis. The raw data and analysis data will then be stored on a secure password-protected site at the University of Otago for 5 Years.

Computer Usage Data: Software usage data will be manually transferred to a portable hard-drive each month from the participant's computers by the doctoral investigator (Senorita John). To address the dangers associated with employing portable storage devices for the purpose of data transfer, the external hard-drive to be used will be specially configured for this study and incorporate full encryption. These data will be transferred to, stored and analysed on a secure password-protected site at the University of Otago for 5 Years.

Field Discussions Data Set: In the first instance, notes from these sessions will be uploaded to a secure password protected web site for shared access by the researchers. These data will then be downloaded to the researcher's computers for collaborative analysis. The raw data and analysed data will then be stored on a secure password-protected site at the University of Otago for 5 Years.

15(e) Who will have access to personal information, under what conditions, and subject to what safeguards? If you are obtaining information from another source, include details of how this will be accessed and include written permission if appropriate. Will participants have access to the information they have provided?

Participants will have access to the information they provide throughout the study period and at completion of the study. Requests for access to this information can be raised at any time and will be discussed at the regular discussion sessions. On completion of the study participants will be presented with a memory stick containing both a complete and an abridged version of their computer usage data.

Members of the research team will be responsible for data storage. All image data will remain the property of University of Otago. Upon completion of the study, the data will be transferred to secure password-protected storage at the University of Otago for a period of 5 years, after which the data will be destroyed.

15(f) Do you intend to publish any personal information they have provided?

We do not intend to publish any personal information. Quotes from the discussions may be published but these will be anonymised. Requests by researchers to use photographs must be approved by the participant using a Media Release form. The profile information collected will be used only to describe the sample of participants.

15(g) Do you propose to collect demographic information to describe your sample? For example: gender, age, ethnicity, education level, etc.

The following information will be collected:

- Gender
- Age
- Ethnicity
- Division/department
- Subject area
- Level of study (1st, 2nd or 3rd)
- Time at Otago

15 (h) Have you, or will you, undertake Māori consultation? Choose one of the options below, and delete the option that does not apply:

(Refer to http://www.otago.ac.nz/research/maoriconsultation/index.html).

Yes, we have already undertaken consultation. Please see the attached acknowledgement of receipt from Nagai Tahu Research Consultation Committee.

16. Does the research or teaching project involve any form of deception?

NO – The intent of the study is to be transparent. Participants will have continuous daily access to all the data streams (photographs, GPS data, mood data and computer software data). The weekly discussions will be guided by honesty and transparency.

17. Disclose and discuss any potential problems or ethical considerations:

The use of monitoring and wearable devices for generate research data is relatively uncommon within higher education research. However, they are increasingly commonplace in the business, sport and health research sector. While this may contribute to a degree of familiarity and acceptance, it has not minimised the need for this study to be detailed and transparent in the design, and planning. In fact, the use of such methods as a source of data in research invariably leads to concerns regarding Big Brother. Although this is obviously not the goal of the current research, it is not an unreasonable concern. It is therefore important that we are clear and honest with participants about the approach being employed in this study.

Central to this study is the belief that 1) these devices offer rich data that is not obtainable through any other means and 2) that the design employed ensures participants' have anonymity and confidentiality. The following section sets out a series of actions aimed at migrating against the core concerns raised regarding the capture of the data sets: the sharing of datasets, the management of replicated datasets, and the use of dataset in research outputs.

Participants may become aware of difficulties regarding their involvement only once the data collection has commenced and they have been able to review the captured data. This will be resolved by making it clear to all participants from the outset that their participation with this study is voluntary and they have the right to withdraw from the study at any time. This will also include the deletion of their data. This issue will be raised at the regular meetings.

While every possible attempt will be made to ensure anonymity, we are unable to guarantee absolute anonymity. Notwithstanding, it is important to note that personal data and publications and presentations will be made available for participants to review prior to these being submitted.

The devices are under the daily control of the participant. In both cases participants are able to remove (at will) either device. Participants will have access to their data at the weekly discussion sessions.

Notwithstanding, wearable devices such as cameras have raised a number of ethical and legal issues. For this reason, we have taken guidance from two similar Otago studies: 1) undertaken by Assoc. Prof. Louise Signal in 2013 – Kids Cam[1]: Viewing children's food and physical activity environments and, 2) undertaken by Mr. Russell Butson in 2015 - Pilot Study investigating stress and stressors of doctoral candidates through the use of wearable devices. In these studies, the researchers adopted a framework that consolidated the ethical issues raised in numerous studies and applications for ethical approval, and addressed protocols that uphold key ethical principles. Each of the ethical issues identified are presented and addressed in the remaining part of this section.

Taking Images in Public Places: New Zealand privacy laws state that in New Zealand it is generally lawful to take photographs of people in public places without their consent, so long as they are in a place where there is no expectation of privacy, such as a beach, shopping mall, park or other public place. However, photographs must not be taken if participants are in a place where people would expect reasonable privacy (such as public toilets and changing areas), where the publication would be highly offensive to an objective and reasonable person; when there is potential to stop other people's use and enjoyment of the same place;

[1] Acknowledgement: Much of this section is a replication of the work undertaken by the KidsCam project 2013. We would like to acknowledge the KidsCam team for their support and guidance in creating this section.

or there is no legitimate reason for taking the photos (New Zealand Police, 2012 *(http://www.police.govt.nz/faq/items/23297)*).

To address the issues of privacy and respect raised in this statement, participants will be briefed on when it will be necessary to remove the camera to protect their own privacy and the privacy of members of the public.

Third Party Consent: As automated camera devices are recording apparatus that can be worn throughout the day to objectively document the wearers' environment, it is likely that these devices will be worn in a number of locations - both public and private - unavoidably capturing members of the public during data.

It is likely that members of the public, family members, friends and other students will be unavoidably captured; however, it is impractical to obtain informed consent from every member of the public within the study location. Third parties are not the intended subjects of the images. To protect the privacy of those who may be inadvertently captured in the images, all images used in disseminated material will have identifiable people, street names, and school names blurred following data collection.

In New Zealand it is legal to take photographs in public places, with a few notable exceptions which are mentioned above. Any third parties captured in the photographs will have all identifiable features blurred. Thus, we feel that the privacy of those who have not consented to be part of the study will be protected through these actions.

Capture of illegal activity: Automated camera devices also have the potential to capture images of illegal activity that the wearer is either participating in or witnessing. Although the capture of incriminating images has been discussed in the international literature, there is minimal literature regarding the legal obligations of visual researchers in the New Zealand context. Legal advice sought from the Faculty of Law, University of Otago, Dunedin (Assoc. Prof. Margaret Briggs) by the KidCam project in 2013 indicated that it is unlikely that wearable cameras will capture an illegal action taking place, or that there would be an adequate number of images to provide a context for any illegal action, given the 30 second time delay between image capture. In the unlikely event that illicit activity is captured we would be obligated to pass these on to the Police.

If this situation arises, legal advice will be sought.

Confidentiality and the Capture of Illegal Activity: All images passed on to the research team will be treated as confidential material, unless they adequately capture an illegal incident. Participants will be informed of this on the information and consent form.

Privacy: Continually recording the wearers' environment also raises some concerns for participants' privacy, particularly in relation to the capture of inappropriate images for example, taking photographs in places in which people can expect privacy such as public toilets and changing rooms. Participants will be comprehensively briefed at the beginning of the data collection period, about situations in public and private in which it would be inappropriate to continue taking photographs and the device needs to be removed/reversed or turned off. If inappropriate photographs are taken, the participant and/or researchers can delete that photograph before anyone else views it. Likewise, if an inappropriate photograph of a member of the public is captured it will be deleted.

Taking Pictures in Assumed Public Places (e.g supermarkets,malls, galleries etc): Participants will be given a pre-prepared statement about the study. If approached, they would be advised to explain that they are participating in a study being conducted by researchers from the University of Otago; that the project aims to document their environment; and that they are wearing a camera that automatically takes pictures continually throughout the day. Furthermore, they would be advised to say that they are not intentionally taking photographs of specific people or places. They would also be encouraged to tell interested parties to contact the PI if they have additional information or have further questions (each participant will have a collection of the PI's business card). The consensus from the KidsCam project was that the sufficient others were unconcerned with the device's presence after an explanation was given. In cases where concern might be raised, then the camera can be simply removed, reversed or turned off.

Participant Burden: While there is a degree of responsibility associated with the daily docking of the devices, the disruption to daily routines is relatively minor. It is expected that the benefits of engagement for the participants will match or supersede the burden.

Ownership and the use of participant generated images in research: To prevent the images being released into the public domain by the participants, either in print form or via the internet, transfer of ownership is necessary to safeguard the privacy and anonymity of the participants and any other persons that appear in the images.

A small number of participant generated images may also be used in material that is published, presented or otherwise disseminated. Ownership of these images traditionally lies with the photographer, but can be transferred to the researcher with consent. To address this issue, participants will be informed as to how the images will be used and presented, prior to participating in this study. As a condition of participating in this study, participants will be asked to transfer copyright and ownership of their images as part of the consent process.

Anonymity: Anonymity poses an additional ethical challenge in the collection and use of visual data. Anonymisation is frequently used to protect the identities of photographed subjects and study settings. This process typically involves altering the image, obscuring the individual or place so they are no longer recognisable. In this study all images used in disseminated materials containing identifiable individuals would be processed through a sketch filter to protect the anonymity of the participant and their colleagues, supervisors, family and members of the public captured in their images. This process maintains the basic composition needed for the study but removes anything that may identify individuals. Furthermore, names of identifiable places, retail outlets and businesses would be obscured as a result.

Images can only be viewed via a password-protected application and not directly from the device. This prevents the release of images into the public domain via popular social media and photo sharing sites such as Facebook, Twitter, You-Tube, Instagram and Tumblr. It also prevents the images from being accessed by anyone other than the participant and the research team. Members of the research team will download the image data directly onto a password-protected computer.

It is also possible that devices may be lost during data collection as participants may have to remove the device in certain situations and may forget to take it with them. In these situations, the device is unable to be accessed. Again, the use of a passwordprotected application to access the unit protects against breaches in privacy resulting from the images being released into the public domain.

Data analysis: While we have some indication of the scope of the data we are likely to collect, it is possible that there will be other data collected which we would be useful to analyse but are currently unaware of. In this event, we will apply to the ethics committee for a revision of our ethics approval to allow for the analysis of as yet undetermined data.

Senorita John
PhD candidate
Higher Education Development Centre
University of Otago
Dunedin
New Zealand

P: +64 3 479 8415

E: senorita.john@postgrad.otago.ac.nz

18. ***Applicant's Signature:** ....

Name (please print): ……………………………………………………….

Date: ....

*The signatory should be the staff member detailed at Question 1.

19. **Departmental approval:** *I have read this application and believe it to be valid research and ethically sound. I approve the research design. The Research proposed in this application is compatible with the University of Otago policies and I give my consent for the application to be forwarded to the University of Otago Human Ethics Committee with my recommendation that it be approved.*

Signature of **Head of Department*:*
....

Name of HOD (please print):
……………………………………………………….

Date: ....

**Where the Head of Department is also the Applicant, then an appropriate senior staff member must sign on behalf of the Department or School.

APPENDIX E : ETHICS APPROVAL LETTER

UNIVERSITY of OTAGO
Te Whare Wānanga o Otāgo
NEW ZEALAND

16/160

Academic Services
Manager, Academic Committees, Mr Gary Witte

9 December 2016

Professor R Spronken-Smith
Graduate Research School
Clocktower Building

Dear Professor Spronken-Smith,
I am writing to let you know that, at its recent meeting, the Ethics Committee considered your proposal entitled "**Mining Reality: Detecting Behavioural Patterns in Student Spatiotemporal Data**".

As a result of that consideration, the current status of your proposal is:-
Approved

For your future reference, the Ethics Committee's reference code for this project is:- **16/160**.

The comments and views expressed by the Ethics Committee concerning your proposal are as follows:-

While approving the application, the Committee would be grateful if you would respond to the following:

Information Sheet
Please add the duration of the interviews to the Information Sheet for Participants and include reference to the amount participants will receive for participating in the study, as indicated in question 13 (f) on the application form.

Consent Form
Please add the University logo to the top of the Consent Form.

Please provide the Committee with copies of the updated documents, if changes have been necessary.

Approval is for up to three years from the date of this letter. If this project has not been completed within three years from the date of this letter, re-approval must be requested. If the nature, consent, location, procedures or personnel of your approved application change, please advise me in writing.

The Human Ethics Committee asks for a Final Report to be provided upon completion of the
study. The Final Report template can be found on the Human Ethics Web Page http://www.otago.ac.nz/council/committees/committees/HumanEthicsCommittee.html

Yours sincerely,

Mr Gary Witte
Manager, Academic Committees
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