THE USE OF OBJECTIVE DATA TO ASSESS ACTIVITY AND PARTICIPATION PRIOR TO AND FOLLOWING CRITICAL ILLNESS

Feasibility of smartphone data-capture

A thesis submitted for the degree of

DOCTOR OF PHILOSOPHY

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Acute Care Medicine
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The University of Adelaide

By

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ABSTRACT

This thesis is composed of five distinct chapters that investigate the feasibility of using smartphone data to define activity and participation in patients who have suffered critical illness. Specifically the thesis investigates the current state of play with regards to outcome measurement following critical illness; explores how others have used objective activity data to monitor survivors of critical illness;, investigates the ownership of smartphones and the data available on these devices amongst Intensive Care Unit (ICU) survivors; demonstrates the accuracy of the step data collected by a smartphone; and explores the use of a dedicated smartphone app to monitor patient activity and participation. The thesis comprises 6 distinct manuscripts.

Survival of critical illness frequently leads to the development of Post Intensive Care Syndrome (PICS). PICS is the new or worsening of cognitive, psychological and/or physical function that persists following hospital discharge in patients who have suffered critical illness. While PICS leads to disability its measurement is challenging, often relying on surveys that lack construct validity in survivors of critical illness (Chapter 1.1). Objective measurement of activity following critical illness has been investigated using wearable devices, but not smartphones, that are becoming ubiquitous in modern day life (Chapter 1.2).

We investigated smartphone ownership amongst ICU survivors and were able to obtain step and location data from a minority of these phones using manual techniques (Chapter 2.2). These patients were followed up (Chapter 2.3) at 3 and 6 months following ICU discharge. This study demonstrates that the step data collected from smartphones appears to be accurate when compared to a dedicated wearable device. We were able to show that the location data obtained from smartphones could be used to demonstrate elements of physical participation such as time spent at home, distance traveled and the extent of travel in activity spaces (Chapter 2.4). However, the manual extraction of these data was time consuming, relying on the use of obtaining Global Position System (GPS) data from screenshots of patients' phones. In 2015 Google Maps released a function that allowed the download of a single file that contained an individual's whole location history. We explored the availability of this data in patients admitted under general medicine (Chapter 3.2). Although the data extraction was more efficient and the analysis could be automated, the data were only available on a minority of devices.

Due to the inefficiencies associated with smartphone data extraction, we examined the smartphone user ability in patients receiving renal dialysis (Chapter 4.2). This demonstrated that the majority of smartphone owning patients do have the user ability, or immediate access to assistance to install a smartphone app. The development of a custom-built smartphone app in collaboration with the Software Engineering department of the University of Adelaide allowed the testing of a smartphone app to collect Step and GPS data in patients undergoing Cardiothoracic Surgery. The data generated by the app showed great promise in being able to monitor patient's recovery remotely and link this back to the same pre-morbid metrics, However, the technical failures of the app provide excellent learning opportunities for future studies.

DECLARATION

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

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I must thank my mother-in-law for kindness, support and generosity in all that she does, but more importantly for raising my amazing wife Samantha who during this PhD has raised two delightful children while putting up with long working hours and the stresses that this PhD, a change in career and COVID 19 have brought onto our family. Without your support none of this would have been remotely possible.

COVID 19 IMPACT STATEMENT

The impact of COVID 19 was significant. I took leave from my PhD in 2020 to enable me to return to full time ICU if the numbers of COVID 19 patients increased. Fortunately, that did not happen, but I utilized my expertise in writing education material, producing educational material both with the University of Adelaide, SA health and external providers that had international impact. During 2021/22 I was in a medical administration role and was heavily involved in the medical response to COVID 19 in the North Adelaide Local Health Network (NALHN). I took further leave from my PhD to fulfil this commitment.

FORMAT OF THESIS

This thesis is by publication, supplemented by narrative, as per the University of Adelaide Guidelines. The thesis comprises five distinct but complementary chapters each with a brief introduction followed by the relevant manuscripts and ending with a narrative conclusion of the major findings and future directions.

In total the thesis comprises seven manuscripts; one review of the literature (Chapter 1) and six
original research manuscripts. At the time of submission of this body of work, 4 of the manuscripts were published.

The seven manuscripts are presented in the style of the publication to which they were submitted, accounting for the variance in manuscript structure. The references for all seven publications are included in each respective manuscript and references for each chapter follow each section.

The publications are as follows:

A scoping review to determine the use of wearable devices to evaluate outcomes in survivors of critical illness. Gluck S, Chapple L.S, Chapman M.J, Iwashyna T.J, Deane A.M. Crit Care Resusc. 2017; 19(3):197-204

Wide Disagreement Between Alternative Assessments of Pre-Morbid Physical Activity: Subjective Patient and Surrogate Reports and Objective Smartphone Data. Gluck S, Summers M.J, Goddard T.P, Andrawos A, Smith N.C, Lange K, Iwashyna T.J, Deane A.M. Crit Care Med. 2017; 45(10):e1036-e1042

An observational study investigating the use of patient-owned technology to quantify physical activity in survivors of critical illness. Gluck S, Summers MJ, Finnis ME, Andrawos A, Goddard TP, Hodgson CL6, Iwashyna TJ, Deane AM. Australian Critical Care. 2019; pii. S1036 – 7314 (18) 30236-4 [Epub ahead of print]

The use of smartphone derived location data to evaluate participation following critical illness: A pilot observational cohort study. Gluck S, Andrawos A, Finnis, M.E, Summers M.J, Goddard T.P, Chapman, M.J, Iwashyna, J, Deane, A.M. ACC. 2020

The manuscripts awaiting submission are as follows:-

Development of a protocol for collecting patient data on mobility and activity prior to hospital admission Gluck S, Dasondi A, Ma T, Kumawat M, Chapple L.S, Gilbert T, Woodman R, Thompson C,H.

A point prevalence study of smartphone ownership and user ability in a South Australian dialysis population. Gluck S, Gilbert T, LeLeu, R , Britton A, McDonald S, Jesudason S

The use of a smartphone app to monitor patients prior to and following cardiothoracic surgery. Gluck S, Bacchi S, Kelly A, Singh A, Babar A, Chapman MJ, Iwashyna TJ, Deane A

CHAPTER 1 - THE MEASUREMENT OF OUTCOMES FOLLOWING CRITICAL ILLNESS

1.1 Thesis Introduction

The measurement of outcomes following critical illness has persistently shown that function in survivors remains below that of the general population. However, this assumes the survivors have normal function prior to being admitted to intensive care, this is frequently not the case. Being able to utilize passively collected datasets to objectively define patient function prior to and following critical illness would represent a frame-shift in outcome measurement, not just in intensive care literature but across all of healthcare.

It was initially aimed to use smartphone data and the study recovery compared to standard outcomes, and explore how best to utilize the passively collected data. However, due to the paucity of data a collaboration was established to utilize a smartphone app to collect these data and the aims of the PhD altered to accommodate this.

1.1.1 Overarching objective

To define activity and participation prior to and following ICU admission using data derived from the smartphones of ICU survivors.

1.1.2 Specific aims

To understand how these technologies have been used in ICU survivors to date.
To explore the data availability on the smartphones of ICU survivors.
To explore the feasibility of using smartphone data for outcome measurement.
To describe pre-ICU activity and participation using smartphone derived data.
To match these pre-morbid ICU data to those obtained during recovery.

1.2 Introduction

Critical illness, requiring organ support and admission to an intensive care unit (ICU), comes with a huge physiological insult including dysregulated inflammatory cascades, deranged metabolic state, frequent delirium, injuries that come with high risk of long-term disability and the use of drugs to enforce bed rest to allow the invasive therapies required. These and many other factors contribute to a recognised syndrome in the survivors of critical illness. This Post Intensive Care Syndrome (PICS) describes the disability that remains in survivors of critical illness. Is has been defined as the new or worsening impairments in physical, cognitive or mental health status arising after critical illness and persisting post discharge from the acute care setting[1]. Due to the advancements in critical care medicine, there are increasing rates of survival[2], and thus increasing numbers of patients suffering from PICS.

Limitations in physical function are common, with reduced exercise capacity[3, 4], reduced strength[5, 6] and inability to perform activities of daily living[7, 8]. Cognitive impairment has been reported in 25% to 75% of survivors[9-11] and ICU survivors suffer significant levels of anxiety[12], depression[13, 14] and Post Traumatic Stress Disorder (PTSD)[15-17]. These functional impairments lead to significant disability. The World Health Organisation, in its International Classification of Functioning, Disability and Health (ICF) has advocated for the use of a common language for functioning, disability and health[18]. The ICF defines

disability as an umbrella term for impairments, activity limitations and participation restrictions[18].

Much of the last two decades has been spent trying to reach consensus on a core outcome set for survivors of critical illness. Due in part to the heterogenicity of the group, this has not yet been achieved. Dale Needham's group have gone a long way to defining a core outcome set in a small subgroup of ICU survivors (Acute Respiratory Distress Syndrome (ARDS)[19]. Their extensive body of work is to be commended, however, the core outcome set they have developed still lacks tools required to effectively assess several domains in which the survivors of ARDS report dysfunction[20] and the outcomes they have suggested for other domains[21] lack the construct validity required for the general intensive care population[22].

To drive research and quality improvement it is essential that we are able to capture high quality, granular data that measures outcomes meaningful to our patients, in a manner that is least disruptive to our patients lives over prolonged periods of time and with minimal cost to the healthcare system [23].

With the advent of technologies, such as accelerometry and Global Positioning System's (GPS), and the provision of these in easy to use wearable devices it should be possible to measure human movement in high detail to quantify activity and participation and hence disability.

1.2.1 Objectives

The objectives of this scoping review were to (i) define the extent wearable devices have been used to define recovery following critical illness, (ii) to compare the outcomes used with conventional outcomes, (iii) to evaluate usability and (iv) to explore gaps in the current literature.

1.3 – Manuscript

A scoping review of use of wearable devices to evaluate outcomes in survivors of critical illness

Statement of Authorship

Title of paper	A scoping review of use of wearable devices to evaluate outcomes in survivors of critical illness
Publication Status	Published
Publication details	**A scoping review to determine the use of wearable devices to evaluate outcomes in survivors of critical illness**. Gluck S, Chapple L.S, Chapman M.J, Iwashyna T.J, Deane A.M. Crit Care Resusc. 2017; 19(3):197-204

Principle Author

Name of Principle Autor (Candidate)	Dr Samuel Gluck		
Contribution to paper	Conceptualisation of work, literature search, data collection, manuscript preparation, corresponding author		
Overall percentage (%)	70%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	25/3/2017

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

- The candidate's stated contribution to the publication is accurate (as detailed above);
- Permission is granted for the candidate to include the publication in the thesis; and
- The sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Full Title

A scoping review to determine the use of wearable devices to evaluate outcomes in survivors of critical illness

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Abstract

Objective

Technology may be a cost-effective method to assess functional outcomes in survivors of critical illness. The primary objective of this review was to determine the extent to which wearable device technology, such as smartphones, pedometry, accelerometry and global positioning systems (GPS), have been used to evaluate outcomes in Intensive Care Unit (ICU) survivors.

Design

Studies were included if they were performed in patients surviving ICU admission and measured outcomes using wearable devices.

Data Sources and Review Method

A scoping review searching CINALH, EMBASE, MEDLINE and PUBMED was performed.

Results

The seven studies identified were published since 2012, and were predominately descriptive (n=6) with one randomised controlled trial. All studies described outcomes in cohorts of relatively few participants [range: 11–51]. Duration to follow-up was mostly short, at a median time of three months post-ICU discharge [range: in-hospital to 27 years]. All studies used accelerometers to monitor patient movement; specifically physical activity (n=5), sleep quality (n=1), and infant movement (n=1). The accelerometers were bi-axial (n=3), uni-axial (n=2), combined uni-axial (n=1) and tri-axial (n=1). Common outcomes evaluated were the number of participants walking for < 30 min/day, mean daily step-counts and walking speed.

Conclusions

While wearable devices have been infrequently used to measure physical activity in survivors of critical illness, all identified studies were published recently, suggesting the use of wearable devices may be increasing. Thus far, only accelerometry has been reported, and the wide variation in methodologies used and the outcomes measured limits synthesis of these data.

Introduction

Physical activity and function is frequently impaired in survivors of critical illness [1-11]. While functional capacity after critical illness is an important outcome, to date, both researchers and clinicians have relied upon labour-intensive techniques, such as the six-minute walk test and subjective patient-reported questionnaires, to quantify quality of life (QOL) and physical function [1-10]. Given the logistical challenges and expense associated with these methods there is a need to be able to accurately, yet efficiently, assess physical recovery in survivors of critical illness in a way that is meaningful to patients and clinicians.

Technological advances provide the potential to quantify physical activity in a real-life setting, and in a cost-effective manner. It is possible that quantifying mobility, using daily step-counts, or measuring how much time individuals spend at home, may provide a holistic and patient-centric assessment of physical function.

A number of relatively inexpensive and seemingly accurate pedometers and accelerometers are now available [12]. A pedometer measures the number of steps taken by an individual and an accelerometer responds to acceleration in either one, two or three planes (uni-, bi-, and tri-axial accelerometers, respectively). With the use of differing body mounting and algorithms, accelerometers can be used to assess sleep, the intensity and duration of activity, body position, steps and energy expenditure. They record data continuously, providing a more representative measure of activity. Furthermore, ambulatory global positioning system (GPS) devices record movement through location data. A smartphone contains a tri-axial accelerometer, a gyroscope, a compass, and a barometer, combining these sensors with appropriate software applications (apps) and algorithms has the capacity to wirelessly transmit live data to researchers and clinicians. Such methodology is increasingly described in epidemiological studies, for example McConnell and colleagues recently report using a smartphone app to quantify physical activity from more than 20,000 healthy individuals [13].

Given the recent advances in technology of wearable devices that record physical activity, there has been growth in the number of researchers evaluating these devices across different healthcare settings. Accelerometers and pedometers have been used to assess physical activity in a variety of conditions including chronic obstructive pulmonary disease [14], cystic fibrosis [15], multiple sclerosis [16], diabetes [17] and joint replacement preoperative assessment [18]. To date, however, no review has summarised the current literature on wearable devices in survivors of critical illness.

We conducted a scoping review with the primary objective to evaluate whether wearable devices have been used to measure outcomes in survivors of critical illness. For the purpose of this review wearable devices included smartphones, pedometry, accelerometry and GPS. Our secondary objectives were to compare outcomes evaluated using wearable devices to more conventional methodologies and to evaluate usability in study participants.

Scoping Review Question

Have smartphones, pedometry, accelerometry or GPS been used to assess outcomes in patients who have survived an ICU admission?

Methods

Data sources and searches

On 9 May 2016 we conducted a scoping review of the literature using four online databases (CINALH, EMBASE, MEDLINE and PUBMED). The search criteria are provided in Supplementary Table 1 (online at cicm.org.au/journal.php). All MeSH terms were expanded for further terms and included in the search of all four databases. Reference lists of all retrieved papers were reviewed to identify other eligible studies not captured in the primary search.

Eligibility criteria

We included studies that reported outcomes in survivors of critical illness using wearable devices. We defined wearable devices as smartphones, pedometers, accelerometers, and GPS devices, based on our understanding of current technologies that could be used to assess outcomes following critical illness, which we defined as any condition necessitating ICU admission regardless of the presenting problem. No date restrictions were applied. We excluded studies that did not specify whether they were conducted in ICU survivors, did not report on the use of an aforementioned devices, and were not published in English.

Study selection

Duplicate citations were removed and titles and abstracts were independently screened for inclusion by two reviewers (SG and LC). If it was not clear from the abstract if the citation could be excluded, then the full-text article was obtained. Full-text manuscripts were independently evaluated for eligibility. Disagreements were resolved by consensus or consultation with a third reviewer (AD).

Data extraction

Two reviewers (SG and LC) independently extracted data from included studies using a modified version of a standardised data collection form [19]. Information extracted included study characteristics (author, publication year, country, design, sample size), type/s of technology used, outcomes from the technology used, conventional outcomes compared to wearable devices, and study results.

Quality assessment

Risk of bias for observational studies was assessed using the Newcastle-Ottawa Scale. The Newcastle-Ottawa scores studies on three domains relating to the: selection of study groups; comparability of groups; and ascertainment of either the exposure or outcome of interest for case-control or cohort studies, respectively [20].

Usability of wearable devices

We defined usability as whether the wearable device provided a data point. We measured usability as the number of incomplete records, due to either user or device failure, out of the total number of participant data points**,** with a lesser number signifying greater usability.

Results

Study selection

Our search returned 1317 references, of which 526 were duplicates. Of the 791 abstracts reviewed, 747 did not meet the defined inclusion criteria and were excluded. Forty-four full-text articles were obtained and assessed for eligibility. Of these, 37 were excluded due to: patients were not admitted to ICU (n=10); studies were conducted during ICU admission and not in survivors (n=10); duplicate data (n=9), outcomes not reported (n=5) and only published in abstract form (n=3). Accordingly, seven studies were included in our review [21-27] (Figure 1).

Study characteristics

There were five prospective observational cohort studies [22, 23, 25-27], one case control study [21], and one randomised controlled trial [24] (Table 1). Three studies were nested within larger studies: two within RCTs [23, 27] and one within a longitudinal study [25]. All studies were published since 2012. Using the Newcastle-Ottawa Scale the quality of all the observational studies were low with the major limitation to these studies being their single cohort and/or descriptive nature.

Cohort studied

One study was conducted in neonates who survived ICU admission [24] and one was conducted in adults who survived an earlier ICU admission as neonates [21]. The remainder were in survivors of adult ICU (Table 1), and included various enrolment criteria such as severe sepsis, mechanical ventilation, or ICU length of stay >5 days. All studies described outcomes in cohorts of relatively few participants [range; n= 11–51]. Only one study [25] included a calculation to determine sample size. The majority of studies evaluated their outcomes within three months of ICU discharge, although one measured at 18 months post- ICU, and one at a mean of 26 years [21, 25]. Borges et al and Guyer et al were the only investigators to report on outcomes at more than one time point [24, 26].

Usability of wearable devices

There were 8/301 records across all studies that failed to complete activity monitoring; four in Denehy's [27] study, three in McNelly's [25] study, and one in Edbrooke's [23] study, suggesting the devices were usable.

Technology reported

All studies used accelerometers to monitor activity. The bi-axial AMP331 was the most commonly used accelerometer, with bi-axial accelerometers being used by three groups of investigators [23, 25, 27], uni-axial accelerometers by two groups [22, 24], and combined uni-axial accelerometers [21] and tri-axial accelerometers were used by one group each [26].

Outcomes measured

Studies evaluated physical activity (n=5) [21, 23, 25-27], sleep quality (n=1) [22], and infant movement (n=1) [24]. Reported outcome measures are summarised in Table 1. Several studies reported multiple accelerometer outcomes. The physical activity outcomes measured varied and included simple assessments of body position [26], walking speed [23, 26], duration in dynamic activities [21], distance walked [23, 27], time spent walking [26], time spent inactive [26, 27] and steps [23, 25, 27]. Only daily step-count [25, 27], walking speed [23, 26] and number of participants walking <30 minutes a day [26, 27] were reported in more than one study.

Associations with traditional outcome measures

Two studies reported direct correlations between outcomes measured using wearable devices and more 'traditional' outcomes, such as global reported QOL measures. There was a modest association between the total Physical Activity Scale for the Elderly (PASE) score and mean daily step-count (Spearman's rank coefficient (rho)=0.332 p=0.05) or distance walked (rho=0.313 p=0.05) [27]. Stronger correlations were shown between mean daily step-count and both the Physical Component Summary score (r^2=0.25, p<0.01) and Physical Function score (r^2=0.51 p<0.01) of the SF-36 and with the Clinical Frailty Scale (CFS) (r^2=0.55 p<0.01) [25]. McNelly [25] and Denehy [27] both reported that patients with chronic disease who survived ICU had reduced step-count compared to those without chronic disease.

Discussion

Our scoping review revealed that seven studies have reported on the use of wearable devices to measure outcomes in survivors of critical illness. However, as all identified studies were published within the last five years it appears that the use of wearable devices may be an emerging field of research. The use of wearable devices permits a high degree of 'usability' with only a small number of failed readings/absent data points.

Our review also revealed that the majority of studies in this field have been exploratory in nature, and conducted in small, often single, cohorts of patients, with short-term follow-up. Additionally, the quality of study design was modest. Only one RCT was identified, and three studies were nested in other studies. This would be consistent with an emerging field of research where exploratory studies frequently do not have the methodological rigor of large-scale RCTs [28].

Variety in outcomes reported

While the studies all utilised accelerometry to quantify outcomes, a wide variety of outcomes were measured and reported, such as sleep actigraphy [22] and movement assessment [24]. The outcome most frequently reported was locomotion. Even with this outcome, there was a lack of consensus between investigators on how this should be quantified. While locomotion was recorded in four studies [23, 25-27], the only commonly reported outcomes were mean daily step-count, distance walked, and the number of participants that walked for <30 minutes/day. This variation is expected during the initial phases of a methodology but over time it is important that consistency in core domains is established [29]. The findings of this review highlight the need for the development of core outcome sets for measurement of physical activity in ICU survivors using technology.

We were surprised there was no utilisation of GPS data to create life-spaces [30], activity-spaces [31] or to quantify percentage time spent at home [32], as such measures have been used in other populations e.g. after surgery for peripheral vascular disease [33], spinal disorders [34], and in those with mental health issues [35]. The activity space is a geographic information systems construct that represents the environment an individual interacts with. Such measurements may provide an assessment of recovery from critical illness. We were also surprised that smartphones, with their associated apps, had not been used in any relevant study.

Accelerometer methodologies

Four identified studies reported on locomotion using algorithms to access raw accelerometer data to determine step data. Step data are increasingly reported in other healthcare settings [36-39]. It has been shown that uni-axial accelerometers are adequate for detecting heal strike [40] to calculate physical activity from walking, but this may under-estimate when assessing gait in slower walkers, particularly those with a shuffling gait [41]. It does, however, produce data that are patient-centered and easily interpreted by clinicians.

While using locomotion data may have its advantages, the accelerometer literature suggests that using centrally mounted tri-axial accelerometers to count activity frequency and intensity would provide the best estimate of total physical activity [40], and raises the suggestion of using advanced modelling techniques combining accelerometer outputs to produce estimates of activity counts and energy expenditure [42].

Although less patient-focused, the use of total activity counts to estimate energy expenditure, taking into account intensity and frequency of all movements, rather than just energy expenditure, and hence physical activity, related to walking would, perhaps, provide a better assessment of physical activity. Notwithstanding the limitations of each methodology, the use of a single research methodology is ideal.

Relationships between outcomes obtained from wearable devices compared to other methodologies

It appears that there are fair associations between outcomes after critical illness measured using wearable devices compared with more 'traditional' methodologies, such as self-reported QOL questionnaires. In this review, we found stronger associations between subjective measures than between subjective and objective measures, the subjective assessment of sleep (Pittsburgh sleep quality index) had stronger correlations with the subjective assessments of health-related QOL (EQ-5D and SF-36), than with objective actigraphy measures [22], as did the subjective assessments of physical function (SF-36) with frailty (CFS) than with daily step-counts [25]. It is important, prior to the widespread implementation of step data into critical care research, to establish that measurement of physical activity after critical illness is both clinically important and related to functional outcomes of importance to patients, their care-givers, and the community.

Usability as an outcome for large trials

Although two studies [21, 22] reported that only a subset of patients used the wearable devices due to availability, potentially implying a cost limitation, the cost of follow-up using accelerometers has not been explicitly stated in any study. An AMP331 costs $1200 (and is no longer produced), a Sensewear accelerometer $120 and an Actiwatch 2 (4 is discontinued) $1500. This is likely to be prohibitively expensive for researchers conducting trials involving large numbers of patients and/or sites. Fortunately, however, this cost is likely to reduce over time. An example of the dynamic nature of the technology landscape is that two of the accelerometers used in the identified studies, which were conducted within the last five years, have already been discontinued. The rapid evolution of these technologies and dynamic pricing structures is evident in that 'market leaders' in the commercial space, such as the FitBit One ($130) and Flex ($89) are comparatively inexpensive, and have been shown to be accurate [12]. Therefore, these dynamic changes may reduce costs however, the rapid evolution in makes, models and function could hinder attempts to develop core outcomes and methodologies using these technologies.

Strengths and limitations

Our review is, to the best of our knowledge, the first to appraise the use of wearable devices in ICU survivors. The strengths are: our search technique was relatively comprehensive; we evaluated studies for bias and quality and we used a standardised data extraction tool. However, we only accessed English language literature and moreover, there may be other wearable devices we are not aware of, and were not included in our search terms. Finally, the considerable heterogeneity of differing populations, wearable device outcomes, and time-point to follow-up between studies limits any firm conclusions.

Conclusions

Currently, wearable devices are infrequently used to report outcomes from survivors of critical illness. While accelerometry was the only technology reported, there was considerable variation as to the type of accelerometer used, the specific outcome reported, and the time point that observations were made.

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STRING 1	STRING 2
Critical care (.mp)	Mobile phone$ (.mp)
Critical$ ill$(.mp)	Cell$ phone$ (.mp)
Intensive care$ (.mp)	Smartphone$ (.mp)
ICU$ (.mp)	Smart phone$ (.mp)
Intensive therapy (.mp)	Pedomet$ (.mp)
ITU$ (.mp)	Step count$ (.mp)
	Acceleromet$ (.mp)
	Actigraph$ (.mp)
	GPS (.mp)
	Global positioning system$ (.mp)
	Cell$ telephone$(.mp)
	Life space$ (.mp)
	Activity space$ (.mp)

Supplemental Table 1: Search terms used in each database. $ corresponds to the appropriate truncation command in each database

Lead author	Year	Study Design	Cohort studied	Number of patients	Wearable Device	Time to follow-up	Duration of observation	Observations from wearable device	Other outcomes	Associations
Solverson	2016	Prospective observational cohort study	Adults, >4 day ICU LoS. Excluded TBI, neurocognitive disorders, acute strokes, patients living a distance from the hospital	55 (11 sleep actigraphy)	Sleep actigraphy	3 mo post-hospital discharge	3 nights	Sleep/Awake cycles -Mean total sleep time – 6.15hrs - Sleep efficiency 78% - Number of awakenings (duration) 11 (7mins) - Sleep onset latency – 12 mins.	Sleep Quality - PSQI, ESS. HRQOL; EQ-5D, SF-36. Depression/anxiety; HADS.	No association between total sleep time, sleep efficiency or sleep disruptions and PSQI or PSQI component scores. Significant association with APACHE II score. Total sleep time had no association with HADS, ED-5D individual domains or MCS or PSC.
Edbrook	2012	Prospective observational cohort study (nested in RCT)	Adults, sourced from a concurrent RCT, able to walk >5m without assistance	20	AMP331 biaxial accelerometer	Post-ICU hospital ward	Point in time, in hospital assessment	Reported distance walked, steps taken and walking speed.	Direct observation	Slight underestimations of walking distance (2.79 (walk 1) – 3.11 (walk 2) m over a total of 90m) and walking speed (28.87 cm/s) and a slight overestimation of step-count (0.92, 95% CI -3.27 – 5.11)
Guyer	2012	Randomised control trial	Neonates <32 weeks gestational age	37	Actiwatch mini and Actiwatch AW4	5 and 11 wks post-term corrected age	10 days at each time point.	Reduced activity count per 24 hrs in the DL group at 5 and 11 wks. No between group difference for activity count/night or day. Age-effect noted with increased activity between 5 and 11 wks	Sleep and crying behavior every 5 mins in an auditory diary (3 days), Weight	No correlations with wearable devices were reported.
Van Der Cammen-van Zijp	2014	Retrospective case control study	Adult survivors of neonatal resp distress,(27 with CDH, 30 without)	57 (28 activity monitoring)	4 uni-axial accelerometers	Unplanned follow-up of PICU survivors in adulthood (Mean 26.7 years)	2 days	Reduced duration of dynamic activities in the CDH group. No difference for mean motility and motility during walking. No significant differences between groups	Lung Function - Spirometry Exercise testing – CPET Fatigue – FSS HRQOL - LIFE-H 3.0 and SF36	No correlations with wearable devices were reported
McNelly	2016	Prospective observational cohort study (nested in longitudinal outcomes study)	Adult, >48 hrs ventilation, >7 d ICU LoS. Excluded;- pregnant; lower limb amputees; disseminated cancer, neuromuscular pathology	30 pts (27 provided data) and 30 age and gender matched controls	SenseWear bi-axial accelerometer,	18 mo post-ICU discharge	>5 days, including one weekend day.	Daily step-count was half that of healthy controls. Pre-existing chronic disease was associated with lower step-counts	HRQOL - SF-36, Frailty - CFS	Steps/d vs SF-36 PF r^2=0.51, vs SF36 PCS r^2=0.25, vs CFS r^2=0.55. Variation in steps vs SF-36 PF r^2=0.24 vs CFS – r^2=0.32.
Borges	2015	Prospective observational cohort study	Adult, severe sepsis or septic shock, able to walk without assistance pre-admission, able to complete 2 assessments at ICU D/C Excluded;- previous stroke, neurological disease, TBI, SAH, SCI, fractured limbs or amputation, terminal illness	72 at hospital D/C 51 at 3mo follow-up and 50 healthy controls.	Dynaport tri-axial accelerometer	Prior to hospital discharge and 3 mo post discharge	2 consecutive days at both time points.	Septic patients had a lower walking time in at both time points compared to healthy individuals. Patients were more inactive (sitting or lying) on the ward, than at 3-months. Walking intensity was lower after hospital discharge than healthy individuals. 40% of septic patients walked <30 mins/day vs 15% of healthy individuals	Muscle strength: inspiratory muscles - MIP, handgrip (dominant hand dynamometry) and quadriceps (dynamometry) Exercise capacity - 6MWT	No associations between accelerometer data and any other variable during hospital admission or at 3-mo
Denehy	2012	Prospective observational cohort study, (nested in a RCT)	Adult, >5 d ICU LoS, English speaker, live within 50km, Participation agreed by the attending intensivist. Excluded neurological, spinal or musculoskeletal dysfunction.	49 accelerometer data 45 PASE data	AMP 331 Accelerometer	2 mo post ICU discharge	7 days	Participants took 4,894 (SD – 3,070) steps/day, 80% took <7500 and only 6% >10,000 steps/day. Only 54% of steps were taken in the locomotion category. Median distance walked was 1.69km. 90% of their time was spent inactive, 3% of the time was spent in the locative category. 63% of the cohort spent <30 mins/d in the locomotive category.	Lifestyle - PASE questionnaire Exercise capacity - 6MWD Manual Muscle strength - Timed up and go test (TUG)	Fair correlation between total PASE and mean steps/day rho=0.332 and mean distance walked rho=0.313 at p=0.05. Fair correlation between PASE occupation sub-score and daily steps rho=0.332. Fair correlation between walking <30 mins/day from PASE and steps (rho=0.345) and distance (rho=0.344). 6MWD and SF-36 PF was associated with walking time and steps/da in a univariate analysis, in the multi-variant analysis this was confounded by the presence of chronic disease.

Table 1 - Details of the peer reviewed articles included in our scoping review – *AA – Age Adjusted, 6MWD – Six-Minute Walk Distance, CDH – Congenital Diaphragmatic Hernia, d – Day, D/C - Discharge, CFS – Clinical Frailty scale, CL – Cycled Light, CPET – Cardo-Pulmonary Exercise Testing, DL – Dim Light, D_{LCO} – Diffusion capacity of the lung for carbon monoxide,EQ-5D – EurolQol-5D, ESS – Epworth Sleepiness Scale, FEV_1 – Forced expiratory volume in 1 sec, FSS – Fatigue Severity Score, FVC – Forced Vital Capacity, HADS – Hospital Anxiety and Depression Scale, MIP – Maximal Inspiratory Pressure, MCS – Mental Composite Score of SF-36, PADL – Physical Activities of Daily Life, PASE – Physical activity scale for the elderly questionnaire, PCS – Physical Composite Score of SF-36, PSQI – Pittsburg Sleep Quality Index, SCI – Spinal Cord Injury, SDS – Standard Deviation Scores, SF-36 – Short-Form 36, TBI – Traumatic Brain Injury, TPDA – Time Post-Discharge Adjusted, TUG – Timed Up and Go Test, V_A – Alveolar volume, VAT – Ventilatory anaerobic threshold.*

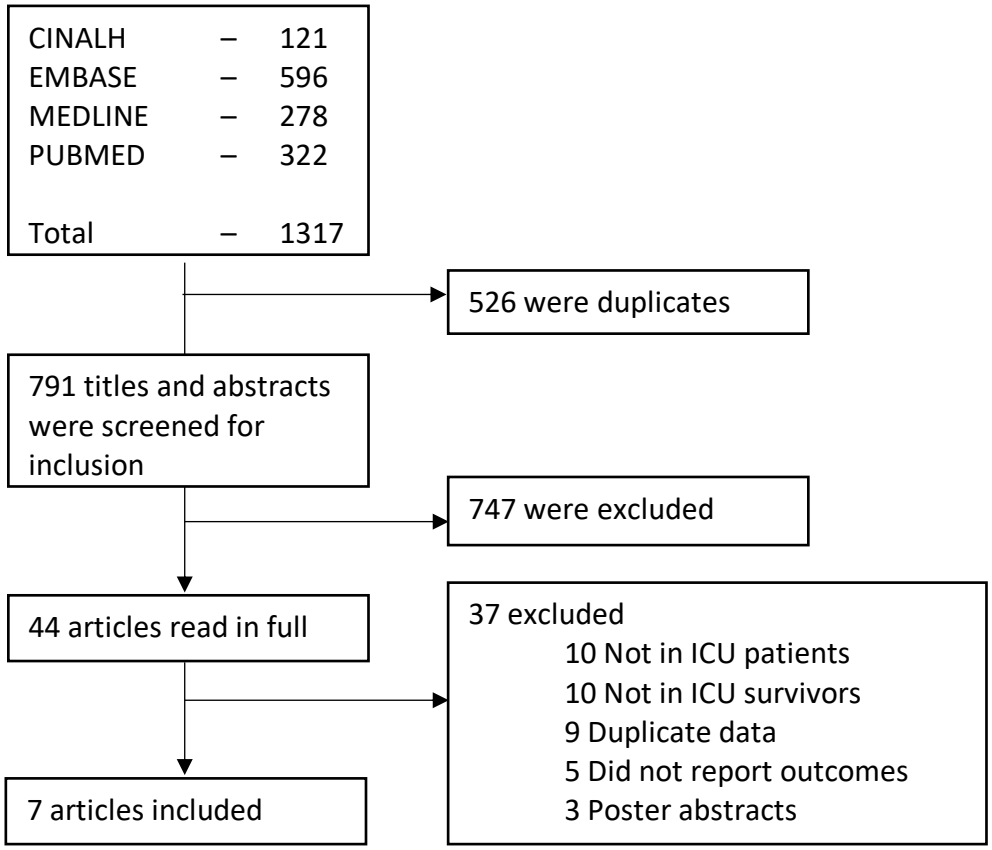

Figure 1 - Flow diagram for selection of studies (ICU - Intensive Care Unit)

1.4 Conclusions

1.4.1 Introduction

Despite its growing prevalence the use of accelerometers in the study of ICU recovery is in its infancy, with the majority of studies being observational in nature and assessing heterogenous outcomes in small numbers of patients. The devices used did have good useability, with little missing data. However, the absence of utilisation of GPS data or smartphones does provide an opportunity for further exploration in an expanding field of mHealth and digital phenotyping.

1.4.2 Contribution of this work to the measurement of physical activity following survival of critical illness

This review has demonstrated that although physical functioning is a key outcome in ICU survivors there has been a strong reliance on physical testing and surveys with a small minority of the literature utilising wearable technologies. The devices appear to be tolerated and usable with minimal missing data. The review has highlighted the heterogenicity in the follow-up period and in the accelerometry outcomes reported. It has demonstrated that while smartphones and GPS data have been used in other areas they have not yet been examined in survivors of critical illness.

1.5 Future Directions

1.5.1 Use of smartphone technology

Utilising the multiple sensors contained within a smartphone would appear to be an advantageous approach. Knowing the level of smartphone ownership within the ICU patient population will enable the assessment of the feasibility of this approach. Additional patient owner devices may contain data about their levels of activity prior to ICU. Exploring the data stored within these devices may potentially allow the collection of objective data that pertain to patient activity prior to their critical illness.

1.5.2 Use of GPS data

While the use of GPS data has been reported in other populations there has been no uptake of this technology to study ICU survivors. Reviewing how this technology has been used and potentially applying the constructs used elsewhere in ICU survivors may be of potential benefit.

1.5.3 Accuracy of smartphone data

While the accuracy of data from research quality accelerometers can be assured, the accuracy of data from a smartphone will need to be validated in free living conditions.

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CHAPTER 2 – THE FEASIBILITY OF SMARTPHONE USE IN SURVIVORS OF CRITICAL ILLNESS AND THE ACCURACY AND USEABILITY OF SMARTPHONE DATA

2.1 Introduction

The sequel following critical illness have been established as Post Intensive Care Syndrome (PICS), which is defined as new or worsening impairments in, physical, cognitive or mental health status arising after critical illness and persisting post discharge from the acute care setting[1]. Measuring the disability PICS causes is a challenge; however, establishing if that disability is new or worsening is near impossible, and a huge limitation of any study reporting ICU outcome measures. Critical illness and injury affects almost 800 people per 100,000 per year in Australia[2], so you would need to prospectively follow tens of thousands of patients over several years to enrol a sample large enough to report pre-morbid disability.

Several authors have been able to demonstrate this using large database studies. Iwashyna and colleagues used the US veterans dataset to demonstrate the physical and cognitive function prior to and following severe sepsis[3]. They demonstrated that there was a burden of functional and cognitive impairment prior to an episode of severe sepsis and this was exacerbated by the critical illness. More recently Jouan and colleagues have used a French medico-administrative database to explore healthcare utilisation prior to and following septic shock and/or Acute Respiratory Distress Syndrome (ARDS) requiring 5 days of mechanical ventilation[4]. They demonstrated that overall there was a significant increase in healthcare utilisation in the year before ICU admission while 28% of the cohort had no prior healthcare utilisation. Fourteen percent had greatly elevated and increasing healthcare utilisation. These findings are similar to those of Lone and Szakmany and colleagues in Scotland and Wales respectively[5, 6].

Other authors have used subjective assessments to assess quality of life at admission to ICU, asking relatives to estimate or asking patients to recall the answers when capacity is regained [7-9]. The discordance between relatives and patients, and the reliance of retrospective recall in a patient population, with an established, high prevalence of cognitive disfunction has been a significant weakness of these methodologies.

Clinicians frequently rely on substitute decision maker estimates of a patient's level of physical activity to determine treatment decisions. The accuracy and agreement between relative and patient estimates of physical activity levels has never been established. Smartphones record activity data in the form of steps and location data in the form of frequent locations and google-map timelines, often storing many years of data. It is possible these data could be utilised to objectively assess the levels of activity prior to ICU admission and overcome the inherent biases in the subjective recall of patients and relatives. Additionally, these data may be able to demonstrate an individual's disability trajectory at admission.

2.1.1 Objectives

The objectives of this chapter, which comprises three manuscripts, were to; (i) Evaluate the relationship and agreement between surrogate and patient estimates of pre-morbid physical activity (Chapter 2.2) ; (ii) Test the feasibility of smartphone data extraction to quantify physical activity (Chapter 2.2, 2.3 and 2.4); (iii) Compare the subjective estimates of physical activity to objective smartphone data (Chapter 2.2); (iv) Determine the accuracy of smartphone step counts when compared to a dedicated pedometer (Chapter 2.3); (v) describe recovery from critical illness using smartphone derived step counts (Chapter 2.3) and (vi) use location data to describe location-based outcomes in ICU survivors (Chapter 2.4).

2.2 – Manuscript

Wide Disagreement Between Alternative Assessments of Premorbid Physical Activity: Subjective Patient and Surrogate Reports and Objective Smartphone Data

Statement of Authorship

Title of paper	Wide Disagreement Between Alternative Assessments of Premorbid Physical Activity: Subjective Patient and Surrogate Reports and Objective Smartphone Data
Publication Status	Published
Publication details	**Wide Disagreement Between Alternative Assessments of Pre-Morbid Physical Activity: Subjective Patient and Surrogate Reports and Objective Smartphone Data.** Gluck S, Summers M.J, Goddard T.P, Andrawos A, Smith N.C, Lange K, Iwashyna T.J, Deane A.M. Crit Care Med. 2017; 45(10):e1036-e1042

Principle Author

Name of Principle Autor (Candidate)	Dr Samuel Gluck		
Contribution to paper	Conceptualisation of work, recruitment, data collection manuscript preparation, corresponding author		
Overall percentage (%)	85%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	6/5/2021

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

- The candidate's stated contribution to the publication is accurate (as detailed above);
- Permission is granted for the candidate to include the publication in the thesis; and
- The sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Full Title

Wide Disagreement Between Alternative Assessments of Pre-Morbid Physical Activity: Subjective Patient and Surrogate Reports and Objective Smartphone Data.

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Key Words
Physical Activity, Exercise tolerance, Technology, Critical illness, Smartphone

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Abstract:

Objective

Surrogate-decision maker and patient self-reported estimates of the distances walked prior to acute illness are subjective and may be imprecise. It may be possible to extract objective data from a patient's smartphone, specifically, step and global position system (GPS) data, to quantify physical activity. The study objectives were to (1) assess the agreement between surrogate-decision maker and patient self-reported estimates of distance and time walked prior to resting and daily step-count and (2) determine the feasibility of extracting premorbid physical activity (step and GPS) data from critically ill patients.

Design

Prospective cohort study

Setting

Quaternary ICU

Patients

Fifty consecutively admitted adult patients who owned a smartphone, who were ambulatory at baseline and remained in ICU for > 48 hours participated.

Measurements and main results

There was no agreement between patients and surrogates for all premorbid walking metrics (mean bias 108% [99% lower to 8,700% higher]; 83% [97% to 2,100%]; and 71% [96% to 1,080%], for distance, time and steps respectively). Step and/or GPS data were successfully extracted from 24/50 (48%; 95% CI 35, 62%) phones. Surrogate-decision makers, but not patient self-reported, estimates of steps taken per day correlated with smartphone data (surrogates n=13, rho=0.56, $p<0.05$; patients n=13, rho=0.30, p=0.317).

Conclusion

There was a lack of agreement between surrogate-decision maker and patient self-reported subjective estimates of distance walked. Obtaining pre-morbid physical activity data from current generation smartphones was feasible in approximately 50% of patients.

Introduction

Some critical care clinicians use pre-morbid physical activity when setting treatment goals [1], and its wider use and central role of accurate prognostication has been advocated [2]. Frequently however critically ill patients are confused, unconscious and/or sedated and ventilated: accordingly, clinicians frequently rely on surrogate-decision makers for this information. While it is imperative that this information is correct, there is limited information to suggest that surrogate-decision maker and patient estimates of physical function prior to hospitalization are accurate [3-5].

An alternative to such subjective reports is to use data recorded on a patient's smartphone prior to hospitalization. Potentially, an individual's smartphone may provide an objective and more precise measurement of pre-morbid physical activity. Smartphones have an inbuilt accelerometer and a global positioning system (GPS) that record pedometer and location data, even if the owner has not specifically activated the function. Pedometers have been used to objectively quantify physical activity after critical illness [6, 7], and in other healthcare settings [8-11]. Beyond step data, GPS data also enables the measurement of 'activity spaces', a concept that has been proposed to measure the mobility of community-dwelling older adults [12-14]. In brief, activity spaces require measurement of the spatial area across which a person travels over a specific time period and, thereby, allows quantification of movement beyond a person's residence [12, 15]. Because activity spaces quantify the environment that with which an individual interacts with, they incorporate both the mobility and social interactions of an individual [16] these activity spaces represent a potential objective measure of pre-morbid physical activity that could be generated using data stored on a patient's smartphone. Outside of critical care, raw GPS data, percentage time spent at home, or activity spaces have been used to quantify physical activity after surgery for peripheral vascular disease [17], spinal disorders [18] and in individuals with mental health issues [19]. However, quantification of mobility using GPS data has not been previously reported in critically ill patients.

Our objectives of this exploratory study were to:

1. Evaluate the accuracy of subjective surrogate estimates of patient's pre-morbid physical accuracy when compared to patient self-estimate—our primary objective was to determine the accuracy of surrogate estimates of distance walked prior to resting.

2. Test the feasibility of smartphones providing additional supplemental data to quantify physical activity; and

3. Compare subjective estimates of physical activity to objective smartphone data.

Materials and methods

We performed a single-center prospective cohort study. We screened consecutive patients admitted to the intensive care unit (ICU) of the Royal Adelaide Hospital between December 2015 and July 2016. This is the Hospital's single ICU and serves all patients, including post-operative, medical, and neurological critical care.

Participants

Patients were eligible to participate if they received at least 48 hours of care in the ICU. We excluded patients admitted following an elective procedure, who had long term inability to mobilize, were aged <18 years, lived >50 km from the Royal Adelaide Hospital (for ease of follow-up), lacked capacity to provide written informed consent, were readmitted to the ICU, were anticipated to die within 6-months, or were pregnant. On meeting eligibility criteria, patients were approached to enquire about smartphone ownership.

Protocol

Our protocol was approved by the Human Research Ethics Committee of the Royal Adelaide Hospital and registered with the Australian New Zealand Clinical Trials Registry (http://www.anzctr.com.au; ANZCTR12616000427471). Due to privacy concerns, phones were only analyzed following written informed consent from each participating patient.

Questionnaires

We created a questionnaire to quantify patients' use of their smartphone prior to hospitalization (Supplementary Table 1). Subjective estimates of physical activity were obtained by asking study participants and their surrogates to estimate, prior to hospitalization, the distance and time the participant would be able to walk prior to needing a rest and the average number of steps they would take each day (Supplementary Figure 1). Patients and their surrogates were also asked to score their activity level on a three-point scale: active, less active than ideal and sedentary and Functional Independence Measures (FIM) were taken from the patient and surrogate [20].

Step and GPS data

Phones were assessed and, if feasible, step and GPS data extracted. Some smartphone data are overwritten after a period of time that varies between phones, generally about two-months. As smartphones were accessed only after written informed consent, data were over-written in some participants. Due to the exploratory nature of this study, we regarded successful data extraction as data extraction for any physical activity variable in the previous 28-day period. However, if consent was obtained proximate to admission and it was achievable to extract physical activity data from prior to hospitalization, data were extracted for the 28-day period prior to admission.

We manually accessed data held in the Health App of phones using iPhone operating system, Apple, Inc (iOS), Google Health App or S-Health of phones using Android operating systems, or any other pedometer app installed on the phone. To obtain GPS data we used 'Frequent

Locations' on iOS devices or 'Timeline' of Google Maps. Locations were geocoded, with a date and time of arrival and departure.

Activity space was evaluated using percentage time spent at home [21] and Minimum Convex Polygon activity space [22]. The time spent at home was measured as the total time spent at home as a percentage of a 28-day period. Minimum convex polygons were created using Daftlogic's Google Maps Area Calculator Tool (www.daftlogic.com). A polygon is convex if it contains all the line segments connecting any pair of its points, or if no internal angels exceed 180^{o} [22] (Supplementary Figure 2).

Statistical Analysis

Due to an absence of pre-existing data we were unable to perform a formal calculation to determine sample size. Rather, we determined, *a priori,* that 50 participants would provide preliminary information about agreement between surrogate-decision maker and patient subjective estimates of physical activity, while also providing important information about the feasibility of extracting smartphone data. When data were skewed, these were log transformed. Data have been reported as mean ± SEM or median [range] as appropriate, with point estimates including 95% confidence intervals. Associations between self-reporting and surrogate estimates, and smartphone data were analyzed via Pearson and Spearman correlations respectively and agreement with Bland-Altman analyses. Bland Altman analyses were performed on log transformed data so bias and limits of agreement are presented as the ratio of patient to surrogate values. Categorical variables were assessed by Cohen's Kappa coefficient of agreement. Feasibility was assessed using 'intention to analyze' such that patients who initially consented were included even if subsequently they could not provide their phone for analysis. Because we were undertaking an exploratory study, we compared demographic data of study participants with those who were excluded because they did not own a smartphone. Data were analyzed using SPSS Version 22.0.

Results

84 of 163 (52%) patients in ICU for more than 48 hours and who did not meet any of the immediate exclusion criteria, owned a smart phone. 50 patients consented to their smartphone being analyzed (Figure 1). Eligible patients who owned a smartphone were younger than eligible patients who did not own a smartphone (Supplemental Table 2).

Demographic data

Of the 50 consenting participants, 33(66%) were male with a mean age of 52±2 years. The mean APACHE III score was 63±5 and median durations of ICU and hospital length of stay were 6 [2 to 32] and 17 [5 to 123] days respectively. Thirty-two participants received invasive mechanical ventilation, for a median of 63 [12 to 635] hours.

Agreement between subjective estimates

Subjective estimates of physical activity from patients and their surrogates are in Table 1. Data were skewed and were therefore log transformed prior to analysis. At the group level surrogates agreed on average regarding distance walked, with a difference of 0 [-17,000 to 18,000] meters, and a time walked difference of 0 [-460 to 300] minutes, but they under-estimated daily steps by 1,000 [-14,000 to 20,000] steps compared to patients. While there were modest, statistically significant, correlations between estimates of distances walked, time walked and daily steps, when evaluating the Bland Altman plots, there appeared little agreement between patients and their surrogate-decision makers (Figure 2). The scatter plots demonstrated disagreement even at low values.

On the three-point scale of active, less active than ideal, and sedentary, surrogate-decision makers agreed with patient estimates 73% of the time, estimated higher in 12% of cases and underestimated 14% of the time (Cohen's Kappa Coefficient 0.52±0.1; $p<0.001$, "moderate" agreement per Landis-Koch interpretation). There were strong associations between Functional Independence Measures from surrogate-decision makers and patients (motor: $r=0.87$, $p<0.001$; cognitive: $r=0.43$, $p=0.002$; and overall: $r=0.84$, $p<0.001$) and these measures were relatively consistently reported between surrogate-decision makers and patients, with differences of 0 [-28 to 3] in the motor score, 0 [-7 to 5] in the cognitive score and 0 [-27 to 5] overall. However, 38 (78%) patients and surrogate-decision makers both scored Functional Independence Measures at the maximal score.

Smartphone data

Estimated smartphone usage is in Table 2. Forty-five smartphones were analyzed. Analyses occurred 11 [2 to 99] days after hospital admission, with 15 smartphones yielding pre-hospitalization data (13 step and 11 GPS data) and 9 yielding only data post-hospitalization (1 step and 9 GPS data). According to our pre-specified intention to analyze approach, we successfully extracted data from 24/50 (48%; 95% CI 35, 62%) phones. Step data were extracted from 14 (28%) and GPS data from 20 (40%) phones with 10 (20%) phones yielded both step and GPS data.

Step data were extracted for 364 patient days. Only two days were recorded as zero steps. Prior to hospital admission participants (n=13) took a median of 3,540 [32 to 12,604] steps per day. In the period 28-18 days prior to admission participants took a median of 3,539 [28 to 21,245] steps per day and in the period 10-1 day prior to admission they took 2,960 [2 to

15,798] steps per day, yet this was not statistically different (median reduction 376 [-8,734 to 17,869], p=0.581).

Extracting pre-hospitalization GPS data was possible from 11 smartphones. While we were able to calculate % time spent at home from all 11 smartphones, in 3 smartphones the data held in frequent locations pertained to just two locations, such that the calculated convex polygon was 0 km^2 resulting in reliable activity space data for only 8 patients. The median percentage time spent at home was 60 [15 to 91] % and the median convex polygon was 122 [7 to 45,639] km^2.

Agreement between subjective estimates and smartphone measures

For the 13 patients for whom we could extract pre-hospitalization smartphone obtained step-counts, when compared to patient self-reported step-counts, there was a median difference of -3,257 [-9,029 to 2,376] steps and no association (rho=0.30, p=0.317) and poor agreement between these variables (Figure 3a). When the smartphone data were compared to surrogate-decision makers estimate of daily step-counts there was a median difference of -3,454 [-21,558 to 2,376] and a moderate association was apparent, although this association just reached the predefined statistical significance and was not adjusted for multiple comparisons (rho=0.56, p=0.049), and inspection of the Bland Altman plot showed poor agreement (Figure 3b).

Discussion

Our overarching objective was to evaluate the accuracy of various methodologies to determine the true pre-morbid physical activity of critically ill patients. Our key observation is that there is a lack of agreement between patients and their surrogate-decision makers when estimating the distance patients walked prior to hospitalization. In particular, the lack of precision persisted at lower levels of physical activity. The discordance between patients and surrogate-decision makers provides a challenge to discerning the truth about the pre-morbid physical activity for individual patients, and we hypothesized that obtaining smartphone data may offer an alternative methodology. We found that smartphone ownership was already relatively common among patients admitted to an ICU, and objective activity data (either step or GPS data) were able to be extracted from the smartphones of approximately 50% of study participants who owned a smartphone.

Currently available methods to determine physical activity

At the bedside, clinicians frequently use capacity to walk as a key indicator of pre-morbid physical activity [23, 24]. Our results show that the surrogate-decision maker estimates of distance walked did not agree with patient self-report. In particular, the relationship did not improve even at lower values (Figures 2a, 2c and 2e), and these lower values may well influence clinical decision making. We did, however, observe reasonable concordance when quantifying physical activity according to an ordinal three-point scale. Whether the loss of granular detail that occurs with the use of such a categorical instrument is balanced by greater concordance depends on factors specific to each situation, such as patient and surrogate-decision maker values, healthcare resourcing and the chosen cut-point [25, 26]. Moreover, the three-point scale may lack the sensitivity required to detect clinically significant levels of activity. Our data are consistent with previous work suggesting that there is considerable disagreement between patients and surrogate-decision makers when reporting other subjective variables, such as pre-morbid quality of life scores [3, 4, 27]. There are other data also suggesting that patients themselves are inaccurate when self-reporting physical activity [7, 28, 29]. Based on the correlation between surrogates estimate of step-counts and smartphone data it may be that patients themselves, rather than surrogate-decision makers, are poor estimators of the truth [3, 4, 27].

Alternative methods to determine physical activity

Given the lack of reliability of these subjective estimates, we propose that an accurate objective methodology to quantify pre-morbid physical activity would be of use to both clinicians and researchers [30]. Based on our observations it appears that smartphones are owned by over 50% of ICU patients and it is feasible, even now, to extract stored data from approximately half of smartphones using relatively simple techniques. We also extracted GPS data, which enabled the first attempt to quantify activity spaces from critically ill patients, which is, to the best of our knowledge, a novel concept.

The use of patient step data after ICU discharge has been recently reported [6, 7]. Survivors of critical illness have been shown to have a mean daily step-count of 4,895 at 10-weeks post ICU discharge [7] and 5,803 at 18-months post ICU discharge [6] which are 50% less than values described for healthy populations [6, 31]. Of interest, these post-ICU step-counts are

similar to the pre-morbid daily step-count in our cohort. We believe that an accurate instrument to quantify pre-morbid physical activity is a priority as clinicians and researchers try and determine the proportions of reduced physical activity observed in survivors that represent the burden of critical illness and ICU interventions, and that which is attributable to their pre-morbid physical condition [32, 33].

Limitations

We were limited to analyzing phones after obtaining written informed consent. Not only did this affect data collection, as GPS and step data were overwritten is some instances, the scenario is somewhat artificial, in that clinicians are likely to want information regarding physical activity on admission. Another major limitation is that we did not have a true 'gold standard' as both our subjective (patient and surrogate) estimates and objective (smartphone) data may be imprecise. We are reassured however that, at least when carried, smartphones accurately quantify steps in the laboratory among healthy young volunteers [34] and that 70% of our cohort reported carrying their phone on them >75% of the time. Finally, currently smartphone ownership is a limitation to the widespread use of this methodology, as those that did not own smartphones were older than the study participants (Supplementary Table 2). It is likely however that the proportion of smartphone ownership, particularly amongst the elderly, is likely to increase over time, but and as our data are from a single center and smartphone ownership may vary between regions this is only speculative.

Future directions

As smartphone ownership increases [35] we need to consider how the micro-sensors, they contain, (Supplementary Table 3) can be used in patient assessment, and how these outcomes relate to current measures. However, obtaining pre-morbid data will be dependent upon how software providers store the required data, to allow automated extraction, and the ethical challenges of accessing this information at presentation, possibly without patient consent.

Conclusions

Our data suggest that there is wide disagreement between subjective surrogate-decision maker and patient estimates of distance walked prior to hospitalization. The implication of our data is that clinicians should be cautious when using subjective estimates of walking and physical activity, particularly if this information is used to set treatment goals. However, the increasing ubiquity of smartphones, as well as their automatically collected and stored data, suggests an evaluation of their potential role as a novel tool to facilitate the collection of objective data is warranted.

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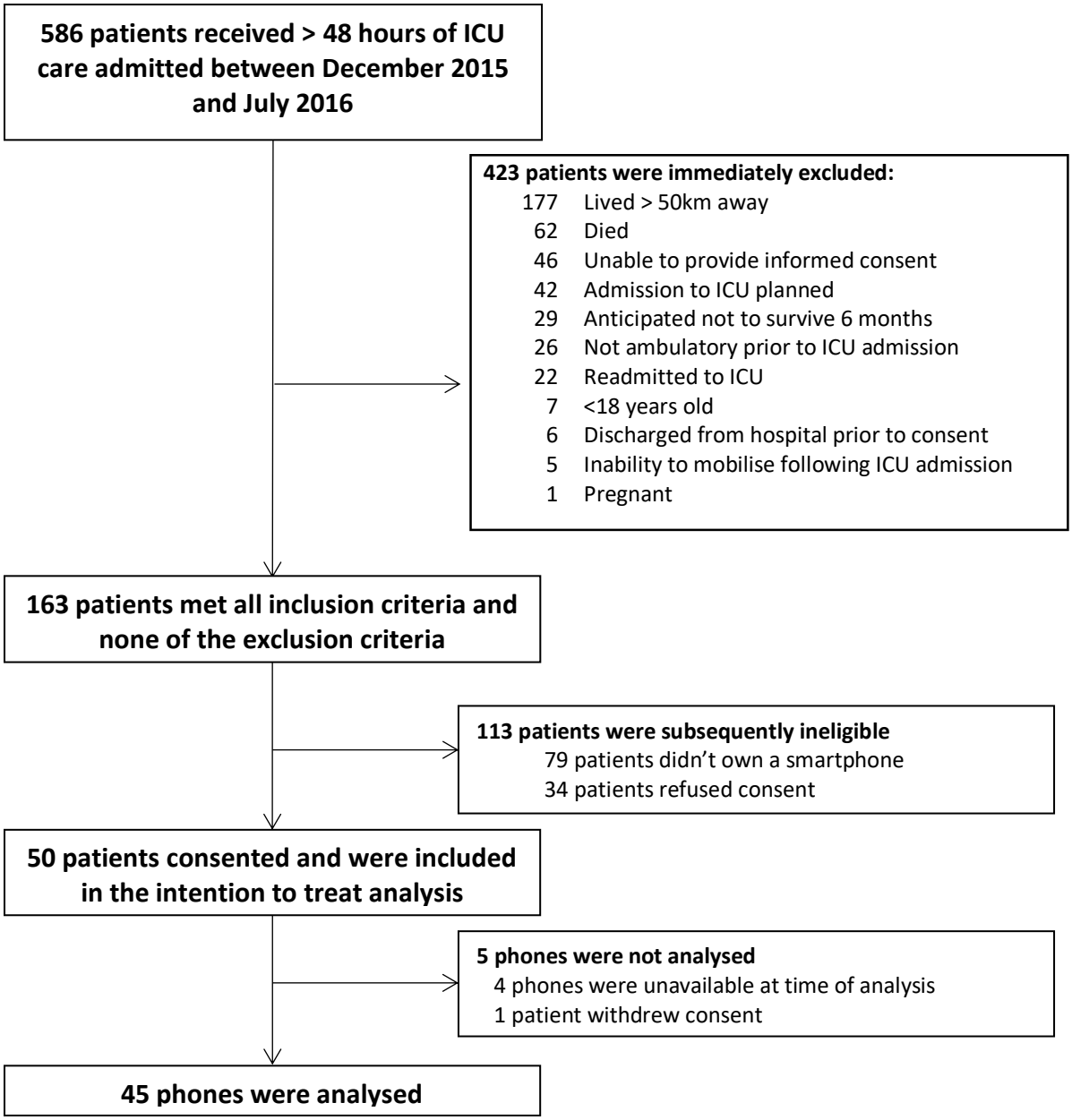


Figure 1 - Consort Diagram

* 3 phones were in the possession of relatives and couldn't be accessed and one phone was no longer working.

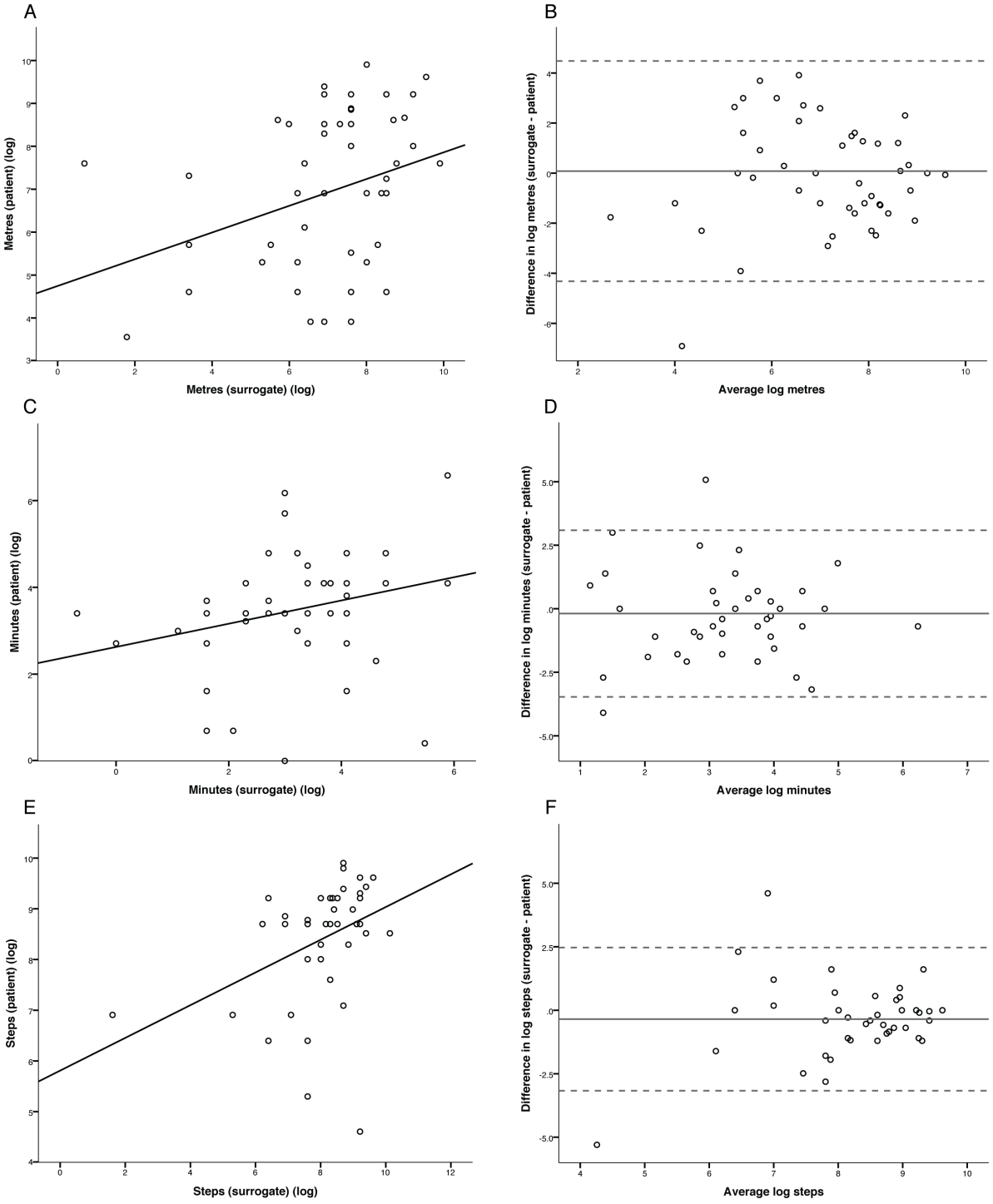


Figure 2 *– Scatter and Bland-Altman Plots for meters (a, b) and time (c, d) walked prior to resting, and daily step-count (e, f) when estimated by surrogate-decision makers and by patients themselves. The Pearson Correlation Coefficients were r=0.31, p=0.028* for distance *(a); r=0.28, p=0.049* for time *(c); and r=0.40, p=0.004* for steps *(e)*. The levels of agreement (mean bias) were 99% lower to 8,700% higher (108%) for distance (b), 97% lower to 2,100% higher (83%) for time walked prior to resting (d), and 96% lower to 1,080% higher (71%) for steps (f).

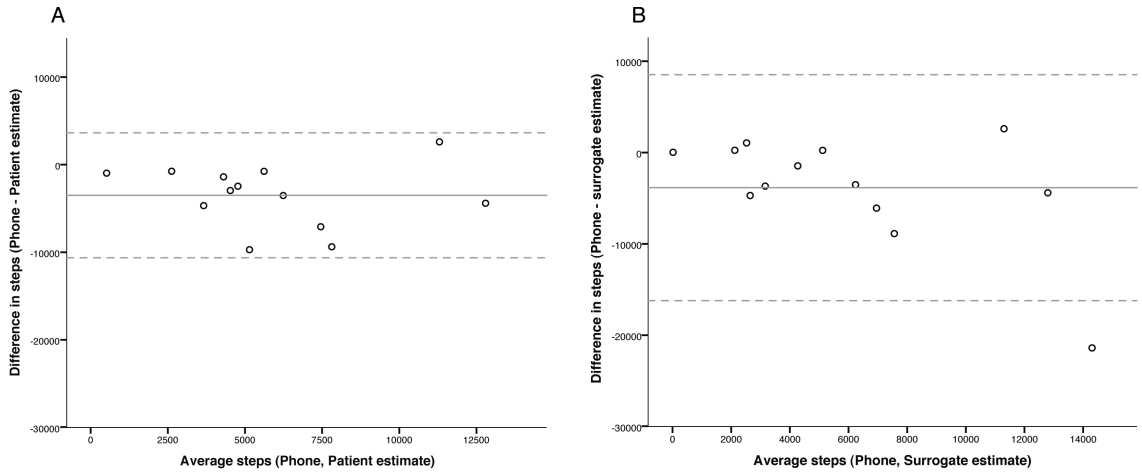


Figure 3 – Bland-Altman plots for patient (a) and surrogate-decision maker (b) estimates versus smartphone obtained step-counts, with limits of agreement (mean bias) -10,631 to 3,637 (-3,497) and -16,214 to 8,526 (-3,844) steps respectively.

Measure		Estimate
Patient estimates n = 50		
	Distance walked prior to resting (m)	1,400 (35–20,000)
	Time walked prior to resting (min)	40 (1–720)
	Mean daily step-count	6,000 (100–20,000)
Three-point scale (%)		
	Active	27 (55)
	Less active than ideal	20 (41)
	Sedentary	2 (4)
Functional Independence Measure		
	Motor	91 (49–91)
	Cognitive	35 (30–35)
	Total	126 (84–126)
Surrogate-decision-maker estimates n = 49		
	Distance walked prior to resting (m)	2,000 (2–20,000)
	Time walked prior to resting (min)	30 (1–360)
	Mean daily step-count	4,500 (5–25,000)
Three-point scale (%)		
	Active	28 (57)
	Less active than ideal	15 (31)
	Sedentary	6 (12)
Functional Independence Measure		
	Motor	91 (49–91)
	Cognitive	35 (26–35)
	Total	126 (84–126)

Table 1 – Subjective estimates of physical activity

Description	n (%)
On their body > 75% of the time	35 (71)
With them sometimes when at home and always when leaving the home	5 (10)
Rarely or never having the phone with them when at home but always when leaving the home	5 (10)
Rarely carried the phone with them	2 (4)
Regularly turned off	0 (0)
Other usage patterns	2 (4)
No response	1 (2)

Table 2 – Phone Usage Pattern Described by Study Participants (n = 50)

Carried their phone on their body ≥75% of waking hours
Carried their phone at all times when they left the house but only sometimes when at home
Carried their phone at all times when they left the house but rarely when at home
Frequently left the phone at home and rarely carried it around home
The phone was turned off more than it was turned on
Other

Supplementary Table 1 – Categories of participant's phone usage

Question 1

When you are well how far can you walk before you need to stop for a rest?

Prompt:- Think of a walk you did recently – can you remember where it was from and where it finished (how long was it) how many times did you stop for a breather?

Question 2

When you are well how long (in time) can you walk prior to needing a rest?

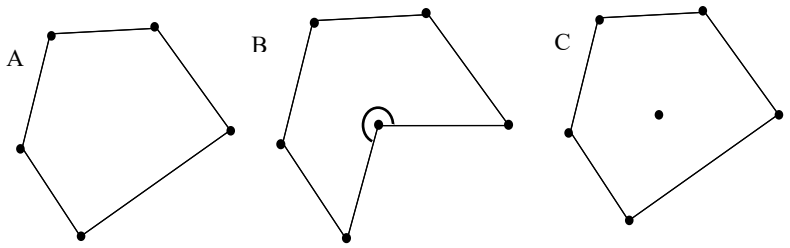
Prompt:- Think of a walk you did recently – can you remember how long did it take? How many times did you stop for a breather?

Question 3

When you are well, How many steps do you take per day?

Prompt;- The Australian average is 6000 steps, do you take more or less than average? How much more than average?

Supplementary Figure 1



Supplementary Figure 2 - Construction of a minimum convex polygon requires that all internal angles are less than 180 degrees. In this example, all visited locations are identified with a closed circle. In panel A, a minimum convex polygon is calculated from each point using straight lines. Panel B would be an invalid polygon because the angle indicated is greater than 180 degrees. Panel C would be the correct polygon, and would contain the central location seen in B.

	Owned smartphone (n = 50)	Did not own smartphone (n = 79)	P value between groups
Male sex (n (%)) $	33 (66)	49 (63)	.850
Age (mean (SE)) #	52.2 (2.4)	63.1 (2.0)	.001
APACHE-II score (mean (SE)) #	18.9 (1.2)	18.9 (0.8)	.944
APACHE-III score (mean (SE)) #	62.9 (4.9)	69.1 (2.8)	.243
ICU LOS (median (IQR)) %	5.8 (6.3)	4.5 (4.0)	.146
Hospital LOS (median (IQR)) %	17.0 (17.6)	18.8 (21.7)	.420
ICU mortality (n (%)) $	1 (2.0)	0 (0.0)	.391
Hospital mortality (n (%)) $	1 (2.0)	6 (8)	.245

Supplementary Table 2 – the differences between owners and non-owners of Smartphones. Differences between groups tested using $ Fishers Exact Test, # Independent Samples t-test and % Mann-Whitney test.

2.3 – Manuscript

An observational study investigating the use of patient-owned technology to quantify physical activity in survivors of critical illness.

Statement of Authorship

Title of paper	An observational study investigating the use of patient-owned technology to quantify physical activity in survivors of critical illness.
Publication Status	Published
Publication details	**An observational study investigating the use of patient-owned technology to quantify physical activity in survivors of critical illness.** Gluck S, Summers MJ, Finnis ME, Andrawos A, Goddard TP, Hodgson CL, Iwashyna TJ, Deane AM. Australian Critical Care. 2019; pii. S1036 – 7314 (18) 30236-4 [Epub ahead of print]

Principle Author

Name of Principle Autor (Candidate)	Dr Samuel Gluck		
Contribution to paper	Conceptualisation of work, recruitment, data collection manuscript preparation, corresponding author		
Overall percentage (%)	80%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	6/5/2021

Co-Author Contributions
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- The candidate's stated contribution to the publication is accurate (as detailed above);
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Full Title

An observational study investigating the use of patient-owned technology to quantify physical activity in survivors of critical illness.

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Abstract

Background

Physical activity after Intensive Care Unit (ICU) discharge is challenging to measure but could inform research and practice. A patient's smartphone may provide a novel method to quantify physical activity.

Objectives

We aimed to evaluate the feasibility and accuracy of using smartphone step-counts in survivors of critical illness.

Methods

We performed a prospective observational cohort study in fifty patients who had an ICU Length of Stay>48 hours, owned a smartphone, were ambulatory prior to admission and likely to attend follow-up at 3 and 6-months after discharge. At follow-up daily step-counts were extracted from participants' smartphones and two FitBit pedometers and exercise capacity (6-minute walk test) and quality of life (EQ-5D) were measured.

Results

Thirty-nine (78%) patients returned at 3-months and 33 (66%) at 6-months, median [IQR] smartphone step-counts of 3,372[1,688-5,899] and 2,716[1,717-5,994] respectively. There was a strong linear relationship, with smartphone approximating 0.71(0.58, 0.84) of FitBit step-counts, P<0.0001, R-Squared=0.87. There were weak relationships between step-counts and the 6-minute walk test distance.

Conclusion

Although smartphone ownership and data acquisition limit the viability of using extracted smartphone steps at this time, mean daily step-counts recorded by smartphone may act as a surrogate for a dedicated pedometer; however, the relationship between step-counts and other measures of physical recovery remains unclear.

Introduction

The quality of survivorship after Intensive Care Unit (ICU) discharge is important to patients and there are calls for it to be reported alongside mortality in clinical trials [1]. Quantifying the quality of survivorship is challenging; however, the capacity to undertake physical activity is a major determinant of this quality [2]. Physical activity is defined as any bodily movement produced by skeletal muscles that results in energy expenditure [3, 4]. There is a 'dose' response, association between physical activity and all-cause mortality [5-7]. The World Health Organization's International Classification of Function places paramount importance on activity levels when assessing an individual's disability [8]. Currently, the assessment of physical activity in survivors of critical illness is limited; hitherto the literature is dominated by subjective health related quality of life (HRQoL) assessments [9-11], which usually include a physical function sub-score, or single point objective assessments of exercise capacity in a laboratory or clinical environment [9, 12, 13]. These assessments require considerable researcher and patient time and/or patient travel, and are not assessing physical activity *per se*. These requirements increase the expense and limit the feasibility of measuring physical activity in clinical trials.

Wearable devices containing accelerometers have the potential to provide a mechanism for continuous assessment of physical activity [14-17]. However, currently available wearable devices remain too expensive to implement in larger clinical trials. Because current generation smartphones have inbuilt accelerometers, it may be feasible to utilise the patient's smartphone to obtain physical activity data in survivors of ICU [18]. It has recently been demonstrated it is feasible to extract pre-morbid step-counts from patients' smartphones on admission to ICU [18], although the validity of these data has not been assessed in the 'real-world'. In addition, smartphones have not been used to quantify physical activity in ICU survivors.

Objectives for our study were: (1) to assess the feasibility of using smartphone step-counts as a surrogate for a dedicated pedometer, (2) describe the change in step-counts over time, and (3) describe relationships between smartphone step-counts and currently used measures of physical activity in a cohort of ICU survivors.

Methods

We performed a single centre prospective cohort study, approved by the Human Research Ethics Committee of the Royal Adelaide Hospital (HREC/15/CALHN 236) and registered with the Australian New Zealand Clinical Trials Registry (http://www.anzctr.com.au; ANZCTR 12616000427471. We approached patients for consent when they re-gained mental capacity, this could have been in ICU or on the ward, extracted data from their smartphones as previously described [18], and invited them to return for study visits at 3 and 6 months following ICU discharge. We mailed participants both hip and wrist worn pedometers, free of charge, with instructions for use (Appendix 1, Supplementary material), to arrive at their home address, at least 10 days prior to study visits. Prior to device delivery, synchronisation with our lab computer was checked. Participants were also asked to install the Moves app on their phone, the Moves app is a validated cross-platform, freely available, pedometer app [19]. At each study visit, patient co-morbidities were recorded and scored according to the Functional Co-Morbidity Index [20] which scores patients on 0-18 on comorbidities likely to impact on physical function. We also extracted step-count data from the participants smartphone and pedometers, and physical activity was assessed by 6-minute walk test and EQ-5D questionnaire. If extraction of usable data was not achieved from the pedometers, or the Moves app hadn't been installed, patients underwent a second study period. Patients were paid an honorarium for attending the follow-up clinic as it was outside of standard care.

Participants

Between December 2015 and July 2016 all patients admitted to the Royal Adelaide Hospital ICU were screened. Patients were eligible if they had received at least 48 hours of ICU care and owned a smartphone. We excluded patients who were admitted following an elective procedure, were non-ambulatory prior to ICU, were aged less than 18 years, lived greater than 50 km from Royal Adelaide Hospital, lacked capacity to provide written informed consent, were readmitted to the ICU, were pregnant, or the treating intensivist anticipated that the patient was unlikely to be alive in 6 months.

Outcomes

Step-counts

Step-counts from participants' phones were extracted from pre-installed pedometer apps, e.g. the Health app (iOS), S Health or Google Fit (Android) or any equivalent pedometer app, collectively defined as 'Smartphone data'. The S health and the Health app have been independently verified as accurate [21, 22], however we are unaware of the accuracy of Google-fit data. In addition, we asked participants to install the Moves app prior to their 3-month appointment and checked its installation before their 6-month appointment. We termed this 'Moves app data', to provide a measure of smartphone step counts on all devices, not just those with a dedicated, pre-installed, pedometer app. Data were extracted by visual inspection of the smartphone apps, this involved opening the app on the participants phone and manually making a note of the daily step counts. Both hip-mounted (Fitbit One) and wrist-mounted (Fitbit Flex) pedometers were sent to participants to arrive at least 10 days prior to each study visit. These pedometers were chosen as they have been validated against direct observation in a laboratory; with Fitbit One previously shown to have the greatest precision and least

bias [19], and the Fitbit flex being chosen as a wrist mounted pedometer has been shown to have the greatest accuracy in slow walkers [23]. We provided participants with detailed instructions for use (Appendix 1, Supplementary material): we instructed them to wear the Fitbit One on the right hip and the Fitbit Flex on their wrist, to wear the devices continuously during waking hours each day and to charge them overnight. Telephone assistance was provided if required. Fitbit devices were synchronized with accounts specific to each individual pedometer and data extracted in accordance with manufacturer instructions, via visual inspection of the data on a lab computer. If, at the clinic visit, we determined an error had led to incomplete data capture, participants retained the pedometers and were provided with a sheet to record smartphone and Moves app step-counts for the 10-day period following their clinic appointment. As we were assessing the validity of the step-counts obtained from phones pre-morbidly patients were instructed, by letter and via a phone call, to use their smartphone as they would if not participating in the study. We defined, *a priori*, that recording of greater than or equal to 7 days of data would be sufficient and representative, as this would include a weekend [24, 25] and only participants meeting this threshold were included for analysis. We performed a cost analysis based on retail price (Fitbit one's - AU$123 and Fitbit Flex's - AU$94) for replacement devices when devices were lost or not returned.

Exercise Capacity and HRQoL

At each study visit participants performed a 6-minute walk test in accordance with published guidelines [26, 27], with the distance walked recorded and percentage of predicted distance calculated [28]. We surveyed HRQoL using The European Quality of Life 5 Dimensions (EQ-5D) [29].

Statistical methods

Proportions are described as n (%) and continuous measures as mean (standard deviation, SD) or median [interquartile range, IQR] as indicated. The relationships between smartphone and dedicated pedometer step-counts, and six-minute walk test and step-counts were assessed by ordinary least squares regression, reported as the coefficient point estimate (95% confidence interval, CI) with associated P-value and R Squared statistic. Secondary analysis of pooled visit data was performed using general estimating equations (GEE) to adjust for repeated measures. Ordinal scale outcomes were assessed by ordinal logistic regression. Concordance between dedicated pedometer measures and between smartphone estimates were assessed by Lin's concordance correlation coefficient (ρ_c) and Bland-Altman 95% limits of agreement (95% LOA). Strength of relationships are reported according to Lin [30].

Because of an absence of pre-existing data, we were unable to perform formal sample size calculations. We planned to recruit 50 participants in order to provide preliminary information to determine the relationship between smartphone and pedometer obtained step-counts. No adjustment has been made for multiple comparisons and, given the feasibility study nature, no imputation made for missing data. All summary measures are referenced to the proportion of subjects providing data and comparisons limited to individuals who provided data at both time points. Analyses were performed in Stata/MP 14.2 (StataCorp LP, Texas, USA). STROBE guidelines for the reporting of observational studies were followed [31].

Results

Of 586 patients who received greater than 48 hours in ICU during the study period we enrolled 50/84 (69%) eligible participants (**Figure 1**). At the 3-month visit 2 participants had died, 7 withdrew consent and 2 were lost to follow-up, with 39 (78%) participants attending the 3 month visit. By 6 months, a further 2 participants had died, 3 withdrew consent and another was lost to follow-up, such that 33/50 (66%) participants completed both study periods. Demographics for patients presenting at 3 and 6 months are shown in **Table 1** with further details in supplementary material table 1.

Step-counts

We were able to extract step-counts from 17 (44%) and 14 (42%) smartphones at 3 and 6 months respectively. The Moves app provided step-counts for 20 (51%) and 17 (52%) individuals at follow-up at 3 and 6 months respectively. Pedometer data were available for just over 60% of participants (**Table 2**). The average daily step-counts at 3 and 6 months for each device and the between device concordance are shown in **Table 2.** None of these measures were significantly different between time periods, analysed by GEE and adjusted for repeated measures with visit as a categorical variable (**Table 2 and Supplementary Figure 1**). The reasons for failed data extraction are shown in **Table 3.**

The relationship for pooled 3 and 6-month smartphone step-counts was strong, 196 + 0.71 (0.58 0.84) times Fitbit One, P<0.0001, R-squared 0.87 n=21.

Sensitivity analysis employing a GEE model to adjust for repeated measures within subject produced an almost identical model, 211 + 0.71 (0.60, 0.82), P<0.0001, with adjusted and unadjusted model lines of fit shown in **Figure 2**. The relationship and strength of association between smartphone and pedometer estimates of step-counts, as assessed by linear regression at each visit, are presented in supplementary Table 2.

Physical function

Distance travelled and percentage predicted distance during the 6-minute walk test, plus the motor score, visual-analogue scale and total score for the EQ-5D at 3 and 6 months are presented in **Table 2**. The relationship and strength of association between the 6-minute walk test and step-counts by pedometer and smartphone at each visit were modest (Supplementary **Table 2)**.

Cost of measuring physical activity

Over the course of the study, a total of 23 (32%) Fitbit devices were lost, unrecoverable or malfunctioned, at an approximate cost of AU$2,150 (**Table 3**), before the postal costs are considered.

Discussion

Although not currently feasibly to employ within larger scale clinical research, extracted smartphone data provided a reliable estimate of step-counts as compared to the hip-worn Fitbit One. However, several factors limit the strength of our assertion.

There were logistical issues with data acquisition and retrieval. The proportion of pedometers returning sufficient data was approximately 60%, significantly less than the 100% reported by Borges and colleagues [32] and the 90% reported by McNelly et al [33]. This may be due to the specific device chosen, or the malfunction or failure of the several devices to synchronize for data extraction, possibly because the participant had, despite instructions to the contrary, attempted to synchronize the devices with their phone. Despite consultation with the manufacturer the cause of the malfunction remains unclear. The option of two study periods, does not appear to have increased data acquisition, suggesting the absence of a familiarization effect over time.

We were only able to extract data from 42-44% of eligible participants' smartphones, despite relying on a simple visual inspection of the smartphone apps. This was hindered by only Apple devices having an automatically activated step-counter in the health app. Moreover, the health app had only recently been introduced. Future studies are likely to have increased data extraction success.

This amount of missing data would limit the usefulness of wearable technology as the primary assessment of physical activity outcome in clinical trials. We could extract these data from apps already present on patients' phones or included with the standard operating system. Similar physical activity could also be extracted from smartphones as patients are admitted to ICU [18]. However, due to patients who provided baseline data being lost to follow-up, immobile or changing their smartphone over the study period, comparing data at baseline with 3 and 6 months was only possible in 7/50 (14%) participants. Smartphone data may therefore allow follow-up comparison at an individual patient level by the comparison of pre- and post-ICU physical activity data. This would be of importance as pre-morbid physical activity has been shown to have a significant effect on functional outcomes following critical illness [33]. Having this pre-morbid data readily available would assist ICU clinicians in communicating risk to patients and their families.

We believe this is a unique and novel methodology worthy of ongoing study. In terms of wearable technology to assess physical activity, there was a significant rate of physical loss with the financial cost in this study being approximately AUD $2,150. Such a cost may prove prohibitive for larger trials and, conversely, strengthens the rationale to evaluate novel methods of data capture, such as patient-owned technology (e.g. smartphone accelerometry).

There was marked variability in performance between "equivalent measures". The concordance between hip and wrist-worn Fitbit devices was poor. This is consistent with controlled laboratory experiments where the accuracy and precision of Fitbit One was superior to the wrist-worn Fitbit Flex [19], although, wrist worn pedometers have been shown to be more accurate in slower walkers [23]. Given our observations of a similar degree of systematic bias between measures we suggest that the hip-worn Fitbit One is a better

reference measure for clinicians and researchers quantifying post-ICU physical activity with pedometers. Similarly, the concordance between the Moves app and smartphone extracted data was poor, with Moves variably recording only a fraction of the steps registered on any given smartphone. These findings portend the marked differences in model fit and strength of association outlined in supplementary Table 2; where the strongest association is seen between smartphone data and Fitbit One. A potential way to overcome variability between devices is measuring percentage change over time using the same device [33].

The number of steps recorded, using either pedometer or smartphone, were considerably less than in previous studies [25, 33]. This may relate to time to follow-up, McNelly and colleagues followed-up their cohort at 18 months post ICU discharge, potentially allowing greater recovery. Alternatively, patients in our study may have had worse premorbid function, or experienced greater barriers to physical activity [34]. However, the six-minute walk test distances are further than those reported by Herridge and colleagues [9] and the reported EQ5D scores are greater than those reported from trauma, septic and general ICU patients [35, 36]. We observed no significant change in step-counts between study visits. The choice of 3 and 6-month intervals was pragmatic in order to assess feasibility, however, may have been insufficient to allow adequate recovery, and step-counts may have increased with longer periods of observation. The weak association between step-counts and 6-minute walk test suggests these metrics relate to different aspects of physical activity and is not entirely unexpected. The walk test assesses maximal performance under supervision in a controlled environment, whereas step-counts in this study reflect average voluntary activity over a 7-day period. In addition, step counts, although more meaningful to clinicians, do not take into account intensity and duration of activity and are a poor estimate of energy expenditure calculated by accelerometry.

There is limited experience when comparing data obtained from smartphones and pedometers to outcomes more commonly measured in the critically ill. However, previous studies using pedometers have indicated strong associations between daily step-count and 6-minute walk test distances in healthy individuals [37], patients with chronic obstructive pulmonary disease [38, 39] and patients recovering from stroke [40] and these have been confirmed with formal exercise testing [41]. There are also associations between daily step-counts and global health related quality of life measures, such as the EQ-5D, in patients receiving chronic hemodialysis [42] and severe mental illness [43].

In addition to the issues with data retrieval and device logistics, where we were only able to extract step-data from 42-44% of the phones analysed, and approximately 40% of pedometers failed to provide analysable data, our study has a number of limitations. At the time the study was conducted, only around half of ICU patients owned a smartphone and this significantly impacted on patient eligibility. However, as technology develops and those with technology integrated into their daily life age, we anticipate this proportion will increase [44]. We did not specify how many hours a day would be regarded as a complete pedometer reading, indeed this wasn't possible with the generic Fitbit software or the simple method of smartphone data extraction. While this may lead to discrepancies in pedometer obtained step data, we did average data over 7 days in order to limit sample variability. The lack of a single gold standard assessment for assessing the level of function and/or activity for a survivor means that any comparison with a newer methodology is difficult.

The major strength of our study is novelty, in that we are the first to report on the feasibility of using smartphone data as an objective metric of physical activity in ICU survivors. While logistic difficulties weakened the findings in this paper, these difficulties are, we believe, intrinsically important in planning for future studies and lend weight to ongoing research into patient-owned technology and related activity measures.

Future work should involve the development of instructions to participants to improve data acquisition, such as specifying how many hours a day they are expected to wear the device, the importance of wearing the device, what to do in the event they forget to wear or loose the device and to clarify the reason for not synchronising the devices themselves. In addition, automating the extraction process, currently done manually, through the use of digital forensics or a specific smartphone app would be essential for this methodology to be widely applied.

Conclusions

While the current proportion of ICU patients owning a smartphone and logistic issues with data extraction limit the viability of utilising patient-owned technology at this time, step-counts recorded from a patient's smartphone may provide a viable surrogate for dedicated pedometer estimates and therefore an objective measure of patient activity.

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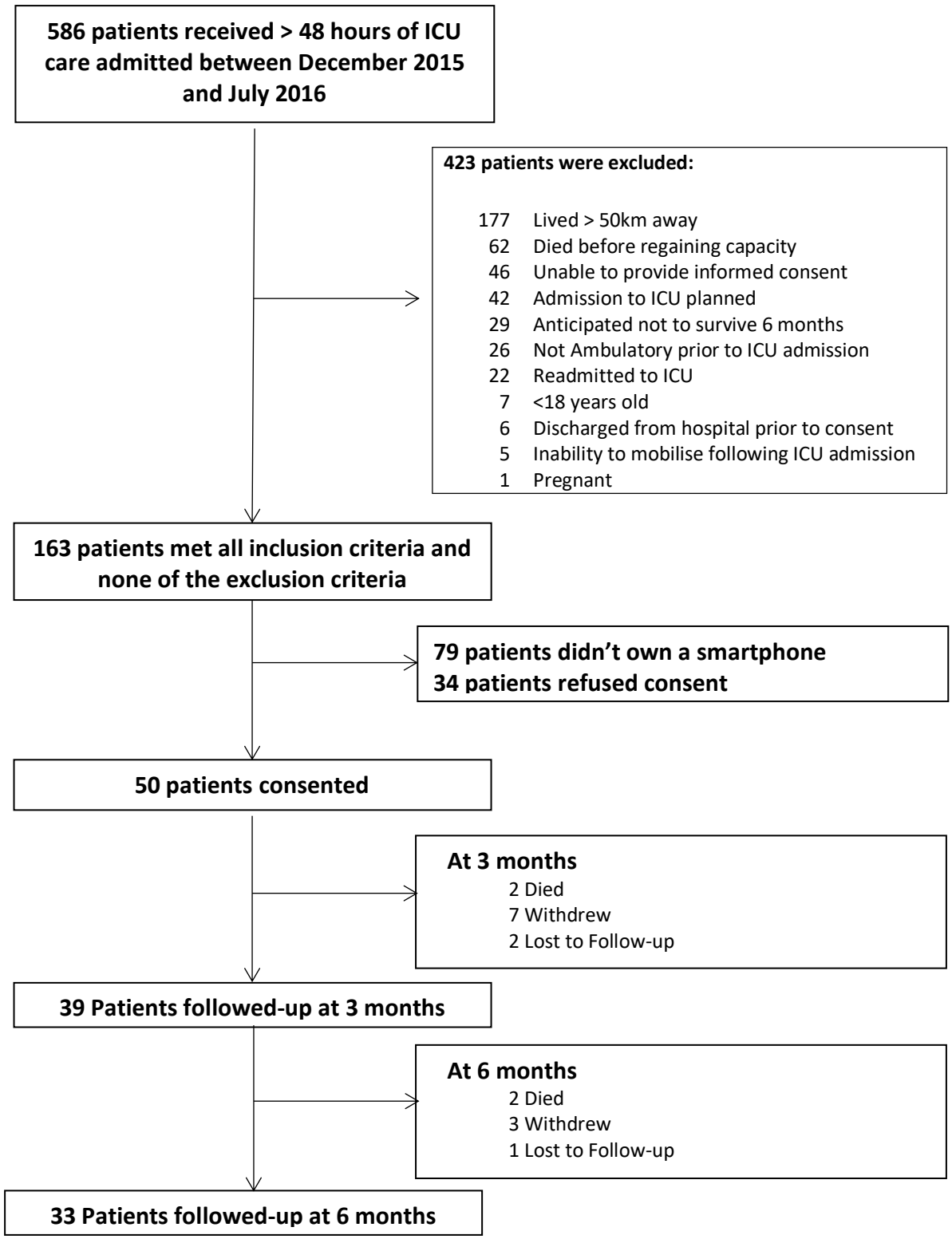


Figure 1. Consort diagram – Patients who provided partial data for the 3 or 6-month follow-up are included as being followed-up.

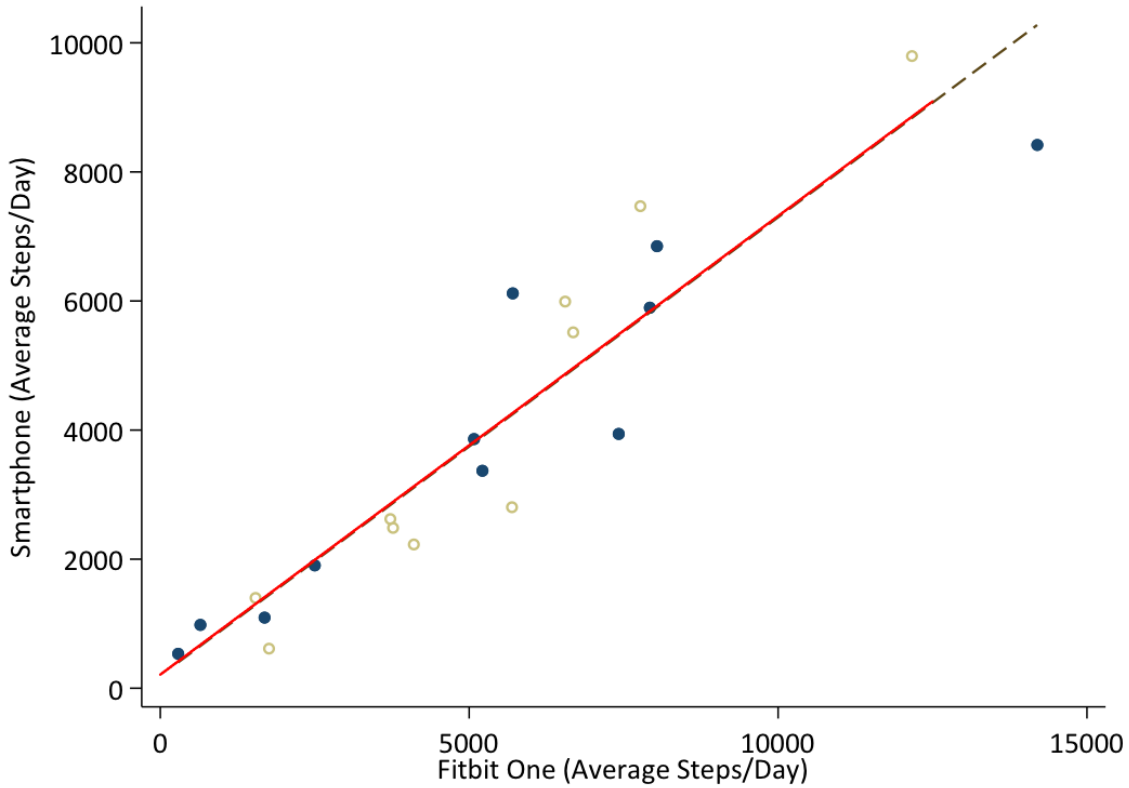


Figure 2. Scatterplot for smartphone mean daily step counts at 3 months (closed circles) and 6 months (open circles) versus hip-worn Fitbit One. Line of model fit by ordinary least squares (dashed line) and adjusted for repeated measures (GEE, solid line). Slope coefficient 0.71 (0.58, 0.84), R-squared 0.87, P<0.0001.

Demographics	**3 months (n=39)**	**6 Months (n=33)**
Male, n (%)	30 (77%)	26 (79%)
Age (years), median [IQR]	56 [44-65]	55 [39-64]
APACHE 3J (score), median [IQR]	59 [37-77]	53 [35-75]
ICU LoS (days), median [IQR]	6 [4-10]	6 [4-9]
Hospital LoS (days), median [IQR]	18 [12-28]	17 [10-25]
Trauma, n (%)	10 (26%)	9 (27%)
Medical, n (%)	27 (69%)	23 (70%)
Surgical, n (%)	2 (5%)	1 (3%)
Functional Co-Morbidity Index, median [IQR]	3[1-5]	3 [1-4]
Phone type		
Apple	15 (38%)	15 (45%)
Android	24 (62%)	18 (55%)
Phone Usage		
Carried phone on person >75% of the time	25 (64%)	22 (67%)

APACHE 3J - Acute Physiology and Chronic Health Evaluation III (version J, at ICU admission)
Functional Co-Morbidity Index [10], scores patients on 0-18 on comorbidities likely to impact on physical function
LoS – Length of Stay
6MWT – 6 Minute Walk Test.
EQ-5D – European Quality of Life Five Dimensions, VAS – visual analogue scale.

Table 1 - Demographic information at 3 and 6 month visits**.**

Outcome Measures		**3 months (n=39)**	**6 Months (n=33)**	**P-Value[1]**
Step-Counts (average count over preceding 7 days)				
Smartphone	N (%)	17 (44%)	14 (42%)	
	median [IQR]	3,372 [1,688 to 5,899]	2,716 [1,717-5,994]	0.95
Moves app	N (%)	20 (51%)	17 (52%)	
	median [IQR]	2,146 [878-4,983]	1,886 [1,063-3,629]	0.28
FitBit One	N (%)	25 (64%)	21 (64%)	
	median [IQR]	2,790 [1,685-6,677]	3,765 [1,762-6,639]	0.29
FitBit Flex	N (%)	24 (62%)	20 (61%)	
	median [IQR]	3,221 [2,189-6,245]	4,061 [1,606-7,246]	0.12
6MWT				
	N (%)	28 (72%)	26 (79%)	
Distance (m)	median [IQR]	479 [441-520]	536 [451-580]	0.004
% predicted	median [IQR]	74 [67-91] %	84 [73-95]%	0.28
EQ-5D				
	N (%)	39 (100%)	33 (100%)	
Mobility	median [IQR]	2 [1-3]	1 [1-2]	0.023
VAS	median [IQR]	60 [50-80]	75 [50-90]	0.10
Total	median [IQR]	10 [6-12]	7 [6-11]	0.07
Concordance between measure				
Fitbit One – Fitbit Flex	Mean difference (95% CI)	-575 (-2684-1533), ρ_c = 0.89 (n=20)	-981 (-4613, 2651), ρ_c = 0.85 (n=17)	
Moves app - Smartphone	Mean difference (95% CI)	-634 (-3593, 2325), ρ_c = 0.79 (n=11)	-776 (-5457, 3906), ρ_c = 0.65 (n=10)	

6MWT – 6 Minute Walk Test.
EQ-5D – European Quality of Life Five Dimensions, VAS – visual analogue scale.
1. Comparison by generalised estimating equations unless specified.
2. Comparison by ordinal logistic regression, clustered on ID.

Table 2. *Outcome measures at 3 and 6 months*

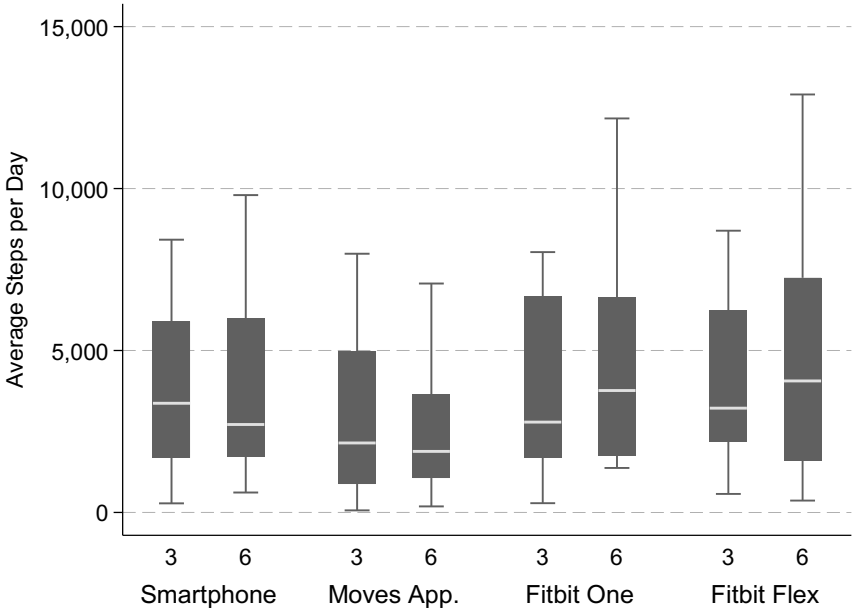
Fitbit One and Fitbit Flex		n	Moves App	n
Used for less than 7 days		14	App didn't record data for >7 days	10
Lost pedometers	In post	6	No reason recorded	4
	During study period	7	App not compatible with phone	2
Synchronisation errors		12	Phone broken	2
Device Failure		4	App deleted due to impact on phone	2
Withdrew prior to data extraction		4	Patient died during study period	1
Patient died during study period		2	Withdrew during study period	1

Table 3 - Reasons for all failed data capture by pedometers and Moves app.

Appendix 1 – Supplementary Information

	3 months	6 Months
Type of phone		
Apple	**15**	**15**
iPhone not further defined	2	2
iPhone 3	1	1
iPhone 4S	1	1
iPhone 5	4	4
iPhone 5S	1	1
iPhone 6	4	4
iPhone 6S	2	2
Android	**24**	**18**
HTC	4	4
ONE	4	4
Motorola	1	1
Nexus 6	1	1
Samsung	16	12
Galaxy not further defined	4	2
Galaxy S2	1	1
Galaxy S3	3	2
Galaxy S4	2	2
Galaxy S6	2	2
Galxay Note 5	3	2
Note 7	1	1
Sony	1	1
Experia	1	1
Other	2	0
Smartphone Usage Pattern		
Carried their phone on their body ≥75% of waking hours	25	22
Carried their phone at all times when they left the house but only sometimes when at home	5	4
Carried their phone at all times when they left the house but rarely when at home	5	4
Frequently left the phone at home and rarely carried it around home	1	1
The phone was turned off more than it was turned on	3	2

Supplementary Table 1 – additional demographic details, Smartphone usage pattern – patients were asked to clarify their usage pattern according to the above classification and also had the option to select 'other'.



Supplementary Figure 1 – Average daily step-counts for smartphone data, the Moves app, Fitbit One (hip) and Fitbit Flex (wrist) at 3 and 6 months post-discharge. (Outlier values have not been plotted for scaling)

Outcome	Predictor	Constant	Coefficient	95% CI	P-Value	R-squared
3 Months						
Smartphone	Fitbit One	670	0.61	(0.43, 0.78)	<0.001	0.86
	Fitbit Flex	1284	0.46	(-0.02, 0.93)	0.059	0.38
Moves app	Fitbit One	-78	0.58	(0.27, 0.88)	0.001	0.56
	Fitbit Flex	323	0.51	(0.03, 0.98)	0.038	0.27
6MWT	Fitbit One	350	22.3	(6.0, 38.6)	0.01	0.33
	Smartphone	430	14.1	(-1.2, 29.4)	0.07	0.25
6 Months						
Smartphone	Fitbit One	-742	0.90	(0.69, 1.11)	<0.001	0.92
	Fitbit Flex	-757	0.77	(0.50, 1.03)	0.001	0.92
Moves app	Fitbit One	595	0.40	(0.03, 0.77)	0.036	0.34
	Fitbit Flex	-80	0.41	(0.22, 0.61)	0.001	0.75
6MWT	Fitbit One	429	16.5	(4.5, 28.5)	0.01	0.35
	Smartphone	480	13.8	(0.82, 26.8)	0.04	0.39

Supplementary Table 2 – Linear regression between smartphone and pedometer estimates of average daily step-counts and the six-minute walk test at 3 and 6 months.

n=7	Premorbid	3 months	Reduction in step count at 3 months	6 months	Reduction in step count at 6 months
Mean steps/day	3840	2748	1239	2487	1720
Median [IQR]	[3483 - 4620]	[817 - 559]	[559 - 3947]	[1705-2716]	[1242 - 2398]

Supplementary Table 3 – mean daily pre-morbid smartphone step counts and comparison with corresponding step counts at 3 and 6 mont

2.4 – Manuscript

The use of smartphone derived location data to evaluate participation following critical illness: A pilot observational cohort study

Statement of Authorship

Title of paper	The use of smartphone derived location data to evaluate participation following critical illness: A pilot observational cohort study
Publication Status	Published
Publication details	**The use of smartphone derived location data to evaluate participation following critical illness: A pilot observational cohort study.** Gluck S, Andrawos A, Summers M, Lange J, Chapman MC, Finnis M, Deane AM. **Australian Critical Care** 2022; 35(3): 225-232

Principle Author

Name of Principle Author (Candidate)	Dr Samuel Gluck		
Contribution to paper	Conceptualisation of work, recruitment, data collection manuscript preparation, corresponding author		
Overall percentage (%)	70%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	6/5/2021

Co-Author Contributions
By signing the Statement of Authorship, each author certifies that:
- The candidate's stated contribution to the publication is accurate (as detailed above);
- Permission is granted for the candidate to include the publication in the thesis; and
- The sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Name of Co-Author	Dr Mark Finnis		
Contribution to paper	Data analysis and evaluated and edited the manuscript		
Signature		Date	12/11/22

Name of Co-Author	A/Prof Adam M Deane		
Contribution to paper	Conceptualisation of work, Evaluated and edited the manuscript		
Signature		Date	28/12/22

Full Title

The use of smartphone derived location data to evaluate participation following critical illness: A pilot observational cohort study

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Keywords

Global Position System, Outcomes, Technology, Critical illness, Smartphone

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Abstract

Background

Disability is common following critical illness, impacting on the quality-of-life of survivors, and is difficult to measure. 'Participation' can be quantified as involvement in life outside of their home requiring movement from their home to other locations. Participation restriction is a key element of disability, and, following critical illness, participation may be diminished. It may be possible to quantify this change using pre-existing smartphone data.

Objectives

The feasibility of extracting location data from smartphones of survivors of Intensive Care Unit (ICU) admission and assessing participation, using location-based outcomes, during recovery from critical illness was evaluated.

Methods

Fifty consecutively-admitted, consenting adult survivors of non-elective admission to ICU of greater than 48-hour duration, were recruited to a prospective observational cohort study where they were followed up at three and six-months following discharge. The feasibility of extracting location data from survivors' smartphones and creating location-derived outcomes assessing participation was investigated over three 28-day study periods; pre-ICU admission and at three and six-months following discharge. The following were calculated; time spent at home; number of destinations visited; linear distance travelled; and two 'activity-spaces', a minimum convex polygon and standard deviation ellipse.

Results

Results are median [IQR] or n (%). The number of successful extractions were 9/50(18%), 12/39(31%), 13/33(39%); percentage time spent at home-time was 61[56-68]%, 77[66-87]%, 67[58-77]%, P=0.16; number of destinations visited were 34[18-64], 38[22-63], 65[46-88], P=0.02; linear distance travelled was 367[56-788], 251[114-323], 747[326-933] km over 28 days, P=0.02, pre-ICU and three-months and six-months following-ICU discharge respectively. Activity spaces were successfully created.

Conclusion

Limited smartphone ownership, missing data and time-consuming data extraction limits current implementation of mass extraction of location data from patients' smartphones to aid prognostication or measure outcomes. The number of journeys taken and the linear distance travelled increased between three and six months, suggesting participation may improve over time.

Introduction

Disability is frequently present in survivors of critical illness, however disability is challenging to accurately and efficiently measure [1-3]. Participation is defined by the World Health Organisation (WHO) as involvement in a life situation and participation restriction is a key element of disability [4] . Patients who survive critical illness have described being restricted by a physical zone of comfort. This physical zone of comfort is relevant as it can impact on their quality of life (QoL), but is not readily quantified using current health-related QoL measures, such as the SF-36 and EQ-5D[5].

Global Positioning System (GPS) or location data have been used to measure personal participation [6-8]. Diaries have been shown to over-estimate activity [9-10], whilst GPS data have been shown to reflect participation reported [11] and GPS data have been shown to be more accurate than diary recall [7, 12]. Social capital, which is the networks of relationships in society that enable that society to function effectively, is a strong determinant of healthcare outcomes [13-15]. Accordingly, whether activity is conducted independently or is supported by social capital – i.e. a carer, a relative or a friend – is of less importance than being able to participate per se. It has therefore been proposed that the ability of an individual to visit out of home locations represents enhanced participation and reduces perception of disability [6-8]; and this out of home behaviour is now possible to quantify using GPS data.

For both clinical and research purposes, it would be beneficial to be able to estimate participation as an outcome from critical illness [16], and it may be possible to quantify participation using novel location-based outcomes. These location-based outcomes are defined as summative data relating to patient travel and out-of-home behaviour, which can be obtained using time-sequenced geospatial data that relate to the patient's position.

Objectively measuring participation using location data obtained from patients' smartphones may be possible, offering a methodology to capture distances travelled with greater precision, rather than rely on self-recording of patient participation in a travel diary [17-20]. With the potential to automate data capture, analysis and reporting, using patients own devices will enable more cost-effective research into interventions to improve outcomes [21-22]. It has recently been demonstrated it is possible to extract step-data, as a marker of physical activity, from the smartphones of survivors of critical illness [23-24]. It may also be possible to use location data from a smartphone, analysed by geographic information systems, to generate location-based outcome measures [25].

Data from GPS devices have been evaluated in several non-critically-ill populations [11, 26-34], including those with cognitive impairment [26, 28, 35], traumatic brain injury [29] cerebral palsy [11], amputees [33,34], stroke [31], mental health conditions [36, 37] and following spinal surgery [30]. The outcomes reported from these studies using GPS data frequently include the number of destinations visited or the number of trips made [11,31,33], the linear distance travelled [11] and time spent at or outside the home [11,28,33]. These studies have mostly utilised monitoring devices [11, 26-28,31,34,35], with one utilising a supplied android device [33] and all have been of an observational nature. These data were predominantly used to describe participation, particularly out-of-home behaviour and

community mobility. Real-time objective data may possess the granularity to describe patient participation automatically and continuously.

Hitherto, Geographic Information Systems (GIS) analysis using individual patient data has seldom been used for quantifying healthcare outcomes. Multiple factors have limited the uptake of this methodology, including confidentiality, consent and available technology to capture GPS data, with the latter of these perhaps the most significant. A potential application, leveraging the increasing use of smartphones [38] and location data [39], would be to also build 'activity spaces', which are a measure of the geographical area an individual covers on a daily basis. Brusilovskiy and colleagues used 'minimum convex polygons' - a type of activity space - to record participation of individuals with mental health disorders [8], and Hirsch and colleagues proposed using several different activity spaces to measure the mobility of older adults in the community [40]. Whilst such activity spaces might provide a useful outcome metric following critical illness, as they may represent the physical zone of comfort that ICU survivors report [5], it is unknown whether it is possible to conduct spatial analysis from location data obtained from the smartphones of ICU survivors.

The objective was to examine the feasibility of extracting location data from the smartphones of ICU survivors and to use the location data gained to describe participation prior to and following critical illness. It was hypothesised that, if extracting location data were feasible, survivors would spend more time at home, undertake fewer discrete journeys and travel less distance after hospitalisation when compared with participation before ICU admission, and that there would be improvement in these participation metrics at six months when compared with three months post discharge.

Methods

This was a planned follow-up study of a previously published work evaluating the use of patient owned technology [23]. Consecutively admitted patients to the Royal Adelaide Hospital ICU were screened between December 2015 and July 2016. The Royal Adelaide Hospital is a quaternary referral centre and the ICU is a mixed medical and surgical unit with approximately 3,500 patient admissions per year.

Participants

To exclude patients with mild disease or who were admitted purely for monitoring, patients were eligible to participate if they received at least 48 hours of care in the ICU. Exclusion criteria were patients admitted following an elective procedure, those who had long-term inability to mobilize, were aged <18 years, lived >50 km from Royal Adelaide Hospital (for ease of follow-up), lacked capacity to provide written informed consent, were readmitted to the ICU, were anticipated to die within 6-months, or were pregnant. Patients were approached to discuss the study when they regained capacity, this was frequently around ICU discharge, or on the hospital ward. Screening ceased at hospital discharge. If following regaining of capacity, they met eligibility criteria, patients were questioned about smartphone ownership. Those patients with a smartphone were then approached to provide informed consent to participate.

Protocol

Following written informed consent from the patient, participants were surveyed on their smartphone usage, location data were extracted and survivors were reviewed in the research department at 3 and 6-months after ICU discharge, at which time smartphone data extraction was repeated. The study protocol was approved by the Human Research Ethics Committee of the Royal Adelaide Hospital (HREC/15/CALHN 236) and registered with the Australian New Zealand Clinical Trials Registry (http://www.anzctr.com.au; ANZCTR 12616000427471)

Location data

Location data were manually extracted from the 'Frequent Locations' app on iOS devices and from Google Maps Timeline. If possible, data were extracted for the 28-day period prior to the study time point, i.e. ICU admission or clinic attendance at 3 or 6-months after ICU discharge. Due to the nature of critical illness and required interventions there was frequently a delay between admission to ICU and capacity of patients to provide written informed consent. Accordingly, to determine the feasibility of extracting data (primary outcome) as proof-of-concept, baseline (before ICU admission) data were defined as successfully extracted for any continuous period of 28-days prior to obtaining patient consent. This continuous period of 28-days may have occurred after hospital admission. This pragmatic decision was undertaken because for some patients smartphone data prior to their admission had been overwritten due to the delay between ICU admission and the capacity to provide informed consent. However, data obtained in this manner were not used for any secondary outcomes as it frequently pertained to a single location (the hospital). Repeated screenshots of the Frequent Locations or Google Maps TimeLine data, for the entire 28-day period, were taken, geocoded and stored in Microsoft Excel. Geocoding is the process of taking location

data, e.g. an address, and converting it to GPS coordinates to identify a position on the earth's surface [41]. Although extracting any location data were counted as a success for the primary outcome, only patients where the location data accounted for >50% of the total 28-day period were included in further analysis. Study data were stored on a secure hospital network drive and were only associated with a study ID with link to patient identification in written documents kept in a secure office.

Location data analysis

Data presented in 'Frequent Locations' and 'Google Maps Timeline' detail the date and time of arrival and departure from a specified location. From these data, several location-based outcomes were calculated:

Percentage time spent at home

The home location is specified in 'Frequent Locations' and determined from analysing 'Google Maps Timeline'. The total time spent at this location over the whole 28-day period (i.e 28 x24 hours) was calculated and presented as a percentage.

Number of journeys made

Discrete destinations are identified within 'Frequent Locations' and 'Google Maps Timeline'. Counting the number of journeys made during the 28-day period was possible by ordering the locations visited by time of arrival.

Linear distance travelled

Using the haversine formula [42, 43] the linear distance between destinations was calculated. The total linear distance travelled was then calculated by summing these distances over the 28-day period.

Activity spaces

It was planned to describe two activity spaces, a minimum convex polygon and a standard deviation ellipse [44]; these would represent experimental location-based outcomes. A minimum convex polygon [8] is a polygon drawn around the outermost points visited by the patient, such that no internal angle is greater than 180^{o} (Figure 1), and is calculated using the convex hull function of ArcMap (V10.3.1 ESRI, California, USA). A standard deviation ellipse [44] is the area enclosed by an ellipse centred on the mean longitude and latitude, with the direction of its short axis being determined by the minimal dispersion and the direction of its long axis by the maximal dispersion. It is calculated using the directional distribution function of ArcMap (V10.3.1 ESRI, California, USA).

Statistical Analysis

Data were analysed descriptively and reported as frequencies and percentages for categorical data and median (interquartile ranges) for continuous data. Differences between time periods were calculated with the Wilcoxon signed-rank test. A P value < 0.05 was deemed statistically significant and adjustments for multiple comparisons were not made. An arbitrary target was set of extracting data from $\geq$ 80% to indicate feasibility. No adjustments were made for missing data. Analyses were performed in Stata/MP 15.1 (StataCorp LP, Texas, USA). No formal sample size calculation was undertaken, rather a convenience sample of 50 patients was selected to assess feasibility. The STROBE guidelines for the reporting of observational studies were followed [45].

Results

Five hundred and eighty-six patients were treated in ICU for greater than 48 hrs during the 8-month data collection window. Of the 163 who met all the inclusion and none of the exclusion criteria, 84 (52%) owned a smartphone. Fifty patients provided informed consent to participate in the study. The flow of participants is shown in Figure 2.

Demographic details at basline and 3 and 6 months are detailed in Table 1. It was possible to extract location data from 19/50 (38%) of phones at baseline, 14/39 (36%) at 3-months and 15/33 (45%) at 6-months. However, due to the delay in obtaining consent in critically ill patients and thereby accessing their phone, complete 28-day data prior to hospital admission were only available for 9/19 (47%) patients at baseline with 10 patients only have part of this time period recorded.

Two participants lacked data to account for >50% of their activity at both 3 and 6 months. In one instance this was due to human error during the data extraction process. Location-based outcomes and the between time-period comparisons are described in Table 2 The number of journeys taken and the linear distance travelled increased between 3 and 6 months.

It was possible to create activity spaces from the extracted data, an example of these is shown in supplementary figure 1. There was wide variation between participants' activity spaces (Figure 3). On direct observation of the polygons of participants with outlier data (n=3) all had interstate travel during this period indicating location data were correctly recorded.

Discussion

This feasibility study demonstrates that it is possible to manually extract location data from over a third of the smartphones of consenting patients who survive critical illness. The findings also suggest that it is possible to use location data to explore useful constructs, for example to describe survivor participation in community life during recovery. These data could be linked to pre-illness data to describe changes in participation.

While many of the patients' smartphones contained location data, the process of data extraction was time consuming. For this process to be feasible for large numbers of participants, it requires automation. In addition, the 'Frequent Locations' function was lacking data for significant periods of time on some phones, which may reflect the locations visited not being recognised as 'frequent' or may be a result of the phone being turned off or having a flat battery. This led to considerable missing data.

As far as the authors are aware, this is the first-time survivors have been assessed using location-based data following critical illness and we have demonstrated that location-based smartphone data may be obtained using patient-owned technology. It is anticipated that these data may eventually represent a useful outcome to quantify participation, which may be important to survivors. Even in other aspects of illness, this is one of the largest cohorts to be studied using location-based outcomes, and the only study the authors are aware of to use the patient's own technology [25]. It is believed that the use of location data from a survivor's smartphone to create location-based outcomes has considerable potential to describe recovery from critical illness, because location data does not rely on self-reporting and recall, which are inaccurate in other settings and may be further impeded by cognitive impairment after critical illness [46]. Moreover, current methodologies to quantify outcomes after ICU have limitations. Lim and colleagues reported that patients perceive limitations with current measures commonly used as ICU outcomes, e.g. the SF-36 and EQ-5D. These measures often lack domains needed to comprehensively assess patient-centred outcomes [5], such as physical zone of comfort, which theoretically may be estimated by location-based outcomes.

Due to small numbers and missing data, it is not possible to make strong inferences from the location data obtained. No abrupt change was observed in the location-based outcomes between pre-hospital and 3-months after ICU. A modest reduction was observed at 3-months, in many of these metrics, which appeared to be improving by the 6-month period.

Raw GPS coordinates were not used, as in previous studies, rather locations held within the Frequent Locations and Google Maps Timeline were geocoded, which makes the present study data difficult to compare with published data [31]. Outcomes over a 28-day period were created, whereas previous studies have used daily, 7-day or 28-day outcomes. It was decided to collect data over 28-days as the existing literature provided only scant data, and it was believed this would provide a more representative level of activity. However, as demonstrated in figure 3, these data are skewed by participants who undertook interstate travel. Future studies may benefit from obtaining daily measures and comparing median values over a longer period (e.g. 28-days), as the influence of outlying values would be reduced. As community mobility was relied on as a measure of participation, although others

have made this assertion [17-20], it would benefit from further validation in the ICU survivor cohort.

McCluskey and colleagues reported participants took 6.2 (SD 3.4 range 0-14) outings a week when followed for a mean of 43 months after a stroke [31], and Hordacre and colleagues reported transtibial amputees made a median of 2.3 [IQR – 1.3-2.8] community trips per day [34], which is a similar number of journeys to the participants in this study. Wettstein and colleagues reported participants visited 4.5 nodes (locations) a day and spent on average 4 hours out of the hour per day [28], however they excluded days where the participants spent all day at home, so the results are not directly comparable to this study.

The location-based outcomes reported are relatively novel and normal values for healthy individuals are unknown. Indeed, the linear distance an individual does travel, how much time they spend at home, how many journeys they make and their activity space will be influenced by many factors beyond their disability or functional limitation, e.g. availability of a car or public transport, the landmass on which they live, and socioeconomic class. These data are objective and pertain to activity prior to critical illness, but cannot currently be benchmarked against the average normal population.

There are potential ethical issues with the use of location data, and these pose challenges to this type of research [47]. These data may identify the patient's home address and their behaviour patterns. Patients provided written informed consent for the data extraction. Following research best practices will alleviate many of the privacy concerns of location data, and patients provided written informed consent for data extraction. However, if these data were held in a data repository, they would need to be randomly manipulated to allow for them not to identify home address details. It is established that participants do have concerns over sharing their location data, and that participation is strongly influenced by the incentive provided [48]. By ensuring good practice guidelines are followed studies such as this shouldn't erode patients trust in this kind of technology [47].

There are limitations to the present study. Data that had already been processed by Apple and Google were relied upon; each use proprietary algorithms that are almost certainly different. For example, 'Frequent Locations' doesn't record time spent traveling and may not have recorded data from locations the algorithm didn't deem were 'frequent', although in some instances locations that were only visited once were recorded. The effect of these differences on the outcomes generated is unknown. It is possible to develop other tools for assessing locations, or clusters, from GPS data [8]; however, how these relate to the data obtained from Frequent Locations or Google Maps Timeline is not known. Even when data were able to be extracted, in some participants there remained missing data, which may be due to inconsistent mobile phone use. As such, participants may have made more journeys or travelled further than has been reported, although smartphone GPS data appears more complete than a GPS enabled watch [49]. Finally, use of GPS data involves a value judgement that a greater number of journeys and distances travelled is a measure of participation and happiness of survivors of critical illness. It should be recognised that without corroborating evidence of greater participation, e.g. accurate diary entry of participation or return work, assumptions about participation are extrapolated from evidence in other fields [6-8].

While extracting data manually from participants phones may not be feasible it is conceivable that, using a custom-built smartphone app [50], anonymous location data could be sent from survivors to clinicians. This is appealing as studies report that many survivors do not have the time, inclination or resources to attend in-person follow up clinics [51-53], and these technologies need to fit seamlessly into existing care [54]. Such an approach could allow a cost-effective methodology for collecting highly granular data about participation. For research purposes, it would be appealing to quantify the effect of ICU interventions on the delta participation (difference between pre-ICU and 3 to 6 months after) [16, 55, 56]. To accurately collect pre-morbid data, GPS data would need to be recorded and stored as standard health outcomes as part of Google Fit or Apple Health Kit as step data currently is [57]. Further research assessing the acceptance of this technology and the meaningfulness of the outcomes to participants is warranted.

Conclusion

This is the first attempt to use location-based outcomes using GPS-derived data to quantify participation in survivors of critical illness, which is a novel concept. Location data were present on only a third of patient's smartphones. Combined with the lack of easy and automated extraction process, it is not currently feasible to use GPS data obtained from proprietary mobile phone software for assessing patient participation. The number of journeys taken and the linear distance travelled were observed increased between 3 and 6 months, which suggests participation increases over time.

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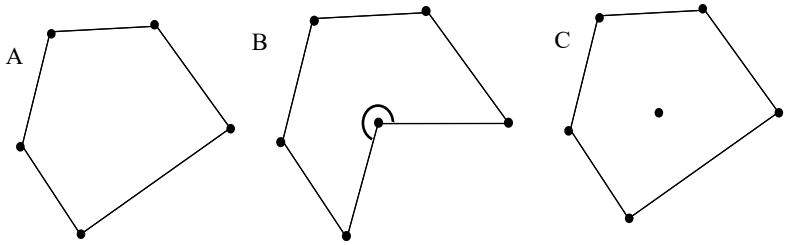


Figure 1 – Construction of a minimum convex polygon requires that all internal angles are less than 180 degrees. In this example, all visited locations are identified with a closed circle. In panel A, a minimum convex polygon is calculated from each point using straight lines. Panel B would be an invalid polygon because the angle indicated is greater than 180 degrees. Panel C would be the correct polygon, and would contain the central location seen in B.

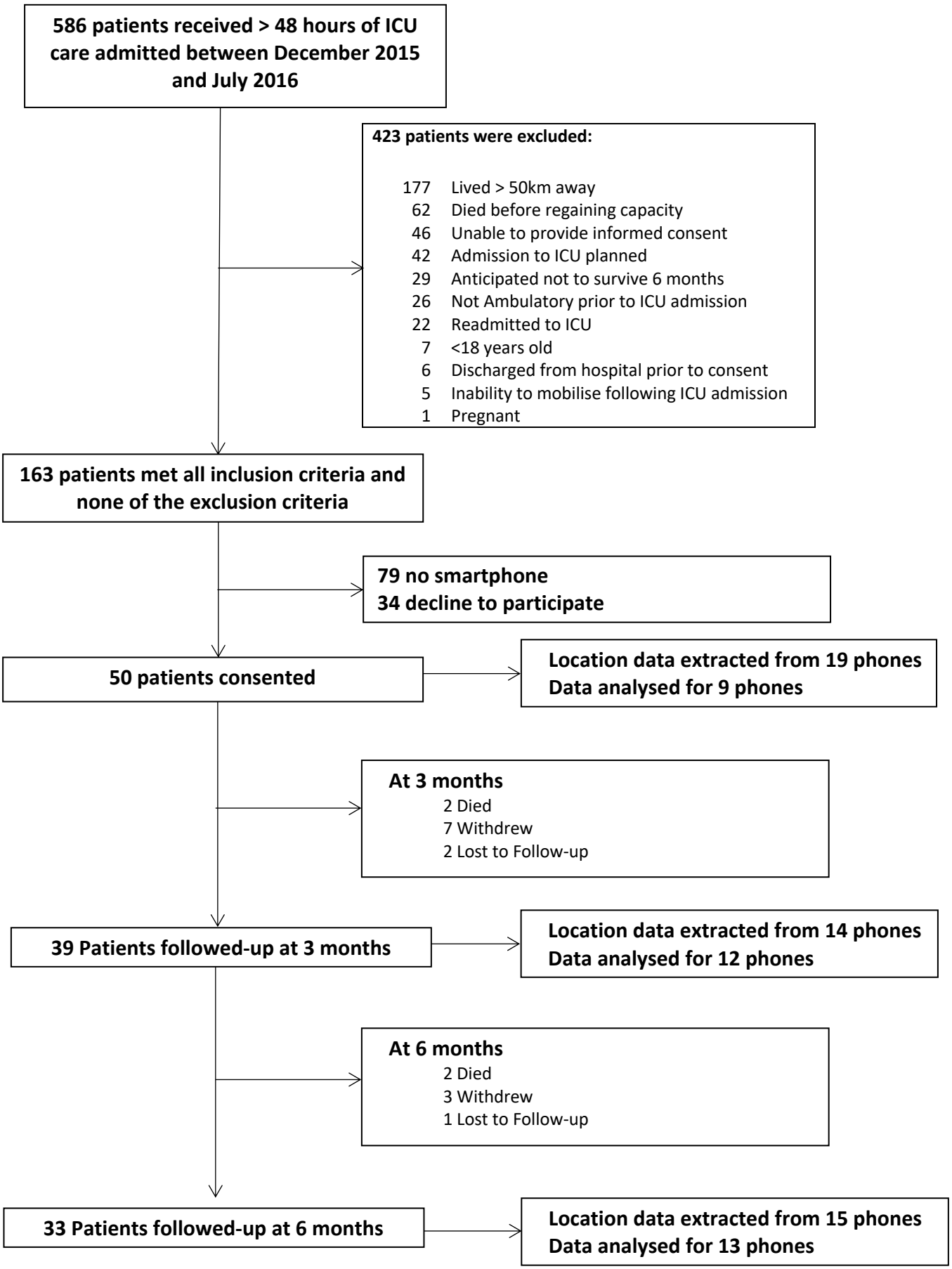


Figure 2 – Study participants through the study

Demographics	**Baseline (n=50)**	**3 months (n=39)**	**6 Months (n=33)**
Male, n (%)	33 (66%)	30 (77%)	26 (79%)
Age (years), median [IQR]	55 [39-64]	56 [44-65]	55 [39-64]
APACHE 3J (score), median [IQR]	54 [39-74.5]	59 [37-77]	53 [35-75]
ICU LoS (days), median [IQR]	6 [4-10]	6 [4-10]	6 [4-9]
Hospital LoS (days), median [IQR]	17 [10-26]	18 [12-28]	17 [10-25]
Trauma, n (%)	12 (24%)	10 (26%)	9 (27%)
Medical, n (%)	36 (72%)	27 (69%)	23 (70%)
Surgical, n (%)	2 (4%)	2 (5%)	1 (3%)
Functional Co-Morbidity Index, median [IQR]	N/A	3[1-5]	3 [1-4]
Phone type			
Apple	20 (40%)*	15 (38%)	15 (45%)
Android	25 (50%)*	24 (62%)	18 (55%)
Phone Usage			
Carried phone on person >75% of the time	35 (70%)	25 (64%)	22 (67%)

Table 1 - Demographic details at baseline and at 3 and 6 month visits**.** Acute Physiology and Chronic Health Evaluation (APACHE), Intensive Care Unit (ICU) Length of Stay (LoS), * *Data extraction wasn't attempted from 5 phones due to staff availability*.

Outcome	Baseline (n=9)	3 Months (n=12)	6 Months (n=13)	P Value 3-6 months (n=8)
% time spent at home	61 [56 – 68]	77 [66 – 87]	67 [58 – 77]	P=0.16#
Number of journeys made	34 [18 – 64]	38 [22-63]	65 [46 – 88]	P=0.02#
Linear distance traveled (km)	367 [56 – 788]	251 [114 – 323]	747 [326 – 933]	P=0.02#
Minimum convex polygon (km^2)	23 [7 – 571]	148 [78 – 517]	186 [68 – 863]	P=0.39#
Standard deviation ellipse (km^2)	21 [4 – 190]	64 [39 – 146]	156 [29 – 333]	P=0.39#

Table 2 - Location-based outcomes at baseline, 3 and 6 months. Results are median [IQR]. # Wilcoxon Signed-Rank Test. P Value calculations are based on the number of patients with comparative data at 3 and 6 months.

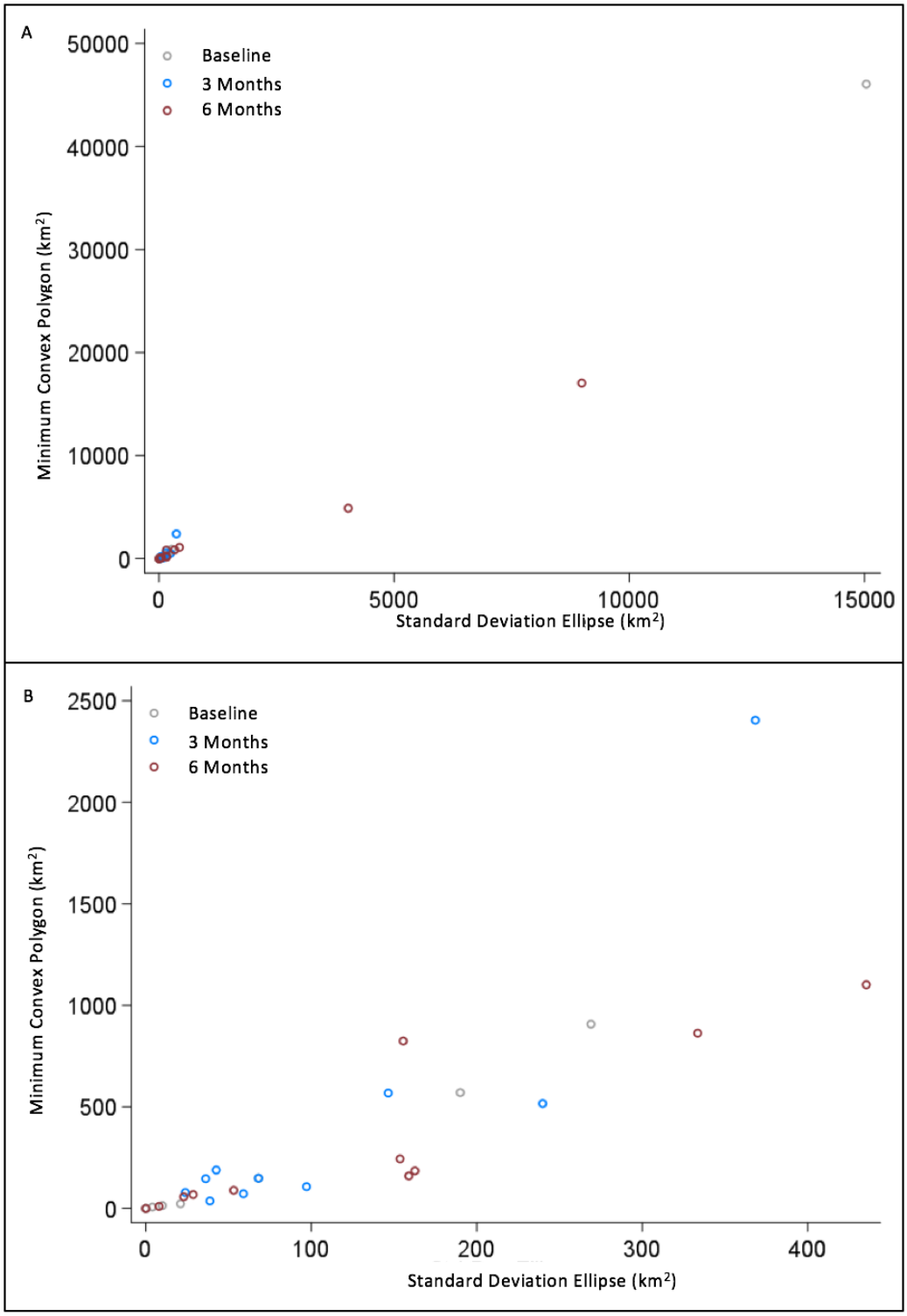
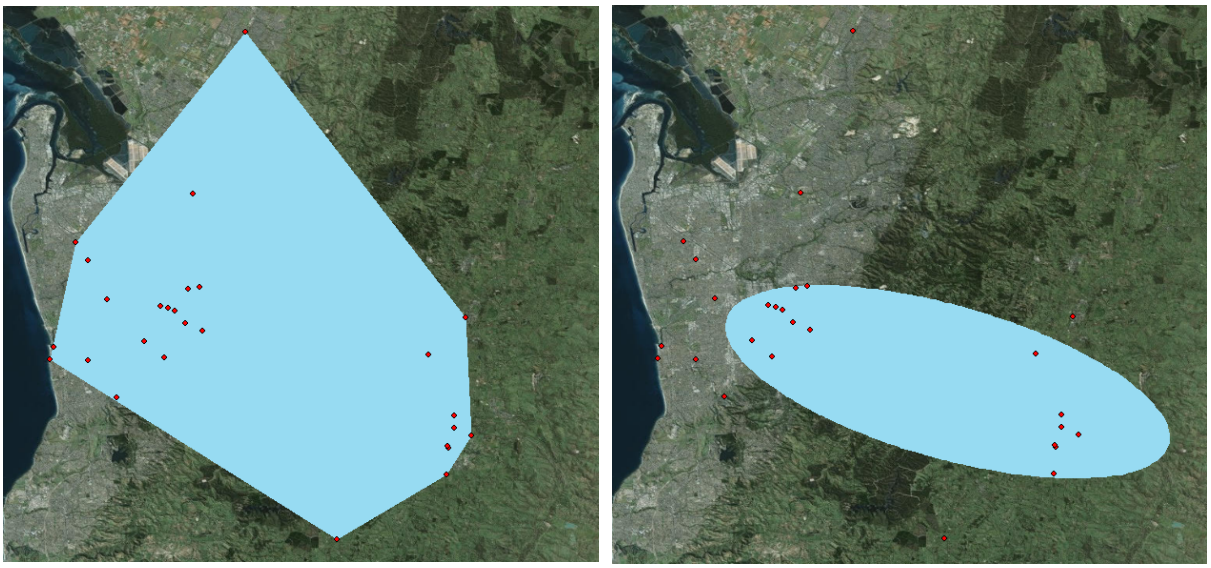


Figure 3 - Scatter plot of standard deviation ellipse and minimum convex polygon (A) All data; and (B) with outlying values removed showing baseline data and data obtained at the 3 and 6 month clinic visits.



A B

Supplementary figure 1 – Examples of a (A) Minimum Convex Polygon and (B) Standard Deviation Ellipse activity space

2.5 Conclusions

2.5.1 Introduction

This chapter concurs with the existing literature that demonstrates the discourse between patients and their surrogates estimates of pre-morbid assessments. With regards to activity levels (Chapter 2.2) this raises important clinical concerns, as clinicians frequently rely on these data to inform treatment plans. However, in the absence of an agreed gold standard, the surrogates appeared to be the better estimators of premorbid activity, when compared to smartphone data, with patients tending to over-estimate their activity levels. Smartphone ownership was relatively prevalent in the ICU population, and it was possible to extract either step or GPS data from nearly 50% of the phones analysed during patients ICU stay.

The step counts obtained from a smartphones do appear to be a suitable substitute for a dedicated pedometer in a free living environment. Additionally, it was possible to manually extract location data from a third of the smartphones examined and use these data to generate useful constructs that may describe patient participation.

2.5.2 Contribution of the work described to the measurement of pre-morbid activity

The measurement of pre-morbid function, and the relationship with subsequent outcomes is of vital importance to ICU research. This is incredibly hard to achieve, as measuring pre-morbid function frequently relies on subjective recall. We have established that there appear to be significant inaccuracies in the subjective recall of patients and their surrogates. Therefore, being able to measure pre-morbid function objectively and retrospectively, is important, as it will enable a comparison with function during and following recovery. We have demonstrated that the passively collected and stored data held in various smartphones datasets may be able to perform this function.

2.5.3 Contribution of the work described to the measurement of outcomes I critically ill adults

The work performed by the ICU research community has focused on designing or validating specific tools that address the domains that are limited in ICU survivors. However, in their International Classification of Function, the World Health Organisation (WHO) advocated for a common language in the assessment of disability focusing on activity and participation. In utilising patients own devices there is the potential to collate data relating to activity and physical participation. Many devices owned by patients passively collect pedometry and location data. It may be possible to use pedometry and location data to define outcomes, such as time spent active or time spent out of the home. Outcomes such as these are objective, can be passively collated and possibly wirelessly transmitted to clinicians or researchers. They are also important to patients. The use of smartphone technology in this regard represents a novel methodology that could be applied to ICU outcomes research.

2.5.4 Contribution of the work described to the use of smartphones to measure healthcare outcomes

Mobile Health (mHealth) is a growing field and the digital phenotype an increasingly used term. Being able to use passively collected data to monitor patients via their smartphone is an unobtrusive research methodology. We have demonstrated that smartphones are able to collect both step and GPS data. In using activity spaces, distance travelled and number of steps per day we have used these data to utilise outcomes that can allow for inter-individual comparison.

2.6 Future Directions

2.6.1 The automation of data extraction

This chapter has demonstrated that the data present on phones is difficult to extract, requiring physical photos of the phone to be taken. For step data, this enables the daily step counts to be transcribed into a spreadsheet, however, the data held in the pedometer apps is at a far higher resolution. The data held in databases included the time the individual started walking, the time they stopped, the number of steps taken and in some devices the distance walked. Manually extracting this data is simply not feasibly as it represents hundreds to thousands of lines of data per day. The manual extraction of GPS data required the screenshots to have each individual datapoint geocoded manually to find its GPS position. This was incredibly time consuming and would not represent a long-term solution. Being able to access the databases on the phones where these data are stored will be necessary. This was attempted using a collaboration with digital forensic scientists, however, they were unable to extract the required data. Automatic data extraction would allow for the full automation of analysis making the whole process faster and easily assessable. This is a hurdle that would certainly be worth further investigation.

2.6.2 The assessment of the accuracy of Smartphone GPS data

The accuracy of the smartphone data we are extracting has not been studied. The data from both frequent locations (iOS) and GoogleMaps Timeline are not in the format of GPS positions, but rather an image of position on a map, researchers time is then spent finding the GPS data for analysis of these data in Geographic Information System software. The way that both Apple and Google determine which locations they display on the map is currently unknown, especially with regard Apple's frequent locations. What Apple determines a 'frequent' location is unknown, this could have huge implications for the distance a participant travels or the size of their activity spaces. If these databases were able to be automatically extracted and only provide details of the specific locations knowing how these data compare to a GPS tracker would allow comparison of these data with other such studies. There is additionally limited data on the accuracy of smartphone GPS data and no evidence regarding the use of smartphone data to determine time spent at home or activity spaces. Comparing the outcomes generated using frequent locations, GoogleMaps timeline or other GPS data with the outcomes generated through a dedicated GPS transponder would warrant further investigation.

Chapter 2 References

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CHAPTER 3 – AUTOMATION OF GLOBAL POSITIONING SYSTEM DATA EXTRACTION

3.1 Introduction

Chapter 2 demonstrated that highly granular and passively collected datasets are contained in smartphones and are potentially of use in determining the activity and participation of individuals in the community. These datasets may be able to define outcomes that are meaningful to patients. Combined with healthcare data these datasets may add value to existing predictive models[1]. For these potentials to be realised the extraction and analysis of these data requires automation.

While in the previous chapter it was demonstrated that Global Positioning System (GPS) data is present on the phones of ICU survivors, the extraction of these data was a slow manual process. Being able to automate some, if not all, of this process would be a significant improvement in the methodology. Both Apple and Android are becoming increasingly defensive of the GPS databases held on their devices. While there is no way to access the 'Frequent Locations' database on iOS devices, Google have enabled greater transparency by allowing the end user the ability to view and more recently download the data held in Google Maps[2, 3].

Being able to test the availability of these data in ICU survivors would be ideal, however, the recruitment for such a study would require daily screening, waiting for patients to be able to provide consent following extubation and thus, take several months of recruitment. Therefore, performing this feasibility study in a General Medical population with daily admissions of 15 – 40 patients would increase the recruitment potential in a similar population.

3.1.1 Objectives

The objectives of this chapter were to establish the availability of Google Maps Timeline (GMT) data and the feasibility of data extraction from the smartphones of patients admitted under the General Medicine Unit. We aimed to assess the proportion of patients with smartphones, the number of phones with GMT data available, and the completeness of the GMT data in the 180 days prior to admission.

3.2 Manuscript

Development of a protocol for collecting patient data on mobility and activity prior to hospital admission

Statement of Authorship

Title of paper	Development of a protocol for collecting patient data on mobility and activity prior to hospital admission
Publication Status	Pending Submission – Formatted for Australian Health Review
Publication details	**Development of a protocol for collecting patient data on mobility and activity prior to hospital admission** Gluck S, Dasondi A, Ma T, Kumawat M, Chapple L.S, Gilbert T, Woodman R, Thompson C,H.

Principle Author

Name of Principle Autor (Candidate)	Dr Samuel Gluck		
Contribution to paper	Conceptualisation of work, literature search, data analysis, manuscript preparation, corresponding author		
Overall percentage (%)	70%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	25/12/2021

Co-Author Contributions
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Development of a protocol for collecting patient data on mobility and activity prior to hospital admission

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Ethics approval

The study received ethical approval from the CALHN Human Research Ethics Committee (approval ID - HREC/18/CALHN/801) and all patients provided written informed consent.

Competing Interests

The authors declare no competing interests.

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Abstract

Objective

Subclinical deterioration may be present prior to hospital admission which may present as a reduction in activity. GoogleMaps can store personal Global Positioning System (GPS) data using GoogleMaps Timeline (GMT). This study aimed to assess whether these data can provide a record of patient activity prior to a hospital admission.

Methods

A feasibility study was conducted in patients admitted under the General Medical unit at the Royal Adelaide Hospital to assess the availability of GMT data on patient phones, the feasibility of data extraction and the quantification of change in activity over the 180 days prior to hospital admission. Following consent, demographic details were recorded and extraction of GMT data attempted. GMT data were used to calculate daily distance travelled and two activity spaces in the 180 days preceding admission.

Results

Fifty-three patients consented, four withdrew and 49 completed the study. Of these, 35 (71%) owned a smartphone and GMT data were present on 10 (29%) phones. Data could not be extracted from two phones, and four contained no data for the preceding 6 months. Valid data were extracted from four phones. Distance travelled and activity spaces were determined for 531 (73%) days in the 6 months prior to admission. While significant variation and potential errors were observed in these data, a potential subclinical deterioration in one of the participants was detected.

Conclusion

GMT data from smartphones of General Medical inpatients are difficult to extract and was of poor quality. Further exploration of activity-related data to predict hospital admission is required.

Key Question Summary

1. What is known about the topic?

Subclinical deterioration may precede a hospital admission. Extracting highly granular data from passively collected datasets may indicate activity changes as a manifestation of subclinical deterioration. It has recently been shown that 80% of student owned smartphones contain 'GoogleMaps Timeline' (GMT) data, and these show a second by second record of the participants GPS track.

2. What does this paper add?

We have demonstrated that in a cohort of General Medical patients the level of smartphone ownership is lower than that seen in the Australian general public (88%), GMT data on the smartphones of patients admitted to a general medical unit are limited, and variably complete. We discovered potential inaccuracies in these data. We used the GPS data extracted to generate outcomes that might reflect altered activity patterns and signify subclinical deterioration. To collect enough data for a meaningful analysis we would need to approach >50,000 patients.

3. What are the implications for practitioners?

Activity-based, non-health related passively collected datasets potentially hold useful information to predict subclinical deterioration. However, the methodology to do this efficiently is not currently feasible and requires further investigation.

Introduction

Admission avoidance is a key goal of every healthcare system globally [1] with a hospital admission associated with worsening functional [2] and cognitive capacity [3] for patients and significant healthcare expense [4]. An ageing population will place greater pressure on healthcare, such that hospital avoidance will become increasingly important [5]. While not all admissions are avoidable [6, 7], an admission may follow a period of subclinical deterioration that leads to an admission-triggering event such as a fall or delirium [2, 8]. Certain characteristics may help identify those patients at risk of hospital admission over a set period of time, for example 28 days [9, 10] or 1 or 2 years [11, 12]. However, it is unknown which patients may be at greatest risk of hospital admission on any particular given day [10, 13]. This is a limiting factor for targeted pre-hospital intervention.

In other populations, there has been an exponential growth in the use of the 'digital phenotype' [14]. The digital phenotype refers to an individual footprint produced from the analysis of information collected by digital devices such as smartphones [14, 15]. These data are often collected passively in the background, incidental to the primary role of the digital device. The digital phenotype has a potential role in healthcare; for example, it has been shown to strongly correlate with disease severity in serious mental health conditions [15, 16], and with cognitive impairment [17-19]. Location data derived from a smartphone contribute to the digital phenotype, and can be used to describe how much an individual interacts with their local community.

Data on an individual's location are collected on a continuous basis through a number of different platforms. For example, Google has been tracking their users' location through Google Location History on Android devices since 2012 and with GoogleMaps Timeline (GMT) across Android and Apple iOS platforms since 2015. These data are usually collected in an opt-out fashion, and so are often stored without the user's knowledge. GoogleMaps, with over a billion monthly users [20], is a potentially rich data source for healthcare research and perhaps clinical use. It is feasible to download an individual's location history data from free-living individuals, such as from student phones [21]. It has been shown that Cystic Fibrosis [22] and Chronic Obstructive Airways [23] disease state correlates closely with activity. It is unknown, but conceivable, that these data may detect the subclinical deterioration that occurs prior to a hospital admission. Agarwal and colleagues showed that geotagged internet searches accurately predicted future patient healthcare utilisation events [24]. Several methods have been proposed to analyse these data, such as distance travelled and activity spaces (the geographical area an individual interacts with on a daily basis) [25]. Detecting changes in activity space and distance travelled prior to hospital admission may allow for detection of subclinical deterioration, which may thereby present an opportunity for targeted intervention, attenuating acute decline and avoiding hospitalisation.

This study aimed to assess the feasibility of extracting GMT data from the phones of patients admitted under the General Medicine unit at the Royal Adelaide Hospital (RAH). In addition, we aimed to use the extracted data to describe location-based outcomes, such as distance travelled and activity spaces for the six months prior to hospital admission, investigate a meaningful difference in step and GPS data prior to admission and to describe the relationship

between these location-based outcomes and the number of readmissions over 180 days following hospital discharge.

Methods

This was a feasibility study of a convenience sample of patients admitted under the General Medicine unit at the RAH between May 2019 and Feb 2020. Patients were deemed eligible if they were aged ≥18 years, able to provide written informed consent and able to answer the initial questionnaire. Patients were screened on days when a member of the medical student team was available and eligible patients approached for consent by a medical student team.

The study received ethical approval from the CALHN Human Research Ethics Committee (approval ID - HREC/18/CALHN/801) and all patients provided written informed consent.

Comparative data were taken from the lead authors smartphone.

Demographic data

Following consent, patient demographic details (age, gender, years of education, smartphone ownership, and mobility), a Clinical Frailty Scale and the Charlson Comorbidity Index were recorded. For patients who owned a smartphone, data extraction from GMT was attempted. If GMT data were available, data completeness over the 180 days prior to admission was assessed.

The number of public Emergency Department presentations and public hospital readmissions in the 180 days following hospital discharge from the index admission were extracted from the South Australian healthcare administrative dataset.

Outcomes

GMT data handling

The GMT data were extracted as a JavaScript Object Notation (json) file before being converted to a Python Pandas DataFrame for calculation of distance travelled, minimum convex polygon and standard deviation ellipse activity spaces using ArcGIS (ESRI, California, USA) Python libraries. The feasibility of data extraction was defined as being able to extract any data from the phone during the 180 days prior to patient admission.

GPS outcomes

Distance travelled

The total distance travelled between individual GPS positions was calculated using the Haversine formula [26, 27] in a Pandas DataFrame.

Minimum convex polygon

A minimum convex polygon (MCP) [25] is an activity space consisting of a polygon that bounds the outermost points of travel such that no internal angle of the polygon is greater than 180 degrees. It is calculated using Python script derived from the convex hull function in ArcGIS (ESRI, California, USA) (Figure 1).

Standard deviation ellipse

A standard deviation ellipse (SDE) [28] is an activity space consisting of an ellipse where the short axis is formed by the minimum standard deviation and its long axis by the maximum standard deviation in longitude and latitude. It is calculated using a Python script derived from the direction distribution function in ArcGIS (ESRI, California, USA) (Figure 1).

Clinical Frailty Scale

The Clinical Frailty Scale is a nine-point scale [29] (ranging from 1 to 9) that describes an individual's level of frailty. It has been extensively validated and shows good inter-rater reliability. The Clinical Frailty Scale comes with a visual and descriptive scale and was assessed by the medical student team.

Statistical analyses

Summary statistics are n (%), median [interquartile range], or mean (SD) depending on distribution. GPS data extraction from json were performed in Python, GPS analysis was performed in ARCMap (ESRI California USA) and summary statistics were collated in Excel (Microsoft Washington). Between group analysis was performed in Python using Mann Whitney U rank test from the SciPy library.

Results

Six hundred and sixty three patients were admitted under General Medicine on days the research team were available. A total of 426 patients were approached for consent, of whom 373 were excluded as they were unable to provide written informed consent. Fifty-three patients consented, of which four withdrew during the initial questioning. A total of 49 patients completed the study (Figure 2).

Smartphone ownership and GMT data extraction

Patient demographics and pre-morbid function are detailed in Table 1. Of the 49 patients who completed the study, 35 (71%) owned a smartphone. GMT data were available on 10/35 (29%) phones, however, data were only successfully downloaded from 8/35 (23%) phones, and only contained data relating to the preceding six months for 4/35 (11%) patients. Of the 10 phones that had GMT data available 60% (n=6) were iPhones and, of the four phones with usable data, 3 (75%) were iPhones.

GPS data description

The four patients with eligible data contributed a total of 89,715 GPS positions in the six months preceding their hospital admission. GMT data was available for 180, 177, 119 and 55 days for the 180 days prior to hospital admission. GPS summary results are presented in Table 2.

These data were highly variable, from activity spaces that reached across the globe to days when patients did not leave their home (Figure 3). One patient simultaneously (within hours) had data from Europe and South Australia. On further investigation we discovered that the data was also linked to another device used by a family member who had travelled to Europe. Due to the small number of patients included, the large variation in data and the discovery of potential errors in the data source, further assessment of a change over time was not feasible; neither was the aim to assess the relationship with healthcare utilisation.

GPS data case study

Data from one individual is presented to demonstrate the difficulties encountered. Plotting the change in Minimum Convex Polygon and Standard Deviation Ellipse over the 180 days prior to admission is distorted by large positive 'outlier' values (Figure 4A) that related to interstate travel between Adelaide and Melbourne (Figure 4D). The largest of these was 121 days prior to admission. With these outliers removed, a reduction in activity space that commenced around 66 days prior to admission was observed (Figure 4B). These stepwise changes were not as obvious in a healthy adult (Figure 4C). The median MCP area was 50 [25-97.5] km^2 prior to day 66, and 20 [9.25-27] km^2 ($p<0.0001$) after day 66. The median SDE was 39 [22.5 – 67.5] km^2 prior and 19 [6.25-23.75] km^2 following day 66 ($p<0.0001$).

The 49 patients in this study had 1 [0-2] further public hospital admission and 1 [0-2] presentation to an Emergency Department in the six months following their index admission. Assessing the relationship between pre-morbid GPS data and days free from hospital at day

180, and investigating a meaningful difference in step and GPS data prior to admission was not possible due to the small number of patients with GMT data.

Discussion

This study showed that, despite a relatively high level of smartphone ownership in our target population, GMT data were infrequently available and difficult to extract. Available data were challenging to download and frequently out of date, with GPS data from the six months prior to admission being available for just 4/49 (8%) of the cohort. However, when present and extracted, these data did appear complete.

The number of patients with valid data was significantly less than for the study that prompted this investigation [21]. Ruktanonchai and colleagues found that 85% of Android devices had extractable GMT data. While they focused on Android devices, given this was historically where these data were available, we believe our study is the first to extract data from both Android and iOS devices. We have demonstrated that the granularity of data extracted is consistent with that of previous reports [21]. However, the ability for location data to be collected simultaneously from different devices means future studies should consider excluding patients who have GoogleMaps running on multiple devices, especially if these devices are not always in their possession, in order to increase data accuracy.

While this is the first time GMT data have been extracted from the phones of patients admitted to a General Medicine unit and from iPhones, we were unable to collect sufficient data to assess their value at predicting hospital admission. Only 29% of phones had data present and only 11% had data pertaining to the 180 days prior to admission. This might have been a failure of data extraction as patients were not always aware of their password, making the login process difficult. Additionally, there appeared to be variation over time on the location of the data within the patients' Google accounts. Therefore, the training provided to the medical students, responsible for extracting the data, may have become outdated over the study duration. However, to extract data from 4 phones we approached 663 patients. To scale this up to a level required to perform any meaningful analysis (for example, meaningful data from 500 patients), you would need to approach >50,000 patients for consent. This is not feasible with the current methodology.

This is the first study to attempt to extract location data prior to hospital admission in a General Medical population. Our group have previously attempted this in ICU patients [30]. However, data were manually extracted from screenshots and GMT data were not so widely available in the general population at the time. We demonstrated that four patients lacked recent GMT data. This may have been due to changes in privacy settings made by the individuals or by upgrades to operating systems. Despite the limitations, as younger generations age and smartphone user ability increases in hospitalised patient populations, these data may become more readily available [31, 32]. Although there did appear to be a high level of smartphone ownership, this is probably biased by excluding patients who were unable to provide written informed consent, as the average patient age (67 [51-80] years) was significantly younger than our normal patient population.

We were able to demonstrate a clear reduction in SDE and MCP in the pre-admission period with a reduction in SDE and MCP from day 66 prior to admission. This same stepwise reduction was not present when compared to an individual who did not suffer a hospital

admission (the lead author). This makes GPS a potential target for patient monitoring in the community although far more investigation would be required.

We demonstrated that using smartphone data to predict hospital admissions using the current methodology is not a feasible solution, due to the configuration and data availability on patient phones. Future studies could consider using a designated phone application to collect GPS data in large cohorts of patients to enable a retrospective assessment of how these data change prior to a hospital admission. This may enable the detection of subclinical deterioration, encouraging interventions aimed at arresting the decline and preventing hospital admission.

In conclusion, it was not feasible to extract GMT data from an adequate number of the smartphones of patients admitted under the General Medicine unit. The use of GPS data to predict hospital admissions requires further investigation.

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Demographics	n=49
Age (years)	67 [51-80]
Gender, Male	26 (53%)
Years of education	13 [10-15]
Smartphone owner	35 (71%)
Smartphone Details	**n=35**
iPhone	19 (54%)
Android	16 (46%)
Mobility	**n=49**
Uses a mobility aid	20 (41%)
Drives	26 (53%)
Access to a driver	43 (88%)
Use public transport	21 (43%)
Taxi/hospital transport only	6 (12%)
Frailty and comorbidities	**n=49**
Clinical Frailty Scale	4 [2-5]
Charlson Comorbidity Index	1 [0-2]

Table 1 *- Demographic details and baseline functional status of patients that completed the study, results are median [IQR] and n (%) as appropriate*

Measure (per day)	**Patient 1**	**Patient 2**	**Patient 3**	**Patient 4**
Distance travelled (km)	21.8 [10-39.7]	35.6 [23.3-53.9]	22.2 [5.7-35.2]	0.4 [0.3-18.1]
SDE (km^2)	7.2 [1.5-24.4]	25.1 [16.8-51.7]	15.9 [4.6-56.0]	0 [0-4]
MCP (km^2)	14.2 [4.5-36.4]	33.1 [18.3-70.7]	16.9 [2-55.6]	0 [0-11.7]

Table 2 *- GPS outcomes of patients that provided GPS data, results are median [IQR]. MCP – Minimum Convex Polygon, SDE – Standard Deviation Ellipse*

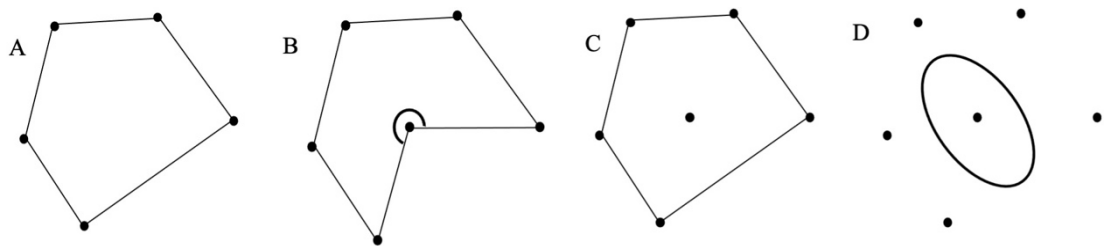

Figure 1 *- Construction of a minimum convex polygon requires that all internal angles are less than 180 degrees. In this example, all visited locations are identified with a closed circle. In panel A, a minimum convex polygon is calculated from each point using straight lines. Panel B would be an invalid polygon because the angle indicated is greater than 180 degrees. Panel C would be the correct polygon and would contain the central location seen in B. Panel D represents the standard deviation ellipse for the same GPS positions.*

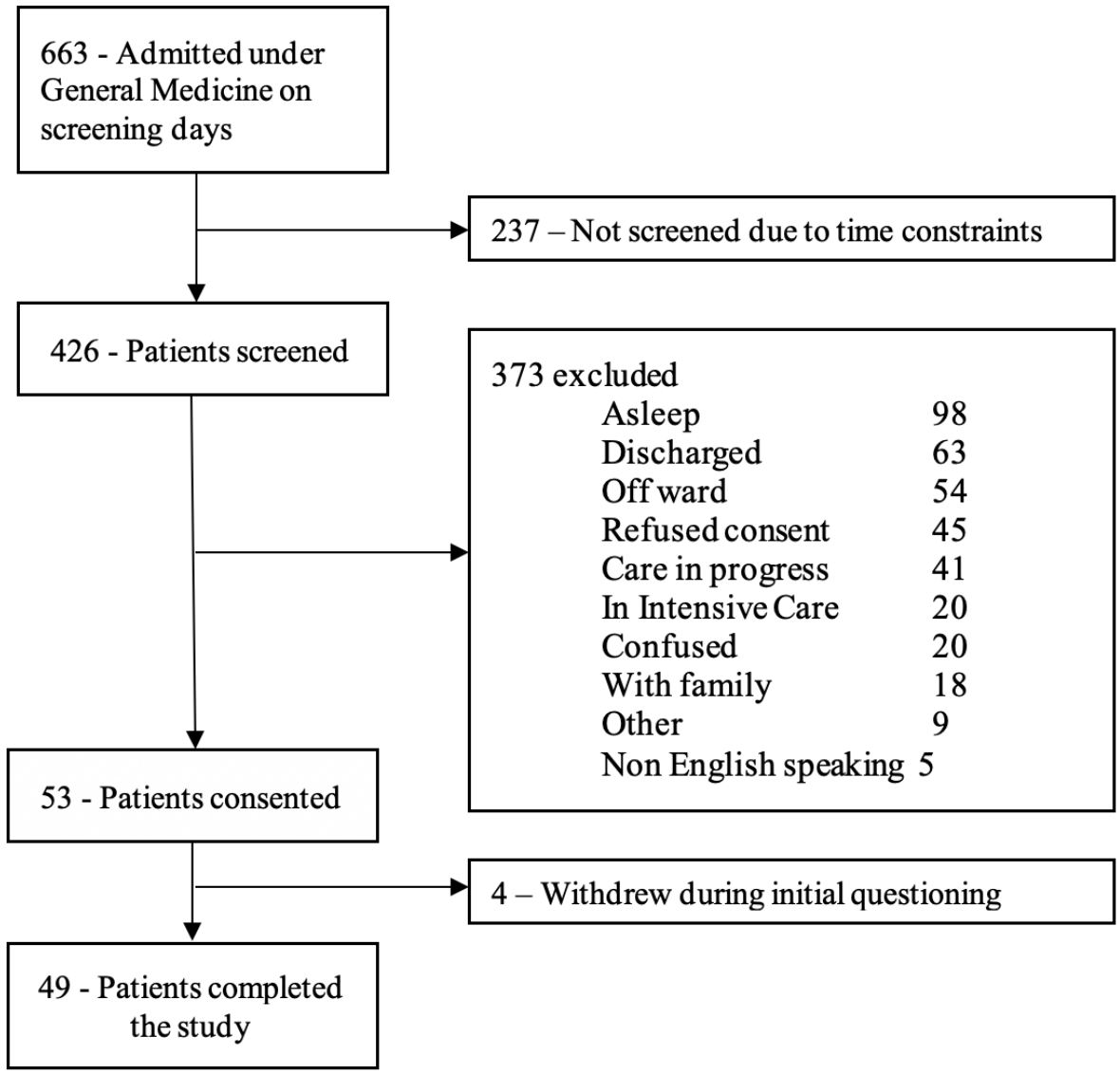

Figure 2 *- Consort diagram*

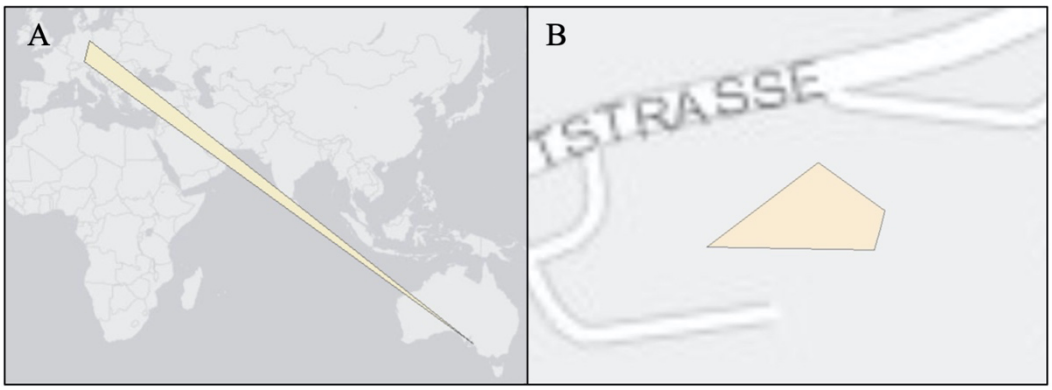

Figure 3 *- Demonstration of the vast difference in Minimum Convex Polygon activity spaces; (A) demonstrates travel from Australia to Europe, where as (B) demonstrates an activity space limited to a block (this polygon has been shifted to conceal the location of the patients address). These activity spaces were from the same individual.*

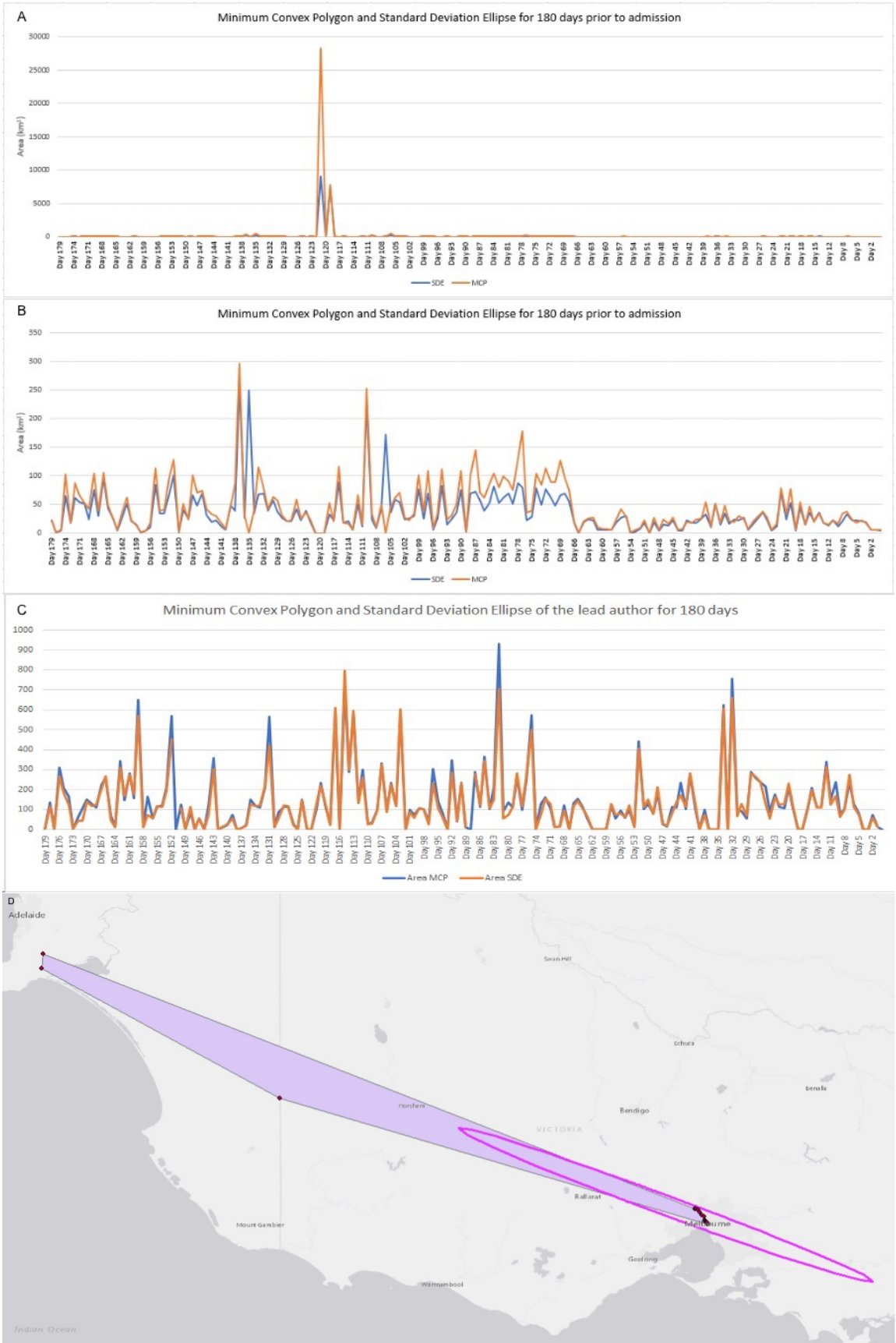

Figure 4 *- Panel A shows a plot of Minimum Convex Polygon (MCP) and Standard Deviation Ellipse (SDE) against time for one of the participants, Panel B has outlier values removed. Panel C shows the lead authors MCP and SDE for 180 days and Panel D shows the activity (SDE and MCP) of the selected participant on day 121 (day with the largest activity spaces).*

3.3 Conclusions

3.3.1 Introduction

Being able to automate the process of data extraction would have been a huge step forward in the methodology. We had hoped, as had been previously demonstrated [3], to extract GPS data from a significant number of participants and use this to describe a change in function prior to hospital admission. Unfortunately, the low number of patients who had valid GMT data means this methodology is not feasible. Indeed, the number of participants with valid GPS data was less than is demonstrated in Chapter 2. To get enough data, for any future meaningful analysis, more than 50,000 patients would need to be approached for consent, and this is not feasible.

One patient did show some evidence of a reduction in distance traveled and activity spaces prior to admission, but this was not measurable at a group level due to large variation within and between individuals. This demonstrates that there may be benefit of using these data to monitor patients in the community, and is worthy of further study.

3.3.2 Contribution of this work to mHealth

As far as we are aware, this is the first study that has extracted GMT data from iPhones. This development has emerged from the addition of the timeline function to the iOS Google Maps Timeline App. Despite this expansion of function, it hasn't been widely taken up by patients admitted under General Medicine. This is also the first study to extract this data in patients, with the only previous studies[3, 4] being conducted in healthy individuals.

3.4 Future Directions

3.4.1 The use of a dedicated smartphone app for data collection

One way of potentially collecting these data would be through the use of a dedicated smartphone app. The app would be able to report step and GPS data to a cloud server on a regular basis to enable the automated reporting of patient outcomes. The benefits of this approach would be that in designing the app we would be able to determine the algorithms used to report the GPS data, and to conduct the analysis. It would be easier to compare these outcomes with those of traditional GPS transponders. Being able to have a continuous dataset would represent a paradigm shift from the current methodology.

3.4.2 Data availability in other population

Due to the focus of this body of work being around the use of smartphone data to define outcomes prior to and following critical illness we have focused on patient populations that have the same age range as an adult ICU population. These older populations reduce the number of smartphone owning patients[5-7], and therefore the availability of smartphone data. Being able to explore the availability of these data in younger patient cohorts may provide for greater data yields and be of greater use to researchers. Exploring these data in the obstetric population may be of use given the uptake of mHealth in these populations [8, 9].

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CHAPTER 4 – THE USE OF A SMARTPHONE APP TO QUANTIFY ACTIVITY AND PARTICIPATION PRIOR TO AND FOLLOWING CRITICAL ILLNESS

4.1 Introduction

In the preceding chapters we describe a lack of success in the manual and automated extraction of the highly granular, passively collected step and GPS data held in smartphone databases. However, we have demonstrated that there is potential utility in using these data in describing patient activity and participation.

One way to collect these data could be through the utilization of a custom-built smartphone app. Smartphone apps have been used in a variety of different fields to collect patient data including step and GPS data. However, the feasibility of our patient cohort to utilize a smartphone app may be limited by smartphone ownership and user ability.

We utilized a collaboration with the University of Adelaide's Software Engineering Department to develop the Health Tracker App. The app was designed to store a GPS position every minute and to extract step data from GoogleFit (Android) and Health (iOS) databases. The app reported the data to a secure cloud database when the phone had a WiFi connection, to minimize participant data usage. The app was tested by the department prior to deployment.

4.1.1 Objectives

The objectives of this chapter were to describe the smartphone ownership and user ability in a cohort of patients at higher risk of admission to critical care and to assess the feasibility of smartphone app use in patients who would undergo elective admission to ICU. We aimed to report on the ability of dialysis patients to install a smartphone app with and without assistance and to assess the ability of the Health Tracker App to collect step and GPS data prior to and following cardiothoracic surgery.

4.2 Manuscript

A point prevalence study of smartphone ownership and user ability in a South Australian dialysis population

Statement of Authorship

Title of paper	A point prevalence study of smartphone ownership and user ability in a South Australian dialysis population
Publication Status	Submitted – rejected x2 – in the process of re-submission – Formatted for Australian Health Review
Publication details	**A point prevalence study of smartphone ownership and user ability in a South Australian dialysis population** Gluck S, Gilbert T, LeLeu, R , Britton A, McDonald S, Jesudason S.

Principle Author

Name of Principle Autor (Candidate)	Dr Samuel Gluck		
Contribution to paper	Conceptualisation of work, literature search, data analysis, manuscript preparation, corresponding author		
Overall percentage (%)	70%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
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Co-Author Contributions
By signing the Statement of Authorship, each author certifies that:
- The candidate's stated contribution to the publication is accurate (as detailed above);
- Permission is granted for the candidate to include the publication in the thesis; and
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Full Title

A point prevalence study of smartphone ownership and user ability in a South Australian dialysis population

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Work performed at the Discipline of Acute Care Medicine, University of Adelaide.

Keywords
Smartphone, Dialysis, Outcomes, Patient Experience, mHealth, PREMS, PROMS, Automation, Digital ability, mobile health, telehealth

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Abstract

Objective

Most of the Australian population now own a Smartphone (88%). These may help improve interactions with patients requiring complex care for chronic disease. Mobile technology can aid collection of clinical and research information, provide patients with information, collect patient experience measures or facilitate passively collected datasets to define or even predict outcomes. To assess the feasibility of developing smartphone-related programs in a chronic dialysis population we evaluated ownership and user ability in a South Australian cohort.

Methods

Multi-site point prevalence study of all patients undergoing dialysis with the Central Northern Adelaide Renal and Transplant Service (CNARTS) dialysis centers and home dialysis.

Results

Responses were received from 400 (75%) eligible patients. Smartphones were owned by 236 (59%). Of these, 91% carried their phone with them >75% of the time they left the house and 62% could install an app without assistance. Of the remaining 38% of patients, 78% would be able to install an app with assistance and only 9% would be totally unable to install an app.

Conclusions

In conclusion, smartphone ownership in patients receiving dialysis in South Australia is less than in the general population. At the current time this is a limitation for using smartphones in a research capacity in this population.

Key Question Summary

1. What is known about the topic?

Smartphone ownership is increasing in the general population. Smartphones provide a useful way to interact with patients and collect data that may be useful in monitoring their outcomes. While smartphone ownership in the dialysis population in the United States of America is known, the same data for Australia is unknown

2. What does this paper add?

We have explored smartphone ownership and user ability in the South Australian Dialysis population. We have found that 59% of our dialysis patients own smartphones and that amongst users there is good user ability. However, the penetration of smartphone ownership into this population is considerably lower than that of a similar population in the United States of America.

3. What are the implications for practitioners?

Practitioners need to be careful when implementing smartphone based mobile health interventions or relying on smartphone ownership for patient interaction i.e. embedding a URL into an SMS message or using QR codes. A large number of patients would not have the capacity to use such methods. Further work needs to be done to develop digital technology capability in people with chronic disease so the benefits can be leveraged for patient care improvement.

Introduction

There is increasing ownership of smartphones globally and in Australia [1,2]. Smartphones bring with them the potential for many communication applications, a multitude of sensors and the ability to interact with outside sources such as responding to surveys. These data have been shown to be accurate [3,4] and smartphones can transmit clinically relevant information to the treating team. This presents an opportunity to use patient-owned devices to communicate with patients [5] and provide them information [6], collect feedback on patient experience [7], collect data on and improve patient outcomes [8] and remotely monitor patient movement and function [9].

Chronic dialysis is a life-saving therapy for kidney failure. In Australia, over 130,000 people receive regular dialysis therapy [10]. These patients have a high burden of symptoms and research programs are evolving to leverage mobile phone technology to evaluate and address this symptom burden [11,12].

The passively collected datasets that a smartphone generates include highly granular location and step data. These datasets have the potential to provide a significant insight into a patient's community behaviour. Smartphone collected data may be used to monitor patients for deterioration in the community, to record and potentially predict patient-centered outcomes such as time spent active or time spent out of the home. If these more granular data were collected from those transitioning to dialysis, they have the potential to be used to inform clinicians and patients about possible functional outcomes before these eventuate.

Smartphones have been used to assist in dietary management in dialysis patients [13] and smartphone ownership has been assessed in an American dialysis population [14]. However, there is no data on the prevalence of smartphone ownership within the dialysis population in Australia and the ability of this population to install an application (app) on their phone has never been assessed. For future smartphone-based research to be successful, it is essential these questions are answered.

Methods

To better understand the pattern of smartphone ownership and user ability, we performed a simple multisite point-prevalence study of all patients receiving dialysis in the Central Northern Adelaide Renal and Transplant Service (CNARTS). CNARTS is a renal service based in metropolitan Adelaide that oversees dialysis care through 4 metropolitan and 11 country satellite haemodialysis facilities, with an average of >600 chronic haemodialysis and peritoneal dialysis patients per annum. During a one-week period, in October 2019, patients receiving dialysis in CNARTS hemodialysis centers and at home supervised by the CNARTS home dialysis unit were asked the following questions:

> Do you own a smartphone?
> If yes, do you carry it with you for more than 75% of the time when you leave your house?
> Could you install an app on your phone without assistance?
> If you could not install an app yourself, could you do so with assistance?

Staff approached patients at each dialysis shift over the course of the week, to eventually cover all potential patients. Home therapy patients were contacted via telephone as part of routine monitoring. Dialysis nurses were provided with a simple data collection tool and provided with a training video about the study and delivering the survey. Ethics approval was obtained from the Central Adelaide Local Health Network Human Research Ethic Committee (HREC Application - 11619), with a waiver of consent approved.

Results are n (%), mean (SD) and between group comparisons were performed in SPSS (v23, IBM, Armonk, New York USA) using chi squared statistic and a student T-test as appropriate. Missing data was noted and denominators adjusted accordingly. Missing data will be reported for transparency but no adjustment made.

Results

All CNARTS dialysis units were invited to participate (15 units, n=609 patients receiving dialysis at that time). Four regional units that dialysed a total of 72 patients did not participate. Eleven units participated in the study. We received responses from 400 of 537 eligible patients (response rate=75%). This included 7 regional units (n=92 patients), 4 metropolitan units (n= 226 patients) and home dialysis (home HD or PD) n= 82 patients (Figure 1).

Demographics of the included cohort are shown in Table 1. Smartphone owners were more likely to be younger (age 56 (15) vs 69 (12) $p<0.001$) and utilize home dialysis; there was no significant difference in gender. Of those surveyed, regarding question 1, do you own a smartphone? 236 (59%) owned a smartphone. For the further questions;-

2) if yes, do you carry it with you for more than 75% of the time when you leave your house?
3) Could you install an app on your phone without assistance?
4) If you could not install an app yourself, could you do so with assistance?

there were missing data. Of those who owned a smartphone 204/234 (91%) carried their phone with them >75% of the time they left the house and 136/221 (62%) confirmed they would be able to install an app without assistance. Of the 85 patients who were unable to install an app without assistance 69/85 (78%) would be able to install an app with assistance and only 19/221 (9%) would be totally unable to install an app on their phone (Figure 2).

Discussion

This brief survey reveals that smartphone uptake is not universal in dialysis cohorts. The prevalence of smartphone ownership in South Australian patients is marginally higher than that found in ICU survivors [15] and higher that that found in general medical inpatients (unpublished data), but less than the 88% of the general Australian population [2], and less than 81% in a recently reported study in a dialysis population in the United States of America [14]. The consistent finding with the previous work is that younger patients are more likely to be smartphone owners. This suggests that smartphone ownership will rise as these populations age, although the lack of smartphone ownership and user ability could represent a functional limitation.

The 22% difference in smartphone ownership between the dialysis population in the US and Australia is surprising and unexpected as smartphone penetration in the two countries is similar [14]. This could reflect differences in population demographics, ease of access to smartphones, different pricing systems and other market drivers.

With the current 59% smartphone ownership in this Australian dialysis population it would not be feasible to use patient owned devices and a smartphone app as a research tool to determine outcomes in all dialysis patients. Additionally, we would need to be cautious whether patients, specifically those who don't own a smartphone or who are unable to install an app without assistance, can reliably interact with an app to provide survey responses; although this may be overcome with training and the provision of devices with a tested user interface. As the population ages smartphone ownership is likely to increase in these patient populations so could well represent a technology of the future.

There may be further limitations to the use of smartphones in research if patients have significant privacy concerns regarding the provision of data to third parties. In addition, if the apps utilized phone data to interact with the researchers then this would be a significant concern for many participants who have limited data allowances. Being able to convert apps into different languages is an additional hurdle, as well as for use in patients with significant co-morbidities common in the renal failure population such as macular degeneration (~2%) who might struggle with the use of smartphones or be more reliant on caregivers. However, if apps are co-designed with patients and with digital assistance offered in-clinic (e.g. peer support) these apps have the potential to overcome significant language and health literacy barriers seen in these populations.

The limited smartphone ownership also has implications for relying on smartphones for interacting with patients, such as requesting feedback by embedding a URL into a SMS message, or using QR codes, as it would not be possible for 41% of this population to respond to such a message. However, using an app that functions in the background to monitor patient function would be feasible in the 54% of the dialysis population who own a smartphone and are able to install an app with or without assistance. Due to the wealth of data a smartphone app could provide, it may be feasible to better measure outcomes in smartphone owners and use this data to better inform future patients.

There are limitations to our study. We used the term ‘smartphone’ which may not be familiar to all patients. However, they had the opportunity to clarify directly with the nurse conducting the survey. We were unable to capture data from the whole SA dialysis population. Despite providing easy to use data capture forms and video education for nursing staff, some units did not return survey data (this is the 4 regional units who are recorded as not participating). Further, in order to reduce the data collection burden for nurses given the cohort size, we kept the survey very simple to address the key question.
Consequently, we did not collect extended demographic data (ethnicity, postcode for socioeconomic status measures, comorbidities, English as a second language, education level) and other potential confounders.

Conclusion

In conclusion, smartphone ownership in patients receiving dialysis in South Australia is lower than in the general population. Among owners, smartphones were carried with the patient almost all the time, over 60% of patients had fully independent application use and very few had no ability to load an app even with assistance. Therefore, if smartphones are used in research, providing a phone and assistance in loading applications would facilitate the use of smartphone for collection of data to better inform clinical practice and consumer choice.

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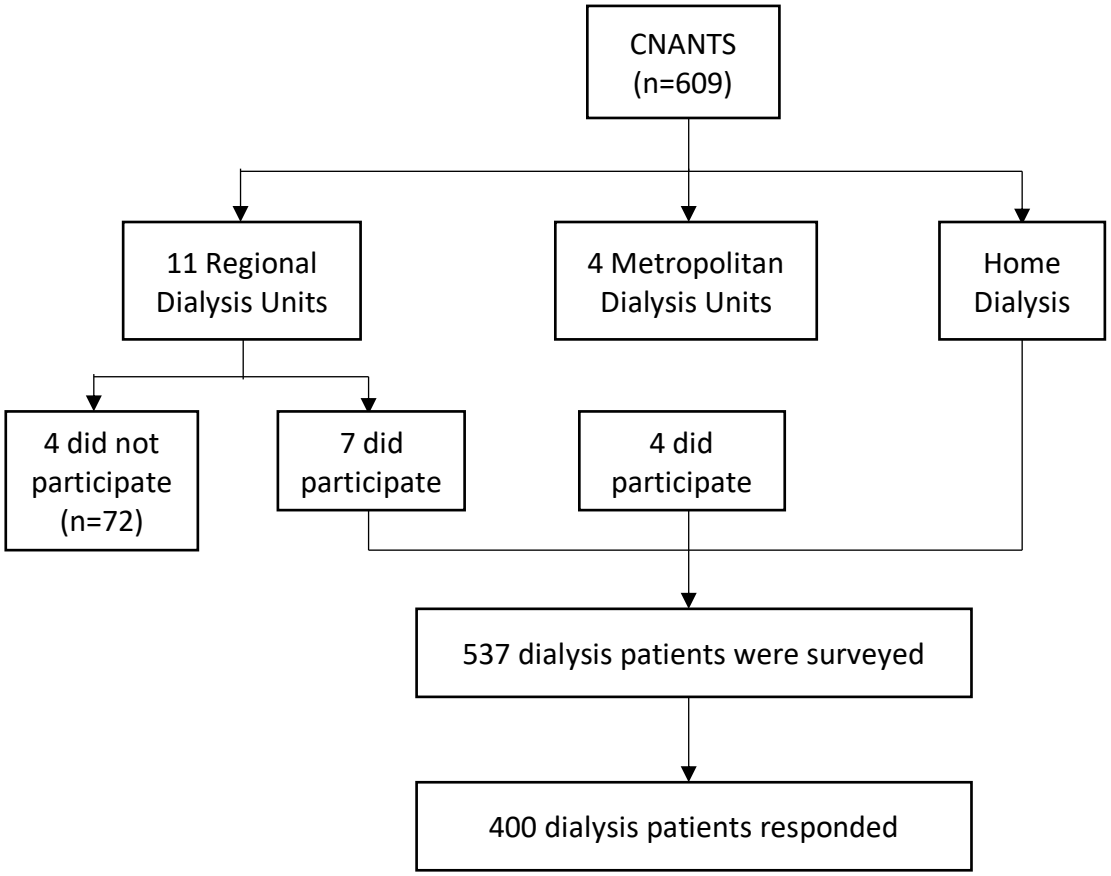

Figure 1 – Recruitment flowchart

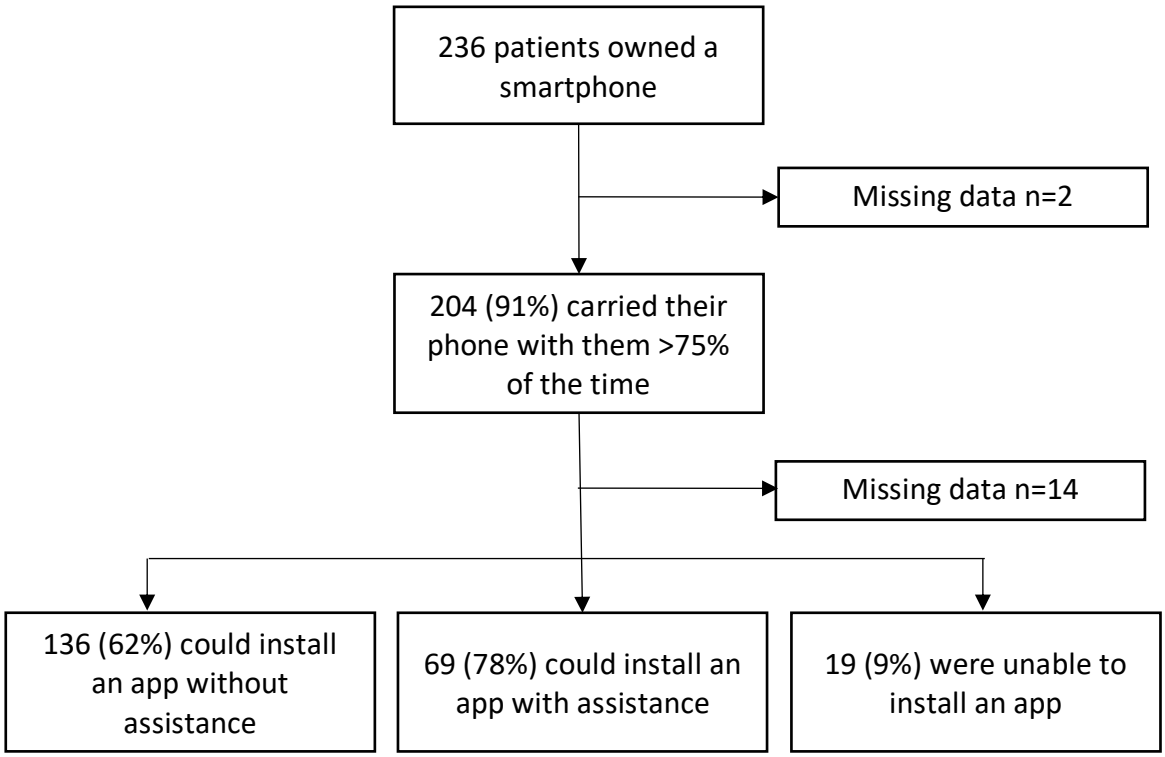

Figure 2 - Consort diagram

Demographics		Total	Smartphone Owners	Non-Smartphone Owners
Age (mean (SD)) years		61.8 (15)	56 (15)	69 (12)
Male (n (%))		233 (58%)	144 (61%)	89 (54%)
Mode of dialysis (n (%))	HD	318 (80%)	175 (74%)	143 (61)
	PD	63 (16%)	43 (18%)	20 (9%)
	HHD	19 (5%)	18 (8%)	1 (0.4%)

Table 1 – Demographics. HD - Haemodialysis, HHD - Home Haemodialysis, PD - Peritoneal Dialysis

4.3 Manuscript

The use of a smartphone app to monitor patients prior to and following cardiothoracic surgery

Statement of Authorship

Title of paper	The use of a smartphone app to monitor patients prior to and following cardiothoracic surgery
Publication Status	Pending Submission
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Principle Author

Name of Principle Autor (Candidate)	Dr Samuel Gluck		
Contribution to paper	Conceptualisation of work, literature search, data collection, manuscript preparation, corresponding author		
Overall percentage (%)	70%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
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Co-Author Contributions
By signing the Statement of Authorship, each author certifies that:
- The candidate's stated contribution to the publication is accurate (as detailed above);
- Permission is granted for the candidate to include the publication in the thesis; and
- The sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Contribution to paper	Conceptualisation, protocol development and manuscript preparation		
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Full Title

The use of a smartphone app to monitor patients prior to and following cardiothoracic surgery

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Work carried out at the Royal Adelaide Hospital

Key Words:
Smartphone, Cardiothoracic Surgery, Pedometer, Step-count, Global Positioning System

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Disclaimer

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Abstract

Background

Step and location data extracted from a patient's smartphone may be used to measure activity and participation. We aimed to assess the feasibility of using a custom-built smartphone app to report step and GPS data prior to and following cardiothoracic surgery.

Methods

Consecutive smartphone owning patients scheduled for elective cardiothoracic surgery at least 7 days later subsequently downloaded a smartphone app, which remained active for 90 days after surgery. Accelerometry and global positioning data were recorded to provide step and location data. Feasibility was determined as the extraction of complete data for more than 30% of days monitored.

Results

Sixty-two patients were approached and 10 (17%) declined to participate. The app was successfully installed and activated on the smartphone of 41/52 (78%) participants. Complete step data were accessed for 197 of 1913 (10%) pre-operative days and 359 of 3690 (10%) postoperative days. Complete GPS data were obtained for 67 of 1913 (4%) pre-operative days and 173 of 3690 (5%) postoperative days. Activity was less during the postoperative period when compared to preoperative: mean daily step count decreased by 1,260 (95% Confidence Interval (CI) 582 to 1,939) steps, distance walked decreased by 431 metres (95% CI 120 to 743) and time spent active decreased by 51 mins (95% CI, 17 to 85). Participation was also reduced during the postoperative period: total distance travelled decreased by 35,191 metre (95% CI -68,988 to -1,395), the total distance travelled between locations decreased by 7,675 metre (95% CI -10,088 to -5,262).

Conclusion

Technical issues resulting in data loss currently limit the feasibility of this technology to reliably assess patient activity in the perioperative period. Based on the limited data available, patients had not returned to pre-operative levels of activity and participation by day 90 after cardiac surgery.

Background

Death after elective cardiac surgery is rare [1,2] and, therefore, mortality may not be the most sensitive outcome to drive quality improvement in service delivery or research in this field. Cardiac registries are key drivers for quality improvement and benchmarking [3,4]; however, the outcomes they use are derived from easily collected data, such as length of ICU or hospital stay or readmission rate. Whilst these outcomes quantify cost effectiveness of care provided, they are not truly patient centered [4,5].

Disability free survival is an outcome that is important to patients having cardiac surgery [6]. Disability can be quantified by measuring an individual's level of activity and participation [7]. Activity and participation can be subjectively measured using questionnaires but these require patient and clinician time, and only offer a point in time assessment [8-12]. Accelerometers and pedometers offer an accurate, objective and continuous assessment of activity [13-15]. In addition, Global Positioning System (GPS) data may provide an estimate of participation [16, 17]. A capacity to quantify activity and participation post-operatively relative to pre-operative baseline values would enhance inferences obtained from studies that did not use randomization or studied smaller cohorts of patients [18].

It may be possible to measure pre- and post-operative activity and participation using patient owned smartphones. Using patient smartphones would provide an efficient and economical method to obtain these data. Smartphone step data have been shown to be accurate [19] and a suitable surrogate for a dedicated pedometer in a real world setting [15]. GPS data have been used to describe pre-morbid participation [20] and to measure recovery following critical illness [21]. Using the patients' own devices and measuring within individual change over time using absolute values overcomes some of the concerns regarding the accuracy of different devices.

We aimed to assess the feasibility of using patient owned smartphones to monitor activity and participation prior to and following elective cardiothoracic surgery. Our secondary aims were to report activity and participation levels for 90-days post operatively and to report patient satisfaction with the process.

Methods

We screened consecutive patients who attended the pre-operative cardiothoracic clinic at the Royal Adelaide Hospital.

Patients were eligible if they had cardiothoracic surgery planned that required cardiac bypass, surgery scheduled ≥ 7 days from screening, were ≥18 years of age, owned a smartphone and had access to a Wi-Fi network at home. Patients were excluded if they were unable to comprehend English or were not ambulatory at baseline.

We approached patients who met all inclusion and none of the exclusion criteria for written informed consent.

Following consent, demographic details were recorded and the European System for Cardiac Operative Risk Evaluation (EuroSCORE) II calculated [22].

The pre-operative period commenced when the app was installed on the participant's smartphone and lasted until the day prior to the operation. The post-operative period commenced on the day of the operation and lasted until day 90 post op.

We developed The Clinical Health Tracker app as a cross platform smartphone app that wirelessly reports step and GPS data securely and anonymously to a cloud database. The app collects data from the relevant phone databases continuously but only transmits data when connected to Wi-Fi. Health questionnaires were incorporated into the app. The app uses the Googlefit and HealthKit Application Programming Interfaces (APIs) to report step data and reports a GPS position every 5 minutes.

When installed, the app requires activation with a unique identifier. Once the unique identifier is entered on a participant's phone, the app connects to a cloud database to verify the unique ID. The check demonstrates that the app was able to connect to the cloud-based database while in clinic. In the clinic, we set up a local Wi-Fi network to enable participants to download and activate the app without affecting the participants' data usage. To reduce the impact on mobile data use, all further uploads of the data were programed to be Wi-Fi dependent.

Patients were provided with written information about the function of the app and it was installed on their smartphone. The app remained on their phone for 90 days. Patients were sent monthly text message reminders to complete a Life Space Assessment. After 90 days they completed a satisfaction survey and the app was deleted from their smartphone.

Our study was approved by the Central Adelaide Local Health Network's HREC (HREC/18/CALHN/307) and registered (ACTRN12618000867291).

Outcomes

Feasibility

We aimed to assess the feasibility using the consent rate and the app successfully activating and sending complete data for each calendar day. Although there was no consensus on what constitutes a complete data-set for GPS data [23], accelerometer studies measuring activity have reported between 6 – 24hrs/day of recording as complete data, with wear time having minimal impact beyond 6 hours [24]. Complete data was therefore determined, *a priori*, as >8 hours of step and/or GPS data per 24-hour period. We calculated the number of days of complete data, the number of days with incomplete data and the number of days with absent data for both step and GPS data. We defined, *a priori*, feasibility as being able to report complete data for >30% of the days studied.

Smartphone outcomes

Step outcomes

We report the daily step count, distance walked, time spent active and walking speed. The step outcomes from the app are derived from the Google Fit and iOS HealthKit API's. These report the date and time activity commenced, the number of steps taken, the distance walked and the date and time activity ceased. Daily step count and distance walked were summed step count and distance for all activity bouts within a 24-hour period. The time spent active was the total time spent walking, i.e. the summed difference between the activity conclusion and commencement. The walking speed was the average walking speed of all the bouts of activity – with speed the distance walked within a bout of activity divided by the duration of activity.

GPS outcomes

GPS data were extracted, and the number of GPS points assessed for data completeness. GPS data were used to calculate a standard deviation ellipse activity space, minimum convex polygon activity space and total distance traveled using methods described below. To overcome the issues associated with GPS epoch in calculating distance traveled [25] we also calculated the distance between locations. We defined a location as a cluster of GPS points within a diameter of 100 meters for 15 minutes or longer.

Standard deviation ellipse activity space

A standard deviation ellipse was centered on the mean longitude and latitude, with the angle and length of the maximal standard deviation represented as the long axis, and the angle and length of the minimal standard deviation represented by the short axis [26].

Minimum convex polygon activity space

A minimum convex polygon [16] was drawn around the furthest extent of travel, such that no internal angle was greater than 180^0.

Linear Distance Traveled

Distance between individual GPS positions were calculated using the haversine formula [27, 28].

Distance travelled between locations

Location was determined using the Spatio-Temporal Density-Based Spatial Clustering of Applications with Noise (ST-DBSCAN) tool [16]. As above, a location was defined as a cluster of 3 or more GPS points, within a 100m radius, within a 15-minute, or greater time-period, with a GPS epoch of 5 minutes. The coordinates of the cluster center were calculated and the clusters ordered in time sequence. The Haversine [27, 28] formula was then used to calculate the distance between locations.

GPS outcomes were calculated using Python script obtained from open-source GitHub libraries (supplementary material includes source code). The code used for minimum convex polygon and standard deviation ellipse were assessed for equivalence with convex hull function and directional distribution function of ArcMap (V10.3.1 ESRI, California, USA) respectively.

Life Space Assessment

The Life Space Assessment [29] is a tool to assess movement pattern and was defined as distance extending from the location where the person sleeps. The Life Space Assessment has been shown to correlate with an individual's level of function, as assessed by independent activities of daily living (iADLs) and activities of daily living (ADLs) [30]. It assesses the extent of movement, the frequency of the movement and the need for assistance in the movement across five domains from bedroom, to home, to neighbourhood, to town, and beyond. The Life Space Assessment is a composite score with a maximum of 120.

Satisfaction

Patients were asked to evaluate their level of satisfaction with the process of using this smartphone app and to describe their recovery on a scale of 0-100, with 0 being poor and 100 being excellent. They were asked if they would be happy to use an app to monitor their recovery following surgery using a 5-point Likert scale; not at all, some aspects, most aspects, almost all aspects and yes, certainly (supplementary material)

Statistics

Descriptive statistics are reported as median [IQR], mean (SD) and n (%) as appropriate. A formal power calculation was not performed; rather, prior to commencing the study 50 patients was considered sufficient to assess feasibility. Generalised Estimating Equation (GEE) models with an exchangeable correlation structure were fitted to evaluate the change over time (from pre- to post-op) of the step count and GPS outcomes. GEE models were used to account for correlation within clusters due to repeated measurements and to take advantage of all available observations. No imputation was made for missing data. Summative GPS data were calculated via the script available at (https://github.com/sluckyy/Clinical-Health-tracker). Data manipulation were performed using Python and analyses using Stata v15 (College Station, TX, USA).

Results

Between July 2018 and May 2019 179 patients were screened with 62 patients meeting all inclusion and no exclusion criteria (Figure 1). Ten (17%) patients declined to participate. Between November 2018 and January 2019, the android app would not load onto devices or connect to the cloud database. During this time patients (n=10) who owned an android phone were excluded. One patient withdrew after enrolment but prior to surgery. Due to technical issues the app could not be installed on the smartphone of 7 participants (n=4 iPhone and n=3 Android) and for 3 participants the app could not be activated once installed (n=3 Android). Therefore 41 (78%) consented patients had the app installed and activated (figure 1). Patient demographic details, phone details and pre-operative phone usage details are shown in table 1.

ICU and hospital length of stay were 2 [2 to 3.5] and 7 [6 to 9] days respectively. Within our sample population no patient died in hospital or by 90 days.

In the 41 patients who completed the study and for whom the app was successfully installed, data were filtered to include and analyse only days with complete data (i.e. > 8 hours). Coding of <8 hours was considered incomplete; an absence of data for that day was considered as no data. The mean value was calculated from the days of complete data prior to and following surgery.

Pre-operative step outcomes

Patients were monitored for a total of 1,913 pre-operative days and we obtained pre-surgery complete step data for 197 (10%) days, incomplete (≤ 8 hrs) data for 12 days and no data for 1,704 (89%) days. Pre-operative step data were recorded by the app in 21/41 (51%) patients. Patients took 2,242 [1,576 to 2,714] steps/day, mobilised 816 [666 to 1,196] metres/day, spent 83 [54 to 99] minutes active and mobilised at a speed of 0.51 [0.32 to 0.86] km/hr.

Pre-operative GPS outcomes

We obtained pre-surgery complete GPS data for 68 (4%) of the 1,913 pre-operative days and incomplete data for 58 days. Twenty-two (53%) patients provided pre-operative GPS data. The standard deviation ellipse activity space was 13.9 [4.2 to 150.4] km^2, minimum convex polygon activity space was 34 [14.3 to 277.3] km^2, total distance travelled was 29,189 [19,603 to 66,498] m and total distance travelled between locations was 2,097 [56 to 15,048] m/hr per day.

Post-operative step outcomes

Patients were monitored for a total of 3,690 postoperative days and we obtained complete step data for 359(10%) days and incomplete (≤ 8 hrs) data for 38 days from 11 (27%) patients and no data for 3293 (89%) days. The median number of steps per day was 578 [400 to 1,610], covering 298 [158 to 1,036] metres, with 43 [18 to 54] minutes spent active and mobilising at median speed of 1.19 [0.69 to 3.61] km/hr.

Post-operative GPS outcomes

We obtained complete GPS data post-surgery for 176 (5%) days and incomplete for 125 days from 16 (39%) patients. The standard deviation ellipse activity space was 0.1 [0 to 7.7] km^2, minimum convex polygon activity space was 0.6 [0 to 28] km^2, total distance travelled was 9,919 [1,595 to 13,392] metres and total distance travelled between locations was 244 [0 to 5,060] metres per day.

Pre and post operative comparisons

The GEE models comparing the pre- and post-operative means for each of the outcomes are shown in Table 2. When comparing post-operative to pre-operative values we observed a statistically significant reduction for all step count outcomes and for total distance travelled and total distance travelled between locations but an acceleration in walking speed.

While using GEE models increased the number of observations used in the models, there were insufficient observations to allow for adjustment for potential confounders without overfitting the models.

Data acquisition

There was lesser data acquisition rate for android than for iOS (complete step and GPS data for all pre and post-operative days studied: iOS 471/4244 (11.1%) vs. android 329/5746 (5.7%) $p<0.0001$. No patients provided complete data and 19/41 (46%) patients provided zero data, with intermittent data transferred for all other patients. Due to the missing data, the performance of the apps were assessed over time by assessing the first 90 days of data sent by the app (this would include pre- and postoperative assessment). The attrition of patients with complete step and GPS data was more pronounced as the study progressed as demonstrated in Figure 2.

Life-Space Assessment

Eighteen patients completed the Life Space Assessment at any stage of the study with 12 completing it only once. In total there were 17 pre-surgery responses and 9 post-surgery responses. The Life Space Assessment was 90 [84 to 101] pre-surgery and 89 [70 to 93] post-surgery.

Patient Satisfaction

We attempted to contact all 51 patients who consented to the study and did not withdraw. Of the 43 patients who completed the survey, satisfaction with the process of using a smartphone to report step and GPS data was 82.5 [79.6 to 95.5] out of 100. When asked *"Would you be happy to use the app to monitor your recovery?"* the majority of patients were happy with at least most aspects 40/43 (93%) (Table 3).

Discussion

We assessed the feasibility of using patient owned smartphones to measure activity and participation prior to and following cardiothoracic surgery. We obtained partial step data for 209 patient days preoperatively and 397 patient days postoperatively from 21 and 11 participants respectively and partial GPS data for 126 patient days preoperatively and 301 days postoperatively from 22 and 16 individuals respectively. Despite recording a considerable amount of novel pre- and postoperative data, due to data loss we did not meet our predefined threshold for feasibility.

Within the limitations of missing data, it appeared that patients were taking fewer steps, were less active and covered less distance in the postoperative phase (up to day 90) when compared to preoperative activity. The signal of reduced activity in the postoperative phase may represent the normal recovery process, with improvement occurring subsequent to 90 days [31], or may be due to attrition of data over time (figure 2b). Data attrition would bias results with less data available in the later phases of the postoperative phase. We also observed that patients were accepting of the technology, with only 17% refusal of consent and high satisfaction levels, which may indicate patients' willingness to engage in processes that assist in reporting patient centered outcomes and using technology to enable remote assessment. This is certainly echoed in the literature. Rens and colleagues demonstrated that 71% of those approached were willing to use an Apple Watch and iOS app to monitor recovery following cardiovascular procedures [32]. Panda *et al.* demonstrated that 57% of patients were willing to install an accelerometer app to monitor recovery following cancer surgery [33]. This acceptance may be more pronounced since the COVID pandemic, as being remotely monitored may be more attractive to patients than attending hospital clinics, and user ability may have increased [34]. Collecting data from other sources during recovery e.g cardiac rehabilitation may have been beneficial.

The feasibility of the technique was impacted by technological failure. The app on both Android and iPhone devices suffered from significant data loss. The cause of this is unclear but is most likely due to multiple factors. While the app was successfully activated for 41 participants and we only included patients who had a home Wi-Fi network, it is possible that some of our participants did not have a connection set up between their phone and home Wi-Fi network or had an unreliable connection. This situation would result in a failure to upload any data, and may have contributed to incomplete data upload. However, this method has been successfully used by others, Panda and colleagues used the Beiwe app to collect accelerometer data, the data were stored locally with the smartphone application utilizing WIFI to attempt a data upload every hour, to reduce participants data costs. [33]. The failure to upload any data may have been a result of a coding failure to use the Apple and Google API's correctly to collect step and GPS data, this may have occurred in certain environments (phone and operating system combinations) thus explaining why these coding errors resulted in some devices working while others did not. Where there is no other study, to the authors awareness, that utilises step and GPS in the perioperative assessment other groups have successfully used apps to collect these data in patients with bipolar [35], schizophrenia [36], and during COVID-19 lockdown [37].

During our study, Apple upgraded the operating system (iOS 12) and with the new operating system introduced new features to automatically terminate apps running in the background; this upgrade might have also contributed to the loss of data and the attrition of app data overtime. However, this attrition of participants has been reported on other m-Health studies, with Miloh et al demonstrating a 37% attrition in a study using SMS messages to improve immunosuppression adherence in pediatric liver transplant recipients[38], Mundi et al demonstrated a 33% withdrawal rate using a smartphone app to prepare patients for bariatric surgery [39] and Semple and colleagues showed that utilisation of a smartphone app to complete a recovery questionnaire and take photos of the surgical site was significantly higher in the first 14 days than during days 15-30 of their 30 day study. Future studies may benefit from:

- more extensive testing prior to implementation
- use of personalized messages
- sending notifications at times where users are more likely to respond [40].

The current study is also a single center study, and smartphone ownership and user ability may vary by location [41]. This could certainly affect the feasibility of the technique presented in this report.

The following strategies could be implemented to reduce the risk of data loss in future studies implementing smart phone collection of activity data:

- extensive testing in a multitude of different environments;
- use of the participants data connection rather than relying on a Wi-Fi connection;
- ongoing software support to ensure the apps remain updated;
- regular app check-in to keep the app running in the background and;
- a regular check on the cloud database to ensure ongoing data upload, with a push notification to the participants phone if the data upload ceases.
- Detailed descriptions and ongoing support for participants

Whilst we could not establish feasibility in this study, the capacity to do so could improve the current surgical risk prediction and improve risk stratification for high-risk patients. We observed patients were willing to consent to this process and they reported satisfaction with its use. Being able to monitor patients during recovery may also enable the detection of early deterioration. Finally, with sufficient data it may be possible to predict disability free survival using variables such as time spent active or time spent outside of the home: such information would improve shared decision making before surgery.

Conclusion

We found that it is currently not feasible to assess patients throughout the preoperative and post cardiac surgery phases using our purpose built app. Feasibility was limited by substantial data loss. We have identified several technical reasons for the failure of the app which can be addressed in future studies. Within the limitation of the data we had available, we observed that by day 90 patients had not reached pre-operative levels of activity and participation as determined by step count and distance travelled.

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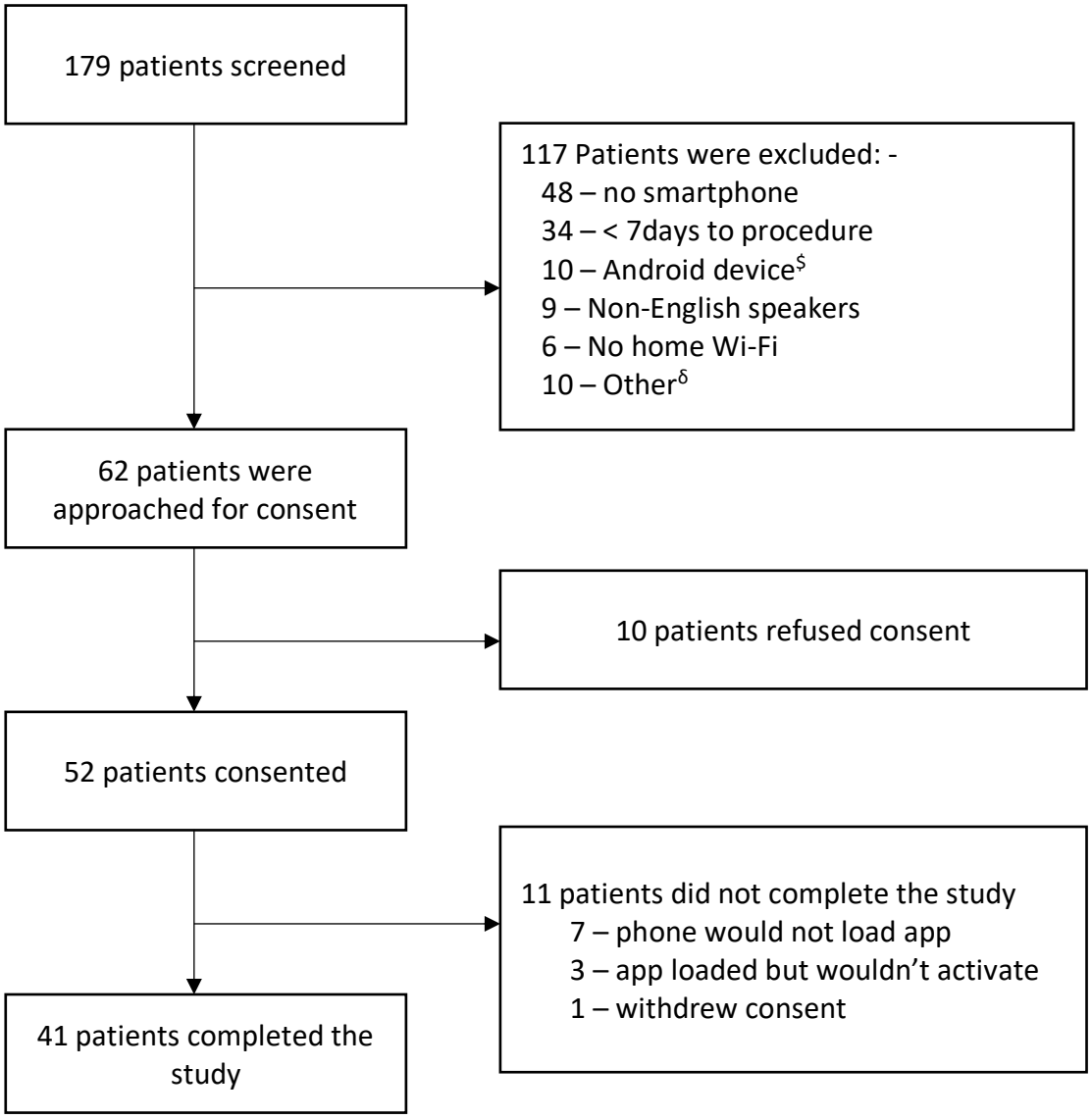

Figure 1 - Consort diagram

$ During the period of technical issues with the android app 10 patients presented to clinic with android phones and were excluded.

$ Other includes two patients with alternative operating system (not iOS or android), one patient had an intellectual disability and one patient was non-ambulatory with 6 patients were missed in clinic.

Patient demographics (n=41)	
Age, years, med [IQR]	61 [53 to 67]
Male, n (%)	23 (56)
Weight, kg, mean (SD)	89 (21.3)
Height, cm, mean (SD)	169 (8.8)
EuroSCORE II RoD % [IQR]	1.0 [0.7 to 1.5]
APACHE II score, median [IQR]	13 [12 to 15]
ANZROD % [IQR]	0.3 [0.2 to 0.7]
Smartphone details	
Android	25 (61%)
iPhone	16 (39%)
Carried >75% of the time	40 (98%)
Shared use	1 (2%)
Surgery details	
CABG	17 (41%)
Valve	19 (46%)
CABG and valve	5 (12%)
Bypass time, min, med [IQR]	84 [62 to 123]
Cross clamp time, min, med [IQR]	67 [38 to 93]

Table 1 – Patient demographic, smartphone, surgery and hospital outcome details. APACHE – Acute Physiology and Chronic Health Evaluation; ANZROD- Australia and New Zealand Risk of Death; EuroSCORE II - European System for Cardiac Operative Risk Evaluation II; CABG - Coronary Artery Bypass Grafting; RoD – Risk of Death

Step count outcomes	**Mean difference (95% CI)**	**P-value**
Daily step count	-1260.44 (-1939.29, -581.60)	<0.001
Distance walked (m)	-431.05 (-742.53, -119.57)	0.007
Time spent active (mins)	-51 (-85, -17)	0.004
Walking speed (km/hr/day)	0.61 (0.04, 1.22)	0.039
GPS outcomes		
Standard Deviation Ellipse activity space (km^2)	-346.25 (-962.28, 269.78)	0.271
Minimum Convex Polygon activity space (km^2)	-416.17 (-1087.02, 254.68)	0.224
Total distance travelled (m)	-35191.49 (-68988.35, -1394.62)	0.041
Total distance travelled between locations (m)	-7674.81 (-10088.02, -5261.60)	<0.001

Table 2 – Differences between pre-operative and post-operative step and GPS outcomes.

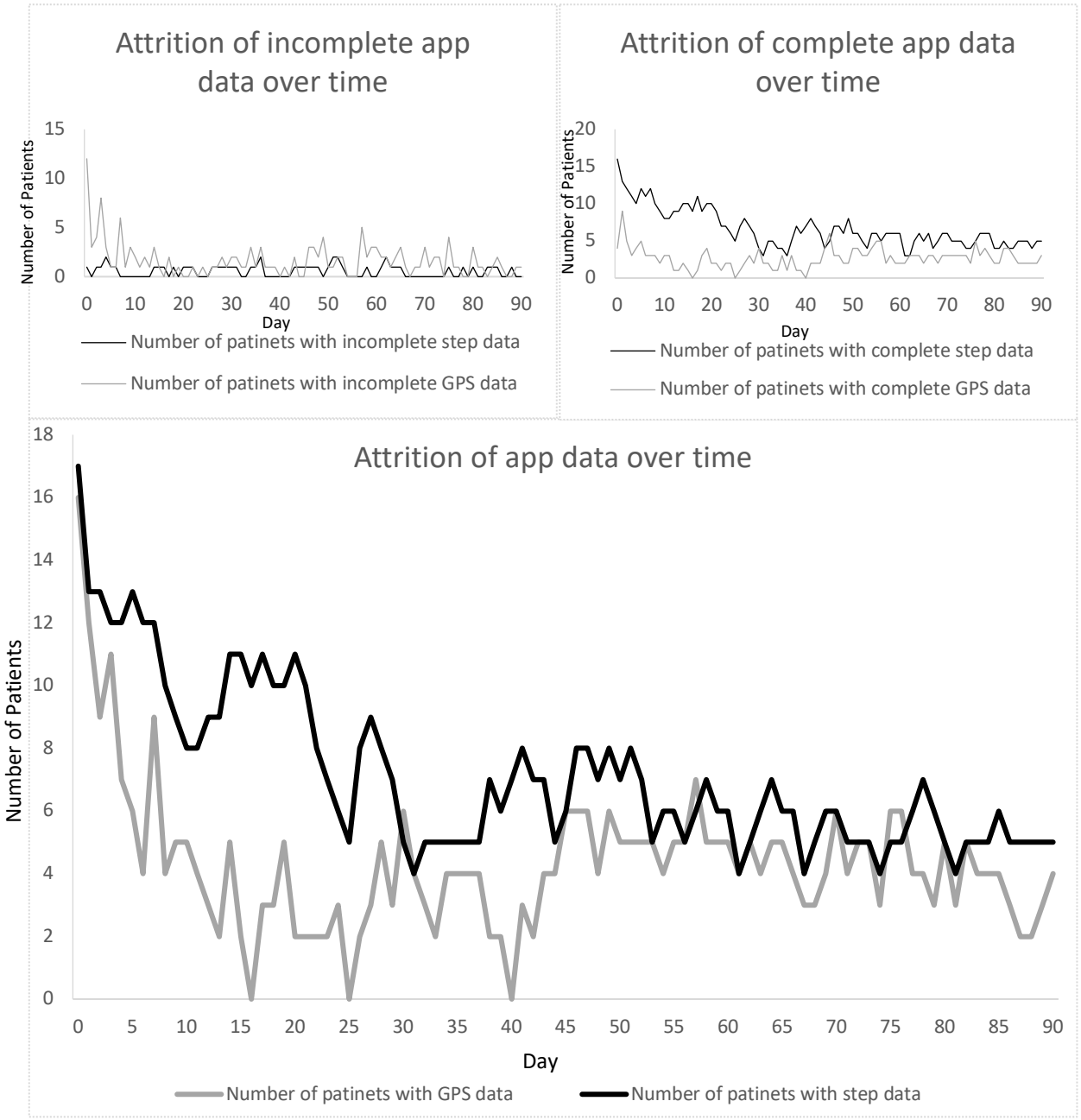

Figure 2 – Attrition of app data over time, number of patients with data on the corresponding day following recruitment – (A) incomplete data, (B) complete data and (C) total data.

Table 3 *- Would you be happy to use the app to monitor your recovery?*

N (%)	Response
1 (2)	Not at all
2 (5)	Some aspects
3 (7)	Most aspects
3 (7)	Almost all aspects
34 (83)	Yes certainly

Supplementary material

Satisfaction survey

Would you be happy to use the app to monitor your recovery?

Not at all Some aspects Most Aspects Almost all aspects Yes certainly

Overall how would you rate the experience of using the smartphone app to report your step and GPS data to the doctors looking after you? Where 0 = poor and 100 = excellent

4.4 Conclusions

4.4.1 Introduction

We have shown that 52% of a South Australian dialysis population would be unable to install a smartphone app onto a device they own (59% ownership, 9% unable to install an app). This will limit the ability of a smartphone app use in broader research in this population. However, it would be feasible to explore the passive collection of smartphone data in dialysis dependent smartphone users, as the outcomes produced could, for example, be used to better inform patients with chronic renal failure about the effect on lifestyle of different dialysis options.

The use of a dedicated smartphone app for the collection of step and GPS data in patients undergoing cardiothoracic surgery showed that patients were accepting of this technology, although this study was conducted prior to the COVID pandemic and privacy concerns have increased since several unsuccessful COVID tracing apps harnessed individuals' location data [1]. However, these concerns appear to be reduced in more elderly populations [2]. The patients in the study detailed in this chapter showed high levels of satisfaction with the app. However, the app we designed did not function as intended, on occasion did not load, or was unable to activate. There was significant (~90%) data loss. This was attributed to a multitude of factors, such as a failure of the patient to connect their phone to their home Wi Fi, incompatibility of the app following operating system upgrades, the app stopping running in the background of the phone and no check with the cloud database to ensure the data was being captured.

It would have been beneficial to conduct the point prevalence study in Cardiothoracic patients, however; to collect the same level of data would have taken over a year, whereas in dialysis patients it could take a week. With hindsight having the same population would have assisted in the investigation of some of the issues suffered with the app failure.

4.4.2 Contribution of this work to smartphone user ability

It has been demonstrated that elderly smartphone users are slower when using a smartphone app [3] and have poorer performance in touch screen puzzles [4] despite previous use of touchscreen devices [5].

It has been demonstrated the in-ability to install a smartphone app reduced the usefulness of a COVID tracking app from 85% to 81.3% [2], however the ability to install a smartphone app is rarely considered a barrier in the literature of smartphone app use in elderly populations [6]. While assistance may overcome this, this is a barrier that will need proactive consideration when embracing this technology.

4.4.3 Contribution of this work to digital app design

While our feasibility study did not collect the required level of data, we were able to draw some important learnings from this failure. We should have used more robust testing in real world environments, not relied on Wi-Fi connections (instead utilizing patient data), scheduled regular check-ins to keep the app running in the foreground, have IT support

available to deal with app changes to overcome the issues raised by operating system upgrades and checks of the cloud database to ensure that the data stream was complete.

4.4.4 Contribution of this work to smartphone app acceptance

The use of a smartphone app to capture passively collected data is not a novel concept, however participants willingness to take part in the study detailed in this chapter appears higher than existing studies suggest. Couper and colleagues showed consent rates between 6% and 67% in their review [7]; 39% [8] of a household panel would be willing to use an app that shared GPS location data. Similarly only 20% of participants surveyed in Revilla's work would consent to share GPS data [9]. The in person contact with the participant by an intensive care doctor may have improved the trust to allow the app install. However, while the consent might have appeared higher, participants may have felt obligated to partake and subsequently uninstalled the app so no data was received.

4.4.5 Contribution of this work to outcomes for cardiothoracic patients

Location based outcomes have never been described for patients recovering from cardiothoracic surgery, and as far as we are aware this is the first time that step outcomes have been described prior to and during the recovery following cardiothoracic surgery. Accelerometers have been used rarely in studies of cardiothoracic patients[10]. Smartphones have been used in studies monitoring patients with Left Ventricular Assist Devices[11] but relied on active involvement of the patient in data collection (surveys and photos) rather than passively collected data. However, the authors make the argument that this is the first step towards remote monitoring.

4.5 Future Directions

4.5.1 Further App Development

Working with collaborators to develop another app and ensuring ongoing support is a costly option, however, partnering with app developers with a similar app and extending the use spectrum of their app may be a possibility. Taking the learnings from our study and from the literature where having human support reduces drop out and non-use attrition [12, 13] and ensuring the app is of benefit to consumers [14] would be key improvements. Any app developed or used would benefit from extensive piloting prior to implementation in a trail setting.

4.5.2 Elective surgery

There are several populations that could potentially be targeted. For instance, younger populations, with higher smartphone use and user ability such as obstetric [15] and cystic fibrosis [16] sufferers. However, the uptake of the app in an elective surgical population does suggest that there is the possibility to use a similar process in all elective surgical patients, not just those who will require an ICU admission. Surgical risk scores focus on health data. The potential to be able to incorporate community activity data is likely to increase the power of these scores [17-20]. Utilising an app which monitors activity and GPS location prior to their

operation, enables the addition of survey data while also monitoring post-operative activity and GPS data would develop a data set that over time could be used to predict individual patient recovery. The app could also be used to record actual recovery and highlight possible post-op deterioration.

4.5.3 Integration of passively created datasets with health data

The power of passively collected datasets has been well demonstrated with Cambridge Analytica being able to use such data to influence US elections and Britain's departure from the European Union [21, 22]. The ability to integrate these datasets within healthcare and use data to determine healthcare outcomes remains an attractive possibility [23, 24]. We know that the majority of preventable mortality is attributable to social determinants of health [25-30], yet as healthcare providers we do little to integrate data that might discern some of these factors, allowing us to provide more targeted heath interventions, better predictions of outcome [23] and improved information sharing with our patients. We must do this without eroding trust in the healthcare sector for sharing this kind of data [21].

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CHAPTER 5 – DISCUSSION

5.1 - Introduction

While the individual papers, and chapters have their own discussions and future directions this concluding discussion is intended as a summary of the findings, the limitations and strengths of the thesis as a whole and a final comment on future directions.

5.2 - Summary of findings

There has been considerable research undertaken in this field since this PhD was embarked on in late 2016. The first use of digital phenotype in the literature was 2015 [1] and the use of 'mHealth' has more than tripled during this time in PubMed. However, Chapter 1.2 of this thesis demonstrates that in the field of critical care the use of these technologies are in their infancy, with only a few, mainly, exploratory studies using accelerometery and pedometry and none using Global Positioning System (GPS) data [2]. Little has changed, in the critical care literature. A repeat of the literature search was undertaken for this discussion with limited additions to the literature observed. Six further studies were discovered. Accelerometers tend to be the predominate device, measuring steps and physical activity in relatively small [3-6], experimental studies, although there is some evidence of main stream uptake with a hip worn accelerometer being used in a sub-study of Targeted Temperature Management 2 (TTM2) [7]. The expansion of the wearable market has brought with it the first study of smartwatches in ICU survivors [8] and geolocation has been used in ICU survivors for the novel function of alerting treating teams of the arrival of Ventricular Assist Device patients to the emergency department [9]. Supplementary Figure 1 details the literature review and supplementary table 1 details the additional six studies.

Chapter 2.2 confirmed that subjective recall of survivors of critical illness and their relatives should not be relied upon as accurate, with patient/relative recall tending to overestimate patient physical activity levels, compared to smartphone estimates. Finding a gold standard, for the reliable measurement of pre-morbid physical activity is important for ICU outcome research [10]. Utilisation of passively collected data, e.g. step and GPS data, from smartphones or other devices could potentially allow critical care physicians to collate pre-morbid activity and physical participation retrospectively. This would allow researchers to confirm or dispel the adage that survivors of critical illness never return to their baseline level of function [11]. This would represent a significant shift in critical illness research methodology.

Despite the potential importance of step and GPS data, this data was not present on the phones of some ICU survivors (52%; Chapter 2.2) and General Medicine inpatients (71%; Chapter 3.2). Further, although Chapters 2.3 and 2.4 demonstrated step and GPS data can be used to generate outcomes that represent the activity and physical participation of ICU survivors, there was a reliance on manual extraction of data. The automated extraction of location data from iOS (Frequent/Significant locations) was not possible despite the use of digital forensics (not presented as part of this thesis). However; in Chapter 3.2 Google Maps Timeline (GMT) did allow for the extraction of a data file detailing historic location data. This had the potential to progress the automation of this previously manual process. Further, it

was possible to use the step and GPS data extracted to create outcome measures that would relate to an individuals daily activity and physical participation, such as daily steps, time spent active, time spent at home and activity spaces [12, 13]. This would, in theory, tie these measures to that of disability in accordance with the World Health Organisations International Classification of Function [14].

Despite the potential benefits of GMT data, Chapter 3.2 highlighted the difficulty in extracting this data in General Medical inpatients although it was the first time GMT had been extracted from iOS devices, the availability of these data was incredibly limited. Data were only successfully extracted from 4 (8%) and only 10 (29%) phones contained GMT data. Obtaining these data retrospectively did not pass the threshold required to prove feasibility and with minimal evidence to support the use of these data as outcome measures it was decided to prospectively collect these data utilising a smartphone app built by the Software Engineering Department of Adelaide University.

Chapter 4.2 showed that in a significantly co-morbid population there was a level of smartphone ownership (59%) and user ability, with only 9% of smartphone users being unable to install an app, to suggest it would be feasible to use a smartphone app to collect step and GPS data. However, despite the adequate level of smartphone use Chapter 4.3, involving the testing of an app developed with the Software Engineering Department of the University of Adelaide in patients undergoing Cardiothoracic surgery, demonstrated significant failures in data capture. The following strategies were suggested to reduce the risk of data loss in similar future studies:-

- extensive testing of the app in a multitude of different environments;
- use of the participants data connection rather than relying on a Wi-Fi connection;
- ongoing software support to ensure the apps remain updated;
- regular app check-in to ensure the app remains running in the background and;
- a regular check on the cloud database to ensure ongoing data upload, with a push notification to the participants phone if the data upload ceases.

Such remote passive monitoring of apps has been very successful in monitoring mental health patients [15, 16].

We have deliberately utilised a description of physical participation. How this related to participation is not known. For example, an individual could be house bound yet still contribute to meetings, take part in hobbies, shop online and play games with friends. This level of participation would not be captured with a GPS device. Being able to compare physical participation with participation captured by diary would be of benefit from a validation perspective. The utilisation of cookie data to track web-interaction may aid the use of participation measurement while relying solely on passively collected datasets.

It is important to consider some general themes that have persisted across the different studies of this program of research. The first of these themes is Smartphone ownership and user ability. In all the populations described smartphone ownership has fallen significantly below the level of the general population. While there will be a generational element to this, with older patients lacking the education to develop the skills to utilize smartphone function, over time this would be expected to change as those with the education and skills. There will also be a functional element with patients with cognitive decline lacking the recall

to be able to interact with a smart device and a poverty element will exist where affording a device will not be feasible. In Australia there is an important cultural element to consider, in that Aboriginal populations use smartphones as community commodities, and they are shared between different members of the greater family.

As we move to a health system that will be increasingly automated by mHealth, we need to be cognizant that certain populations do not, or cannot interact with mobile devices and do not have an online presence. These are often some of the most vulnerable who will be further disadvantaged by some of the mHealth initiatives.

There have been technical challenges caused by the fast-moving nature of the surrounding hardware and software that the devices interact with. This makes keeping apps and protocols up to date with the most recent developments a significant challenge and highlights the need for successful collaborations between software engineers and health professionals.

The concerns over data privacy have certainly increased during the life-time of this PhD. This has come from very public data breaches, poor governance over data usage and increased awareness of the power that these data hold. We need to better engage with the public and industry to truly understand how best these data can be used to benefit the individual.

5.3 - Strengths

This thesis has demonstrated that highly granular data can be passively collected from patient smartphones. This is a novel approach to outcome measurement in critical care. Using these highly granular data to integrate information relating to social determinants of health, activity and participation into the healthcare data set would, in theory, be an attractive proposition as it would passively automate outcome measurement while also providing improved data for outcome prediction. This would lead to improved shared decision making and expectation management for patients. However, collecting these data in the quantities required has been, and will remain, a significant challenge, as both Apple and Google have significantly restricted the access to location data in future app design. Despite these challenges these technologies have been successfully deployed in mental health where patients with bipolar affective disorder show a reduction in activities when depressed and an increase in activities when manic [15], and there is promising use of a digital phenotype in schizophrenia [16] where social media interactions strongly corelate with disease state. Using an ‘internet of things’ approach, where an array of devices with different sensors digitally interact, wearable sensors have shown a reduction in daily steps and an increase in sleep following COVID 19 vaccination [17, 18].

5.4 - Limitations

Using GPS transponders in Chapter 2.4 would have enabled the validation of the smartphone GPS data something that has been assumed throughout the thesis. Although there is data to support their accuracy [19, 20] it has not been confirmed in ICU survivors. This would have allowed the direct comparison of data gathered from frequent/significant

locations, data generated from a proprietary Apple algorithm with that of a GPS transponder. Nonetheless, given studies have confirmed the accuracy of smartphone GPS data [19, 20] this limitation should not have impacted on the outcomes of the current research or have a major impact on future studies that rely on smartphone apps.

For ease of recruitment the automation of data extraction (Chapter 3.2) was attempted in general medical patients. However, general medical patients are generally older than ICU survivors. Although smartphone ownership was similar between the ICU and General medicine cohorts it has been shown that the level of GMT data was significantly less than that of students[21], suggesting the level of data availability may be something that diminishes with age as the usage profile of the phone and apps change. Therefore, translation of the data to ICU survivors is difficult and further studies are needed, specifically in ICU survivors, for confirmation.

In Chapter 4.2, again for ease of recruitment, the ability of a renal patient population to install an app was surveyed. Considering cardiothoracic surgery patients were the eventual target population, it would have been preferable to assess this specifically in this cohort of patients, especially considering, with hindsight, this was one of the potential limitations of the cardiothoracic study. Additionally, it would have been beneficial to ask if they knew if their smartphone connected to their home Wi-Fi network, as this would have better informed the app design.

The biggest limitation of this thesis relates to the loss of data suffered in the final study. There are learning points that have been taken from this which will enable improved app design and testing in the future. Notably, the testing for the app was limited by time pressures; which should be a significant warning for future researchers in this area. However, recently both Apple and Google have significantly limited access to smartphone users location data to the extent that no app can be released that simply collects location data without providing immediate and obvious benefit to the end user.

The design of the app would have benefited from co-design methodology and qualitative studies with ICU survivors and their families may have improved engagement and hence opportunities for data extraction. This may assist with the ongoing development of subjective outcomes while there is ongoing development in the passively collected objective data field. This is a huge missed opportunity and one that potentially undermines the trust placed in researchers by the patients who take part in such studies.

5.5 - Future directions

Using these data to better predict outcomes would be an attractive proposition. Using these data in a peri-operative setting to provide individualised recovery prediction and monitoring would certainly improve shared decision making. In addition, utilisation in younger patient populations, such as the obstetric population where smartphone usage and ability would be greater, could be beneficial. This would be supported by the significant difference in GMT data availability between General medical inpatients and students [21].

The increasing availability of wearable data in the form of smartwatches presents an exciting opportunity. One in 4 smartphones is now paired to a wearable device, providing more accurate accelerometery data, along with waveform level data relating to heart rate and oxygen saturations. The addition of weight, sleep data, nutrition data and medication history into the standard health apps will provide a greater level of data that can potentially be utilised in the measurement of healthcare outcomes. Finding ways to integrate these data into national health datasets will drastically improve the future research opportunities. However; the increasingly stringent data protection laws have already led to restrictions on location data being used for research, this may extend to other data in years to come. The software development kits developed by Google, Apple and Microsoft do enable developers greater automated access to many of the databases on a smartphone ensuring there is a wealth of passively collected data available. The Android (Google) developer platform has introduced Health Connect and iOS (Apple) has introduced the Health Kit to allow developers access to health data.

However, the greatest challenge to researchers and app developers must be the privacy concerns of using this type of data. The Cambridge Analytica scandal [22, 23] has brought this to the forefront, with further concerns raised during the roll out of COVID19 apps and the major data leaks from industries, including Optus [24] and MediBank [25], in Australia. This, along with the unsuccessful application of technology, as demonstrated in this thesis, will undermine the confidence of the public to allow access to their data. Therefore, future applications must provide value to the end user from the start, they must empower the public to be custodians of their own data, be totally transparent about the data usage and ensure robust security.

There is certainly scope for improving how clinicians engage patients with this kind of technology and how the technology engages with the patients and clinician. In their systematic review of improving adherence to mHealth Apps, Jakob et al demonstrated that personalization or tailoring to the individual needs of the user, push notifications acting as reminders, user-friendly and technically stable app design, and personal support to the digital intervention were the factors that drove adherence across all domains with gamification driving adherence across several domains [26]. It is also important to engage with users to continually improve the app and ensure a co-design process is in place. Putting these principles into practice would certainly aid future studies

5.6 – Conclusions

While the use of a smartphone app does hold promise for the passive collection of step and GPS data to better inform patient care, using this data to retrospectively measure the activity and participation of a patient admitted as an emergency to ICU is not currently possible. Therefore, the objective measurement of activity and physical participation to define disability and function will remain a panacea of ICU research.

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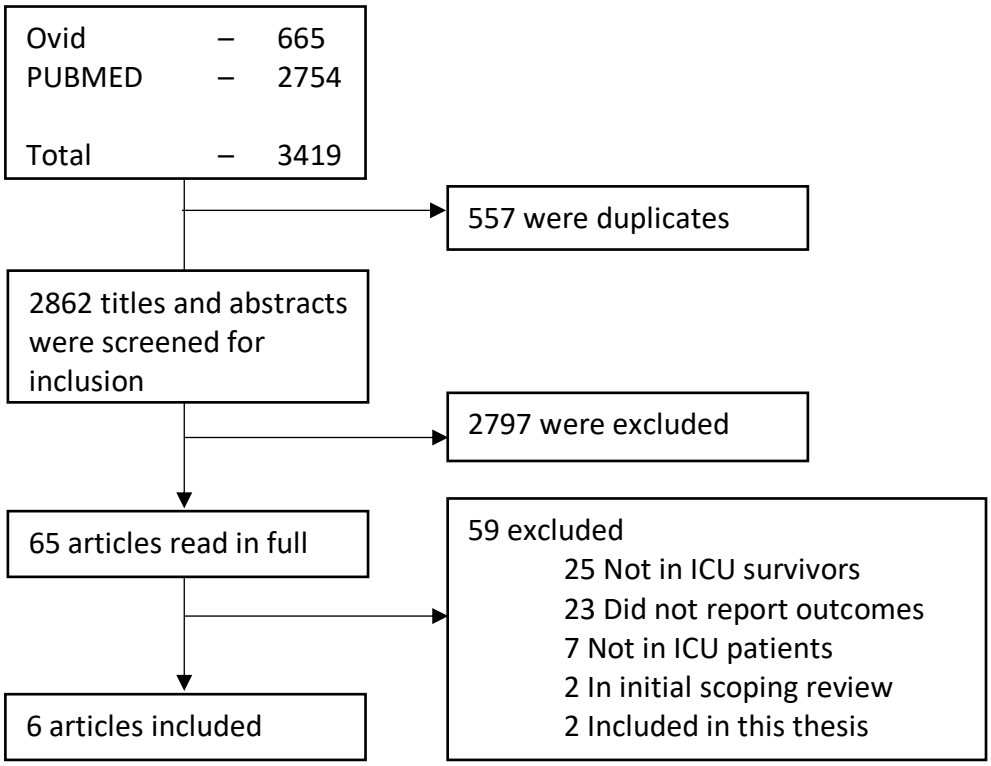
Chapter 5 Supplementary Material



Supplementary Figure 1 – Consort diagram of repeat scoping review filtered for all studies published since 2016

Lead author	Yr	Study Design	Cohort studied	Number of patients	Wearable Device	Time to follow-up	Duration of observation	Observations from wearable device	Other outcomes	Associations
Gandotra	2021	Prospective observational study	Previously independent adults aged 55 or older, undergoing mechanical ventilation for up to 7 days	22	Tractivity; Kineteks Corporation (accelerometer)	3 days prior to ICU discharge, prior to hospital discharge, the first 3 days at home and days 4-6 post discharge	Continuous till 1 week post discharge	Mean daily step count	Short Physical Performance Battery	Correlation between steps and Short Physical Performance Battery scores were poor at ICU and hospital discharge; moderate correlations immediately upon return home.
Kim	2021	Prospective observational study	ICU survivors, aged 55 years and older	12	Fitbit Charge HR	4 weeks	4 weeks	Step count, physical activity, sleep, and heart rate (HR).	Clinical Frailty scale	Daily step count was strongly correlated with the CFS at 4-week follow-up
Capin	2022	Pilot randomised feasibility study.	Discharged home following hospitalisation with COVID-19	44 (7 admitted to ICU)	Fitbit activity monitors	6 and 12 weeks post hospital discharge	12 weeks	Step counts	Moca-Blind, MRC Dyspnea Scale, Balance Confidence Scale, Three-Item Loneliness Scale, PROMIS Short Form General Self-Efficacy, PROMIS Short Form Self-Efficacy for Managing Chronic Conditions, PROMIS Scale Global Health Measure, CFS, PHQ8, The four-stage balance test, 30s chair stand test, TUG	Step counts increased by week 6, and plateaued after week 6 to week 12
Estrup	2022	Prospective cohort study	ICU patients	44	Micro Sleep Watch a wrist worn accelerometer	Discharge and 3 months	3 months	Mean activity counts per day; mean activity per hour during daytime, mean difference between day and night; max activity in 1 hr on day 2; total activity count on day 2; and daytime activity on day 2.	CPAx, Short Form Health Survey (SF 36), Hospital Anxiety and Depression Scale, Repeatable Battery for the Assessment of Neuropsychological Status (RBANS), mortality in hospital and within 90 days, and use of opioids at 3 months	Weak correlations between activity measures and CPAx at discharge, weak associations between CPAx and activity measures at 3 months and weak correlations between the diffences in activity and the change in CPAx between discharge and 3 months.
Hunter	2021	Prospective, multicentre observational trial	Moderate or severe lung injury resulting from confirmed COVID-19	50	Fitbit Charge 3	1 year	1 year	Step counts and daily resting heart rates		Steps increased from 4359 per day in the first to 7914 at 1 year. Fitbit was felt to drive recovery.
Defilippis	2019	A prospective feasibility study	Ventricular Assist device patients	21	Patients own smartphone with Position health installed	Ongoing	Ongoing	Attendance at ED	Nil	Nil

Supplementary table 1 - CFS - Clinical Frailty Scale, CPAx - Chelsea Critical Care Physical Assessment Tool, MRC - Medical Research Council, MoCA - Montreal Cognitive Assessment, PHQ8 - Patient Health Questionnaire 8, PROMIS - Patient Reported Outcomes Measurement and Information System, TUG - Timed Up and Go Test

Appendix A – Presentations at regional, national and international meetings
(primary Author unless otherwise stated)

Invited National Presentations

Royal Australian College of Physicians ASM *Adelaide, 1st Dec 2018*
The use of objective data to automate the measurement of patient centred outcomes

Invited regional Presentations

South Australian Association of Internal Medicine *Adelaide, August 2018*
Smartphone data as a patient outcome

SA ACCCN Hot Topic Evening *Adelaide, March 2019*
Survive and Thrive Peer Support Group

International Conferences – Selected for Oral Presentation

SCCM Congress Best Medical Free Paper San Antonio, Feb 2018
Global position system derived values to describe outcomes after critical illness: an exploratory observational study

ANZICS ASM Matt Spence Medal Presentation Gold Coast, Oct 2017
Smartphone step-counts reliably and consistently estimate step-counts from a dedicated pedometer

ANZICS ASM Best Medical Free Paper Gold Coast, Oct 2017
Global position system derived values to describe outcomes after critical illness: an exploratory observational study

ANZICS ASM Matt Spence Medal Presentation Perth, Oct 2016
A Comparison of Subjective And Objective Reporting Of Patient Physical Activity Prior To Critical Illness

Regional Meetings – Selected for Oral Presentation

ANZICS Tub Worthley Travelling Scholarship Trainees Adelaide 2016
The accuracy of surrogate reporting of patient physical activity prior to critical illness

ANZICS Tub Worthley Travelling Scholarship Trainees Adelaide 2017
The assessment of physical activity before and after critical illness

ANZICS Tub Worthley Travelling Scholarship Trainees Adelaide 2018
Global position system derived values to describe outcomes after critical illness: an exploratory observational study

International Conference – Poster Presentation

ICS, State of the Art Meeting London 2016
Wide Disagreement Between Alternative Assessments of Physical Function: Patients Subjective Reports, Surrogate Reports, and Smart-Phone Data.

Intensive Care World Congress Melbourne 2019
Lost in Relocation: Less than optimal medical handover of patients discharged from intensive care. (secondary author)

National Conference – Poster Presentations

ANZICS ASM Adelaide 2018
Long-term mortality of long-stay ICU patients at the Royal Adelaide Hospital, (secondary author)

Regional Meeting – Posters Presentations

Florey HDR annual conference Adelaide 2017
The use of step and GPS outcomes to assess recover following critical illness

Florey HDR annual conference Adelaide 2018
Development of a clinical tool to assess activity and participation.

Appendix B – Prizes awarded and nominations during candidature

2017 Tub Worthley Traveling Scholarship ANZICS
Prize for best presentation at the SA ANZICS Tub Worthley Traveling Scholarship Dinner

2018 Adelaide Medical School Prize
Prize for best poster presentation at the 2018 Annual Florey Postgraduate Research Conference.

2019 ANZICS CTG Novice Investigator Rapid Fire Presentation Winner
A three-minute presentation at the 2019 Noosa meeting of the CTG, novice investigator session.

2019 SA Health Awards – Nominee
Survive and Thrive – a peer support group for ICU survivors and relatives

2021 SA Health Clinical Educator of the Year
Award for junior doctor nominated best clinical educator in SA health

2022 NALHN Partnering excellence award – Finalist
NALHN – Flinders Medical Student Placement Program

2022 NALHN Sustainability excellence award – Finalist
2022 SA Health award – Nominee
2023 SA Premiers Award - Nominee
Australian Medical Council – NALHN Work-Place Based Assessment Program

Appendix C - Grants and scholarships awarded during candidature

2016 Royal Adelaide Hospital Research Committee, A.R Clarkson Scholarship
The development of objective measures of function prior to and following critical illness. Award value $240,000 over 3 years stipend support

2016 Royal Adelaide Hospital Research Committee, Clinical Project Grant Award.
The feasibility and validity of obtaining pre-illness activity data in critically ill patients using 'smart-phone' technology: a validation study. Grant MyIP: 7527 Award MyIP: 2114 Award Value: $49,990

2018 Royal Adelaide Hospital Research Committee, Clinical Project Grant Award.
An open-source smartphone application to monitor patients prior to and following elective coronary artery bypass grafting: A prospective cohort study (The SMART-HEART Study). Grant MyIP: 9768 Award Value: $16,800

2018 Society Of Critical Care Medicine THRIVE Grant
The feasibility of establishing a peer support group for ICU survivors at the Royal Adelaide Hospital. Award Value $US 1,000

2021 Rural Workforce Grant
The placement of 2 interns in Port Pire with education support from NALHN, community engagement and whole system simulation education. Award Value $182,000

Appendix D – Other publications completed during candidature

Patients retrieved to intensive care via a dedicated retrieval service do not have increased hospital mortality compared with propensity-matched controls. Maclure P.T, Gluck S, Finnis M.E, Pearce A. **Australian Intensive Care**. 2018;46(2):202-206.

Prediction of general medical admission length of stay with natural language processing and deep learning: a pilot study. Bacchi S, Gluck S, Tan Y, Chim I.C, Cheng J, Gilbert T, Menon D.K, Jannes J, Kleinig T, Koblar S. **Internal and Emergency Medicine**. 2020 (Online ahead of print)

Evaluation of coagulation status using viscoelastic testing in Intensive Care patients with COVID-19: An observational point prevalence cohort study. Colett L.W, Gluck S, Strickland R.M, Reddi B.J, **Australian Critical Care**. 2020

Patient reported outcomes after critical illness: a randomised controlled trial of online versus paper surveys. Wong H.Z, Brusseleers M, Hall K, Maiden M.J, Chapple L.S, Chapman M.J, Hogdson C.L, Gluck S. **Australian Critical Care**. 2021 Online ahead of print

Mixed-data deep learning in repeated predictions of general medicine length of stay: a derivation study. Bacchi S, Gluck S, Tan Y, Chim I, Cheng J, Gilbert T, Jannes J, Kleinig T, Koblar S. **Intern Emerg Med**. 2021 Online ahead of print

Daily estimates of individual discharge likelihood with deep learning natural language processing in general medicine: a prospective and external validation study Bacchi S, Gilbert T, Gluck S, Cheng J, Tan Y, Chim I, Jannes J, Kleinig TJ, Koblar S. **Internal and Emergency Medicine**; Online ahead of print DOI: 10.1007/s11739-021-02816-7

Improving the accuracy of stroke clinical coding with open-source software and natural language processing Bacchi S, Gluck S, Koblar S, Jannes J, Kleinig T. **Journal of Clinical Neuroscience**. 2021 94:233-236.

Mixed-data deep learning in repeated predictions of general medicine length of stay: a derivation study. S Bacchi, S Gluck, Y Tan, I Chim, J Cheng, T Gilbert, J Jannes, T Kleinig. **Internal and Emergency Medicine** 16 (6), 1613-1617

Muscle Protein Synthesis Following Protein Administration in Critical Illness. LS Chapple, IWK Kouw, MJ Summers, LM Weinel, S Gluck, E Raith. **American journal of respiratory and critical care medicine.** E-pub ahead of print

Gender and linguistic disparities in resuscitation orders: a multicentre retrospective cohort study. S Bacchi, AK Gupta, JG Kovoor, CD Ovenden, MS To, M Jiang, R Goh, S Gluck **Internal medicine journal** 52 (10), 1847-1848

Automated information extraction from free-text medical documents for stroke key performance indicators: a pilot study. S Bacchi, S Gluck, S Koblar, J Jannes, T Kleinig**. Internal Medicine Journal** 52 (2), 315-317

Pre-hospital emergency anaesthesia in trauma patients: An observational study from a state-wide Australian pre-hospital and retrieval service P Maclure, S Gluck, K Kerin, L Boyle, D Ellis**. Emergency Medicine Australasia.** E-pub ahead of print

Antibiotic Prescribing Practices Differ between Patients with Penicillin Intolerance and Penicillin Allergy Labels. Jiang M, Bacchi S, Lam L, Inglis JM, Gluck S, Smith W, Gilbert T. **Int Arch Allergy Immunol**. 2022 Nov 11:1-5.

Lost in relocation: longitudinal surveys evaluating the effectiveness of ICU to ward handover after the introduction of an electronic patient record. Westaway S, Webber T, Gluck S, Sundararajan K. **Hosp Pract**. 2022 Oct;50(4):267-272.

Why do we evaluate 30-day readmissions in General Medicine? A historical perspective and contemporary data. James J, Tan S, Stretton S, Kovoor J G, Gupta A K, Gluck S, Gilbert T, Sharma Y, Bacchi S, **Internal Medicine Journal** (In press)

Perioperative Direct Oral Anticoagulant Assays: A Multicentre Cohort Study. Stretton S, Bacchi S, Kovoor J G, Booth A, Gluck S, Vanlint A, Afzal M, Overden C, Gupta A K< Mahajan R, Edwards S, Brennan Y, Boey J, Reddi B, Maddern G, Boyd M. **Hospital Practice** (In Press)

Low risk cefalexin allergies are associated with inpatient prescribing of second-line non-beta lactam antibiotics. Jiang M, Stephen Bacchi B, Lam L, Lam A, Inglis J M, Gilbert T, Gluck S, Shakib S, Yuson C, Smith W. **Allergo Journal International** (In press)