School of Public Health

Development of a Time-Duration Measure of Continuity of Primary Care: An Application of Econometric Approaches among People with Diabetes

Thi Ninh Ha

This thesis is presented for the Degree of
Doctor of Philosophy
of
Curtin University

February 2019

Author’s Declaration

I declare that this thesis is my own account of my research and contains, as its main content, work which has not previously been submitted for a degree at any tertiary education institution.

To the best of my knowledge this thesis contains no material previously published by any other person except where due acknowledgement has been made. This thesis contains no material which has been accepted for the award of any other degree or diploma in any university. The published papers have co-authors who have identified and acknowledged my contribution, included in Appendix L.

Thi Ninh Ha

Date: 25 February 2019

Ethics Approval

This research was approved from Curtin University Human Research Ethics Committee (RD-42-14) and the New South Wales Population and Health Services Research Ethics Committee (HREC/17/CIPHS/37) under the project title “Does continuity of primary care reduce demand on emergency department presentations and hospital admissions?”

Statement of Contributors

Supervisors:

1. Associate Professor Rachael Moorin
2. Professor Mark Harris
3. Professor Suzanne Robinson

Project coordinator:

David Youens who conducted preliminary data structures and variables for Continuity of Care project which were also used in this thesis.

Co-author:

Professor David Preen, who co-authored the manuscripts presented in chapters 4 to 7

Funding:

Curtin International Postgraduate Scholarship

The National Health and Medical Research Council, project grant APP1078345

Signed Thi Ninh Ha Date: 25 February 2019

Signed Rachael Moorin Date: 25 February 2019

Abstract

In the context of today's increasing burden of chronic diseases, continuity of care is considered essential for high-quality care, patient satisfaction and improved health outcomes. Although continuity of care is a complex concept, encompassing multiple interpersonal, informational and management dimensions, current measures of this mostly capture only the interpersonal aspects. This thesis develops a new continuity measure—the Cover Index—which integrates the time duration between general practitioner (GP) contacts into a measurement of regularity of care, and uses linked administrative data to better capture the management aspects of continuity of care among people with diabetes. The Cover Index, as defined in this thesis, is the proportion of time over a fixed ascertainment period that people with diabetes remain under the potentially protective effect of contact with their GP.

This thesis comprises four individual studies of which two have been published as peer-reviewed journal articles. The first three studies demonstrate exploration and development of the Cover Index using historical individual-level linked administrative data from Western Australia. The fourth study applies the Cover Index to evaluating continuity of care in the contemporary context using data from the 45 and Up Study carried out in New South Wales.

The first study explores the development of a stratification strategy for diabetes severity classification by examining the non-linear relationship between the diabetes complication severity index (DCSI) and diabetes-

related hospitalisations. This study suggests that the optimal stratification of the DCSI to improve risk adjustment in evaluating hospitalisation outcomes sits at levels one, two and three plus. This result is useful for research as it suggests a classification strategy that reduces over-parameterisation of models and provides more accuracy in reflecting the homogeneous effect of diabetes severity on health service utilisations. It provides a mechanism for classifying diabetes cohorts and can be used to support further development of the Cover Index.

The second study offers a preliminary exploration of patterns of GP utilisation among people with diabetes by simultaneously examining multiple attributes of GP utilisations using K-mean cluster analysis. To the best of my knowledge, this is the first study incorporating multiple attributes including frequency and time interval measures of GP contacts (average time interval, maximum time interval and standard deviation of time intervals). The results reveal three meaningful and homogeneous clusters of GP utilisation, namely, moderate, high and very high GP usage. This study is an improvement on more simplistic approaches, which only allow for a single attribution, such as the frequency or regularity of GP visits. This study suggests that time interval between GP contacts is important in examining the relationship between primary health care and hospitalisation. This study is a necessary precursor to selecting predictor variables required for the further development of the Cover Index.

The third study examines the development of the Cover Index in relation to people with diabetes. Using threshold effect models, this study identifies

variation in the relationship between primary health care and hospitalisation across values of the maximum time interval between GP visits. The result identifies optimal maximum time intervals between GP services, a proxy measure of the potentially protective effect of GP care. These calculations are then used in the operationalisation of the Cover Index. Descriptive statistics provide face validation of the Cover Index indicating its utility in quantifying utilisation of primary health care from a management perspective. This will help to identify appropriate subpopulations for allocating resources. This study also provides a practical and novel use of the threshold effects of modelling in health services research using linked administrative data.

The final study is an application of the Cover Index evaluating continuity of care and its association with diabetes-related potentially preventable hospitalisations using contemporary data. Using the same methodology developed in the third study, this study evaluates continuity of care among people with diabetes enrolled in the 45 and Up Study using the Cover Index as a tool. This research suggests that the Cover Index is significantly associated with a lower number of diabetes-related potentially preventable hospitalisations, unplanned diabetes-related hospitalisations and length of stay, after controlling for other continuity-of-care indices and individual socioeconomic characteristics. The result provides a more comprehensive view of continuity of care and supports policies aimed at optimising disease management for people with diabetes.

This thesis makes a significant contribution to existing literature across four important areas:

1) The research reported in this thesis contributes to addressing the challenges of measuring the complexity of continuity of care through developing a new time duration measure (the Cover Index), which adds the concept of a potentially protective effect duration into the existing measure of regularity of GP contacts. This provides a more comprehensive way to measure the management aspects of continuity of care.
2) This research has identified the effect of time duration between GP services as a key driver influencing the relationship between primary care utilisation and potentially preventable hospitalisation. Incorporation of this important attribute will improve our ability to analyse variation in hospitalisations, optimise utilisation of primary health care and contain health care costs for people with chronic conditions.
3) This thesis provides a comprehensive longitudinal evaluation of continuity of care for populations with diabetes to demonstrate the success of primary care enhancement in Australia.
4) The research presented in this thesis demonstrates the useful application of novel data-driven analytic approaches that facilitate and maximise the use of longitudinal administrative data. This research presents an example of a comprehensive stepped approach that can be used to develop a range of latent variables, capturing the complexity of the data surrounding patients' interactions with the health system. Development of such variables will further enhance real-world

evaluation of health service use and provide powerful evidence for investigating the impact of health policy and health care performance.

This thesis contributes to a growing body of literature in capturing and improving continuity of care for people with chronic conditions. The development of the Cover Index establishes a novel metric capable of generating fundamental knowledge about health care utilisation patterns that will be useful for future research seeking to optimise delivery of primary health care. In addition to the value of the methodological approach developed for operationalising the Cover Index, the findings of the applied analysis will be valuable for directing primary health care policy and primary health care practice to better address the burden of significant chronic disease in Australia and worldwide.

Acknowledgements

I would like to acknowledge and express my gratitude to the many wonderful people supporting me in my research journey and making this research possible.

First and foremost, I would like to thank my principal supervisor, Associate Professor Rachael Moorin for providing unique insight, guidance and ongoing daily support that challenged my thinking and facilitated my growth both professionally and personally. I would never have successfully completed this research without your support.

I would like to acknowledge my co-supervisors, Professor Mark Harris and Professor Suzanne Robinson for their great support. Thank you, Mark for sharing your expertise and helping me toward the high standard of econometric knowledge. Suzanne, I am grateful for your very valuable comments on this thesis. I would also like to extend my appreciation to Professor David Preen, thank you for your contributions across all papers of this thesis.

I would like to thank David Youens, project coordinator, for his work in designing and setting up data platform cohorts. I would like to acknowledge the data custodians and the staff at the data linkage unit of Western Australia and the 45 and Up Study for providing the data to enable this research. I would like to acknowledge professional editor, Valerie Mobley, for providing proofreading services according to the guidelines laid out in the university-endorsed national Guidelines for editing research theses.

Finally, I must express my deepest gratitude to my family and especially to my mom, my dad and my husband for your love, encouragement and belief in my ability. A very special thank you to Denese Playford for your care, understanding and helping me through all of the tough times. Thank you, Holly and Phoebe for being my best friends; you both mean a lot to me. I also thank my PhD friends, Yihuey, Himanshu and others for your fellowship and motivation.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

ACSC	Ambulatory Care Sensitive Conditions
AIC	Akaike Information Criteria
AIHW	Australian Institute of Health and Welfare
AMA	Australian Medical Association
APDC	Admitted Patient Data Collection
ARIA	Accessibility/Remote Index of Australia
ATC	Anatomical Therapeutic Chemical
BEACH	Bettering the Evaluation and Care of Health
BIC	Bayesian Information Criteria
BHC	Broader Health Cover
BMI	Body Mass Index
CDM	Chronic Disease Management
CHeReL	Centre for Health Record Linkage
COCI	The Continuity of Care Index
DCSI	Diabetes Complication Severity Index
DOC	Days Out of GP Cover
EPC	Enhanced Primary Care
ER	Electoral Roll
GPS	Generalised Propensity Score
GP	General Practitioner
HMDS	Hospital Morbidity Data System
ICD	International Classification of Diseases

LOS	Length of Stay
MBS	Medicare Benefits Scheme
MACSS	Australian Comorbidity Scoring System
NB	Negative Binomial Regression Model
NSW	New South Wales
PBS	Pharmaceutical Benefits Scheme
PPH	Potentially Preventable Hospitalisation
RBDM	Register of Births Deaths and Marriages
SD	Standard Deviation
SURE	Secure Unified Research Environment
SEIFA	Socio-Economic Indices for Areas
SECON	Sequence Index
UPC	Usual Provider of Care Index
ZINB	Zero-Inflated Negative Binomial Regression Model
WADLS	Western Australian Data Linkage System
WHO	World Health Organization
WA	Western Australia

Chapter 1 Introduction

1.1 Introduction

Chronic diseases cause a high burden of morbidity and mortality world-wide (1). In the context of an ageing population, the burden of chronic disease is placing considerable pressure on healthcare systems (1-3). Diabetes is one of the most challenging chronic conditions due to its complexity and association with reduction in quality of life, high risk of disability and mortality and costly health care (4-7). To address the burden of chronic disease, the health system needs to move away from the traditional medical practice model towards the adoption of a more proactive role, one which provides predictive and integrative care to support long-term effective prevention and management of chronic conditions (1, 2).

Modern chronic disease management models provide comprehensive strategies to support reforming healthcare systems world-wide to meet the complex needs of chronic disease and maintain economic sustainability (1, 8-10). The models highlight the importance of strengthening the role of primary health care in planning care, regular interactions, continued follow up and support for self-management of people with chronic conditions (1, 8, 9, 11, 12). In addition, the philosophy of primary health care also indicates that timely utilisation and ongoing care provided in primary care settings can reduce potentially preventable hospitalisations (PPH) and effectively contain health care resource use (13-16).

In many countries, including Australia, primary health care is seen as a

cornerstone to support effective and efficient chronic disease management (17-21). In Australia, general practitioners (GPs) act as gatekeepers of the healthcare system. Although individuals are not required to register with a single GP, GPs take a leading role in primary care teams as well as preparing care plans and integrating with other health sectors to ensure patient-centred care (20, 21). The Australian Government has provided financial incentives to enhance the participation of GPs in many aspects of chronic disease management, such as the introduction of Primary Health Networks, the Integrated Care Model, Service/Practice Incentive Payments, Scheme items and Home Medication reviews (22). Currently, GPs provide care for approximately 85% of the general population in Australia (17).

Over recent decades continuity has been advocated as an essential component of care for people with chronic conditions. This has led to high quality care, increasing patient satisfaction and economical use of resources (23-27). Continuity of care in this context is a complex concept encompassing multiple dimensions, including interpersonal continuity, information continuity and management continuity (26, 28, 29). Interpersonal continuity of care is concerned with the long-term interaction with a regular provider that enables building trust and a caring relationship between patients and health providers (24, 26). Information continuity offers opportunities to share clinical information between healthcare professionals to better ensure patient-centred care (24, 26). Management continuity is about effective and efficient integration and collaboration across healthcare professionals (24, 26). In the context of an increasing burden of chronic disease, management of continuity of care supports comprehensive service

delivery and ensures care is provided proactively, on time, and with minimum duplication (26). One study found that management continuity, rather than other aspects of continuity of care, explained most variation in patient satisfaction (30). In spite of the importance of management continuity, current measures of continuity of care mostly reflect interpersonal continuity, usually through quantifying the distribution of providers (24, 27, 31, 32). The development of measures that capture the management aspect of continuity of care would therefore be useful and should be prioritised to encourage and evaluate effective continuity of care as well as to optimise the efficiency of chronic disease management.

Many recent studies have considered the management aspect of continuity of care in terms of regularity of the patient's interaction with a general practitioner (GP) (33-36). Literature suggests that regularity of GP contacts is associated with reduced number of hospitalisations and lower hospitalisation costs for some chronic conditions (37-39). The regularity concept assesses variation in time intervals between contacts with a GP, which then provides a proxy measure of how well care is planned via proactive ongoing management (33, 35, 36, 38).

Regularity is amenable to health policy intervention (35, 40); however, because regularity is only integrated with the regularity and not with the length of time intervals between GP visits it is unable to indicate the sufficiency (*i.e.* adequate amount of) continuity of primary health care. While the concept of time interval between services is relatively new in management of primary health care, the concept has been widely adopted in

measuring persistence of medication utilisation (41, 42) and in the field of customer relationship management as an indication the strength of the relationship between customers and service providers (43-46). Knowledge of what constitutes an effective (in terms of management of the chronic condition) time interval between interactions with GPs would offer opportunities for both patients and GPs to arrange an appropriate care plan for updating history of disease, ensuring the needs of the patient are addressed and supporting patient self-management (9, 11). In addition, given that shifting towards proactive care models, it aligns well with current initiatives to re-orient healthcare systems towards primary care (1, 47), this knowledge would also provide further opportunity for the system to excel at improving the efficiency and effectiveness of chronic disease management practice.

This thesis has conceptualised, developed and tested a new metric, the Cover Index, among people with diabetes, using linked administrative data. The Cover Index incorporates a time-duration component into regularity of contact with GPs to better measure management of continuity of care at the individual patient level. In this thesis, the Cover Index is defined as the proportion of days within a fixed ascertainment period that a patient is considered to be under the 'protective effect' of their GP and therefore at lowest risk of a PPH, as illustrated in Figure 1.1. The ascertainment period is preferably one year since this is the time period that current chronic disease management plans are based on (48).

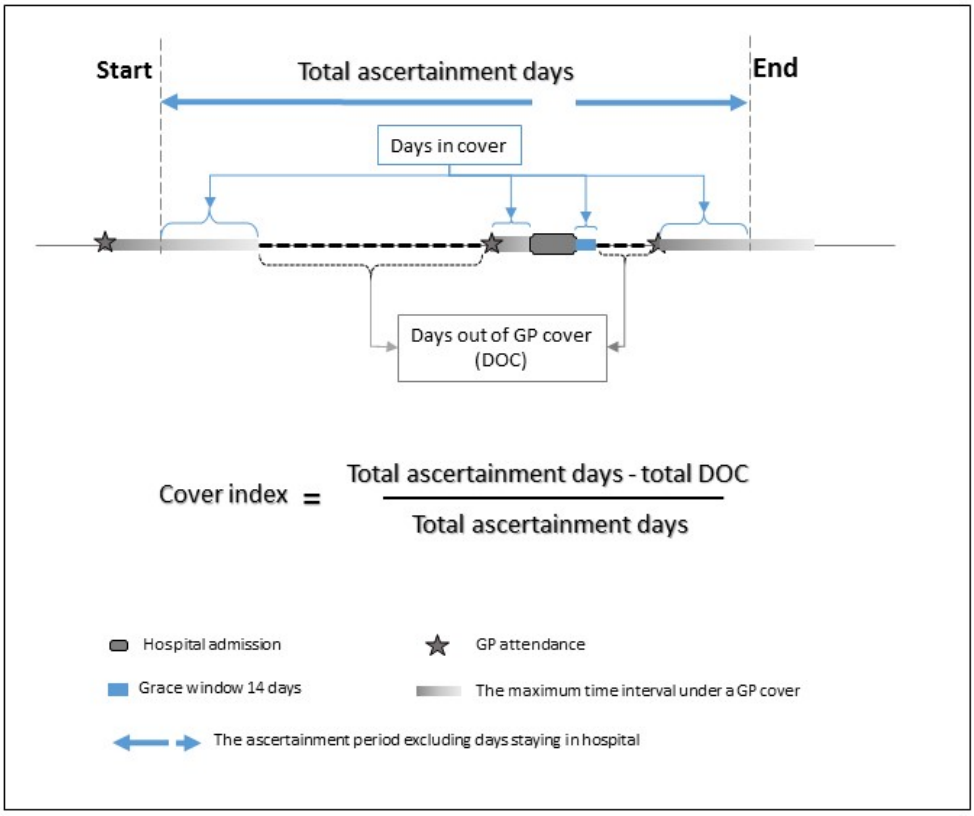


Figure 1.1. Cover Index demonstration

1.2 Aim and objectives

1.2.1 Aim

This study aimed to develop, test and apply a novel time duration measure of continuity of primary care (the Cover Index) using linked administrative data to better capture the management aspect of continuity of care. This will enable better evaluation of the effect of proactive care and also facilitate the optimisation of primary care delivery for people with diabetes in Australia.

1.2.2 Objectives

The aim of this thesis was achieved by setting the following objectives corresponding to four individual studies, where studies 1 to 3 used historical data to develop the methodology and Study 4 applied the methodology to contemporary data.

Objective 1: To develop a strategy that characterises the different burden of diabetes-related potentially preventable hospitalisation within a cohort of people with diabetes.

Objective 2: To identify patterns of GP service utilisation and its relationship with diabetes-related potentially preventable hospitalisation among people with diabetes.

Objective 3: To operationalise the construction of a new time-duration measure, the Cover Index, and test its face validity among people with diabetes aged 45+ years using threshold modelling techniques.

Objective 4: To evaluate continuity of primary health care using the Cover Index and evaluate its impact on health care resource use among people with diabetes enrolled in The Sax Institute's 45 and Up Study.

1.3 List of papers

Paper 1: Stratification strategy for diabetes severity

Thi Ninh Ha, Mark Harris, Suzanne Robinson, David Preen & Rachael Moorin (2017). Stratification strategy for evaluating the influence of diabetes complication severity index on the risk of hospitalization: a record linkage data in Western Australia. *Journal of Diabetes Complications*, 31(7), 1175–1180. doi:10.1016/j.jdiacomp.2017.03.015

Paper 2: Exploring patterns of general practitioner service utilisation

Thi Ninh Ha, Mark Harris, David Preen, Suzanne Robinson, & Rachael Moorin (2018). Identifying patterns of general practitioner service utilisation

and their relationship with potentially preventable hospitalisations in people with diabetes: The utility of a cluster analysis approach. *Diabetes Research and Clinical Practice*, 138, 201–210. http://dx.doi.org/10.1016/j.diabres.2018.01.027

Paper 3: Development of the new time-duration metric of continuity of care: the Cover Index

Thi Ninh Ha, Mark Harris, David Preen, Suzanne Robinson & Rachael Moorin. A time-duration measure of continuity of care to optimise utilisation of primary healthcare: A threshold effects approach among people with diabetes

Submitted in September 2018 to *BMC Health Services Research* — currently under review

Paper 4: Application of the Cover Index in evaluating continuity of care

Contemporary relationship between the Cover Index and hospital outcomes in the context of other continuity of care indices

Thi Ninh Ha, Mark Harris, David Preen & Rachael Moorin. The Cover Index: Evaluating continuity of care incorporating a time-duration effect of general practitioner care on diabetic-related potentially preventable hospitalisations

Submitted in November 2018 to The Sax Institute and Department of Human Services (DHS) for technical review as required before submitting for peer-review journals. The paper is due to be evaluated by the DHS External Request Evaluation Committee on 28 February 2019.

1.4 Outline of the thesis

This thesis consists of eight chapters divided into four parts as illustrated in Figure 1.2. The first part incorporates the conceptualisation of the research area and is presented in chapters 1 and 2. This is followed by exploration and development of the Cover Index presented in chapters 3 to 6. The application of the newly developed Cover Index in a contemporary dataset is presented in Chapter 7. Finally, the outcomes (discussion and implications) of this thesis are presented in Chapter 8.

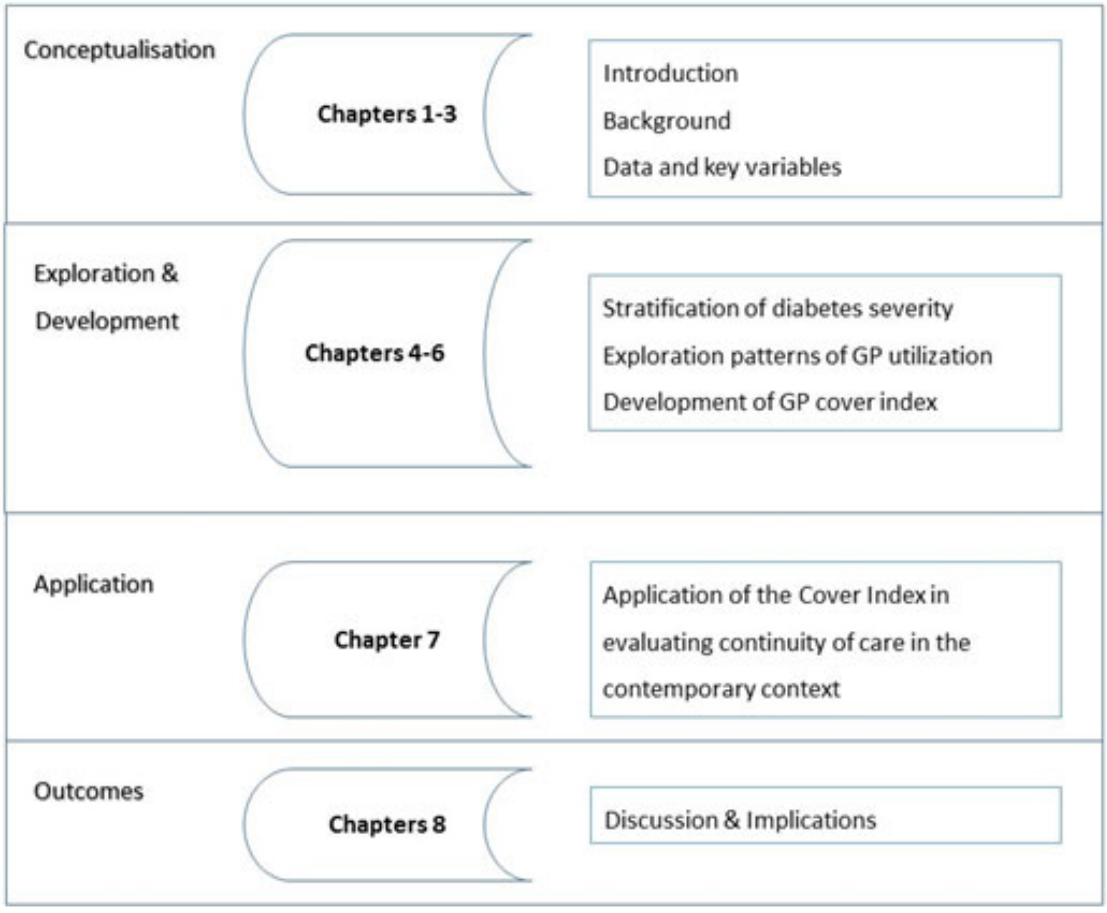


Figure 1.2. Outline of the thesis

Chapter 2 Background

This chapter provides a review of the existing literature that underpins the overall aim of the thesis—development of a new time-duration measure of continuity of care—and sets the scene for the research. Relevant areas covered in this chapter are presented under the following subheadings:

- Burden of chronic disease: providing an overview of the global ageing phenomenon and its associated burden of chronic disease, including the Australian context.
- Chronic disease management models: reviewing conceptual frameworks for chronic disease management to highlight crucial roles of primary health care in addressing the burden of chronic disease.
- Primary health care for chronic disease management: highlighting key characteristics and essential features that support effective and efficient chronic disease management at primary care settings in which continuity of care is considered as an essential element of care.
- Continuity of primary health care: demonstrating the complexity of the continuity concept and analysing challenges in measuring continuity of care that lead directly to gaps in literature and the rationale for this thesis.
- Chronic disease management in Australia: providing the context of the healthcare system, including primary health care and highlighting the role of GPs in managing chronic disease.

- Overview of data linkage for research: presenting Australian data linkage opportunities and challenges for research, using linked data to provide a sense of the data-rich environment in which this research is situated.

This chapter concludes with a summary of evidence presented in the literature, pointing out its relevance to the focus of this research.

2.1 Burden of chronic disease

The world's population is ageing, with about 962 million people aged 60 years or older in 2017 (49). The number is expected to double by 2050, with 2.1 billion who will be aged 60 years and older (49, 50). The number of people aged 80 years or older is projected to triple, from 137 million in 2017 to 425 million by 2050 (49). In the US, the number of people aged 65 years and older is estimated to increase from 37 million in 2005 to 70 million by 2030 (3). Similarly, the number of older people aged 65 years or older in Australia is estimated to increase from 3.8 million (15% of the population) in 2017 to 8.8 million (22% of the population) by 2057 (51).

A high proportion of the population reaching older age has presented challenges to healthcare systems due to high demand for health care and consequent expenditure in the age group (52). This is because the ageing progress leads to a decline in fitness and an increase in the risk of chronic disease (53). In addition, advances in medical treatments that help to reduce the risk of mortality among people with chronic conditions contribute to the burden because they also increase the number of years people live with disability and therefore increase the demand for long-term health care (52,

53).

An estimation for 2010 shows that morbidity among people aged 60 years and older accounted for 23.1% of the global burden of disease and 49.2% of the disease burden in high-income countries (52). In high-income countries, chronic diseases are the leading cause of death, with about 60% of annual deaths caused by common chronic diseases, including diabetes, cardiovascular disease, chronic lung disease and cancer (1, 54). Diabetes has caused a significant public health burden worldwide, accounting for 1.5 million (2.8%) deaths in 2015 (55). It is associated with decreasing quality of life, increasing disability, and an increasing economic burden for both individuals and societies (1).

In Australia, like most high-income countries, the ageing population presents a considerable burden on the healthcare system both in tertiary and primary health care. For hospital services, people aged 65 years and older accounted for 42% of separations and 48% of bed days in 2016–17 (56). In terms of primary care, those aged 65 years or older made an average of 10 GP visits per year in 2017 and accounted for a disproportionately higher share of health service use as they age (51, 57). The high utilisation of healthcare services can be explained by a high prevalence of multimorbidity among this age group, with 60% having two or more chronic conditions in 2014–15 (58). The high prevalence of multimorbidity also presents a high financial burden for the older population due to substantial out-of-pocket payments. A survey among older people in Australia found that older people with multimorbidity (*i.e.* more than two comorbidities) had about three times higher out-of-pocket

costs for healthcare services than those with none or single conditions (59). The out-of-pocket costs increased about 40% for each additional chronic condition in the older people as reported in the survey (59). The authors suggested that although healthcare policy in Australia has made an effort to minimise out-of-pocket payments, multimorbidity still caused a heavy financial burden for older people, especially among people with the lowest incomes (59).

Diabetes is one of the most challenging chronic conditions for the Australian healthcare system with a high prevalence (about 1.7 million estimated in 2018) and incidence (100,000 new cases per year estimated in 2018) (5). It is estimated that the number of people living with diabetes in Australia will increase to three million by 2025 (60). Diabetes is also a costly condition for the Australian healthcare system with a total cost of $14.6 billion per year in 2010 for both primary health care and hospital care services provided for adults (61). At the individual level, diabetes was estimated to cost an average of A$3,468 per year for a person with diabetes without complications in 2012 (62). The cost increases to A$16,698 per person for diabetes with complications (62). Given the high financial burden of diabetes, the Australian government has implemented many primary and secondary preventive programs to address its economic liability (62). However, diabetes management programs appear to have a limited effect, as only 50% of people with diabetes in Australia reportedly achieved good blood glucose control in 2010 (62). Thus, additional strategies to prevent and effectively manage diabetes are required to sustain the healthcare system and improve population health outcomes.

2.2 Chronic disease management models

Chronic diseases such as diabetes are life-long conditions that progress slowly overtime; thus, effective care for people with chronic conditions incorporates routine monitoring, supervision and regular care over a long period of time (2). In addition, chronic disease management needs a high level of involvement of patients in their disease care plan and integration and coordination between healthcare providers to meet their often complex needs (1). As most healthcare systems were designed to respond to acute care episodes, reforming healthcare systems towards strengthening the roles of primary health care and re-orienting in favour of proactive care has been suggested to achieve effective and efficient care for people with chronic conditions (63).

In recent decades, many chronic care models have been developed to provide useful frameworks for designing interventions and improving quality of care for people with chronic conditions and containing healthcare costs (1, 64). A recent systematic review found that two models, the Chronic Care Model and the Innovative Care for Chronic Conditions Model, are the most commonly reported in the literature (1). The Chronic Care Model specifically indicates structural changes within the healthcare system to address the needs of people with chronic conditions. However, as the specific practice of the Chronic Care Model may vary across healthcare systems and countries (65), the Innovative Care for Chronic Conditions model proposed by the WHO (66) has extended the Chronic Care Model to broader environments to enable the replicating or translating of the models to other contexts (1). Both models promote moving healthcare systems towards proactive care and

emphasise the vital role of primary health care in promoting patient-centred care (1, 9, 65, 66). The following sections will briefly describe how each element of the chronic disease framework come together to improve effectiveness in chronic disease management.

2.2.1 The Chronic Care Model

The Chronic Care model was developed by Wagner, Austin (67) in response to deficiencies in many healthcare systems, such as a lack of integration, planning care, and sharing information, all of which are important to promote self-management and to improve the quality of care for people with chronic conditions. The model has been widely adopted in many countries, including Australia, to guide best practice policy for addressing the burden of chronic disease (64, 65). The structure of this model is described by the Health Research Institute, as illustrated in Figure 2.1 (68).

The Chronic Care Model suggests that health outcomes of people with chronic conditions can be improved through four strategies:

1) Enhancing self-management support

2) Promoting decision making based on scientific evidence

3) Designing health delivery systems that will improve quality of care and clinical outcomes of patients

4) Increasing readiness and availability of clinical information for sharing between providers and between providers and patients.

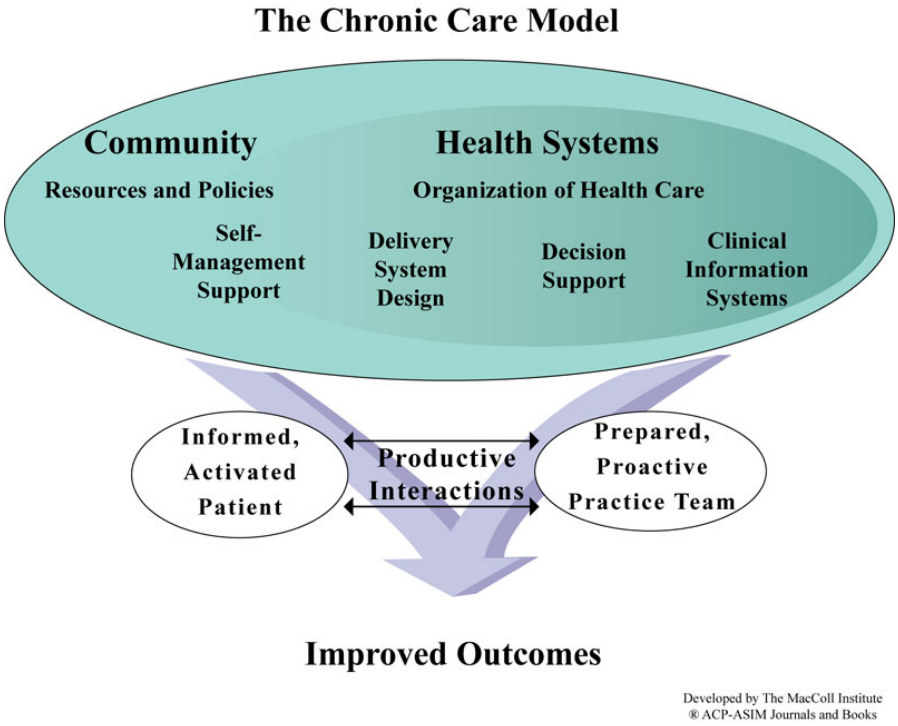


Figure 2.1. **Chronic Care Model**

Sources: *Health Research Institute. (2006). The Chronic Care Model (68)*

In additional to these strategies, the model focuses on motivating community support for chronic disease management interventions through providing resources and appropriate policies (9). The Chronic Care Model strongly suggests that the ambulatory care system needs to reform towards a proactive model of care to address the needs and concerns of people with chronic conditions. The model particularly proposes that patients with chronic conditions require planned care, regular interactions, and continuing follow up initiated by primary care practitioners (9). Based on evidence in the literature, Wagner found that periodic clinical and psychological assessment, sustained follow up and supported self-management offer great benefits for those with many chronic conditions, such as asthma, heart failure, diabetes and chronic obstructive pulmonary disease(9). In the context of Australian

primary health care, interventions targeted in key components of the Chronic Care Model, such as supported self-management, care plan and integrating multiple healthcare professionals in chronic disease management, appear to be effective (64). Thus, facilitating chronic disease management in primary health care settings can help to improve quality of care for most people with chronic conditions.

Overall, the Chronic Care Model has been considered to be more advanced than the conventional acute care model in improving population health outcomes (12, 65). The framework has been used as a roadmap for GPs or primary health care practitioners and policy makers to organise the delivery of ambulatory care to meet the needs of a wide range of complex conditions (1, 65). Evidence from recent systematic reviews suggests that implementation of the Chronic Care Model is associated with improvement in care and health outcomes for people with chronic conditions (1, 11, 12) and greater cost-effectiveness (65, 69).

2.2.2 Innovative Care for Chronic Conditions Model

The World Health Organization (66) has expanded the Chronic Care Model into broader policy contexts to better support the management of chronic disease in the primary healthcare settings of a range of countries. The model suggests eight components to consider when taking action to reduce the impact of chronic conditions as follows: (Figure 2.2).

The first component entails a paradigm shift, as most healthcare systems were primarily designed to address the needs of acute and communicable diseases while chronic conditions require different strategies for

management. For example, people with diabetes, heart disease and asthma often need regular contact with primary healthcare providers to enable effective self-management, better adherence to treatment and reduction of adverse clinical events (66).

The second component is management of the political environment, which highlights essential actions in building consensus and commitment between policy makers, leaders of the healthcare sector, patients and community representatives. These actions are important to ensure all needs are being taken into consideration when transforming the healthcare system to successfully support chronic disease management.

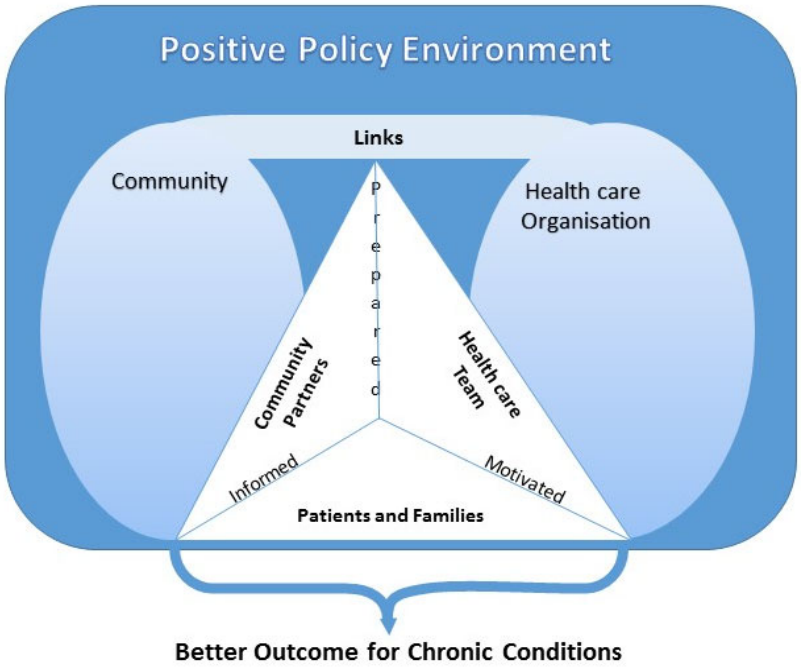


Figure 2.2. Innovative care for the Chronic Conditions Model

Sources*: WHO. (2002). Innovative care for chronic conditions: Building Blocks for Action. Geneva. (66)*

The third component is building an integrated healthcare organisation, which

includes actions in integrating financial systems and sharing information across different levels of the healthcare system. Sharing information needs to be conducted over time, between providers and between settings. Integrating financial arrangements promotes coordination between prevention, primary health care and tertiary health care. Integration of financial arrangements also includes coordination between healthcare interventions and other community activities to better utilise available resources for the management of chronic disease. The integration of healthcare systems helps to improve quality of care and reduce duplication and waste of resources.

The fourth component is the alignment of sectoral policies for health to encourage consideration of the health impact when policies of other areas are developed. For example, a policy for promoting health and safety of workplaces, although belonging to the labour practice sector, may facilitate improvement in chronic disease management if it is successfully aligned with policies in the health sector.

The fifth component is building multidisciplinary healthcare teams so that healthcare personnel are used more efficiently. For example, staff with a less formal medical education background and trained volunteers can be employed to conduct tasks such as patient education, counselling and helping patients with chronic conditions.

The sixth component centres care on the patient and family. This focuses on improvement of care and promoting daily behaviour change for people with chronic conditions through supporting patients and their families, and involving them in designing a care plan that is most appropriate for the

patients' socioeconomic context.

The seventh component is supporting patients in their communities, which is an important aspect to ensure successful management of chronic conditions. The rationale for this is that communities can provide cover for gaps in a patient's life that traditional healthcare services do not reach, such as the workplace or neighbourhood. This component emphases the crucial role of prevention in reducing the burden of chronic conditions. Healthcare interventions can reduce the onset of disease through early detection and promoting treatment adherence and healthy lifestyle behaviour.

Overall, the chronic care models present comprehensive strategies to successfully conduct chronic disease management, in which shifting to proactive care and enhancing primary health care are particularly highlighted. Shifting the healthcare system to proactive management of chronic conditions would ensure appropriate follow up and effective self-management support to address patients' needs in the context of their particular environments (1, 11, 12). Both models indicate that coordinating and integrating care across healthcare professionals and settings are important to meet the complex needs of people with chronic conditions. In their view, chronic disease management in primary health care is the ideal approach to reduce pressure on the health system from the burden of chronic disease and to maintain sustainability of healthcare systems around the world (10, 50).

2.3 Primary health care for chronic disease management

2.3.1 Characteristics of primary health care

Primary health care is considered as the basic cornerstone of effective and affordable healthcare systems, helping to optimise population health outcomes and ensuring equity across subpopulations (19, 69, 70). According to the WHO, primary health care is defined as ‘The first level of contact of individuals, the family and community with the national health system, bringing health care as close as possible to where people live and work, and constitutes the first element of a continuing healthcare process’ (71).

While primary health care has many shared attributes with other types of care, it also has some unique characteristics that mark it as an ideal setting for chronic disease management (72). In terms of accessibility, primary health care is often made universal to all levels of need and at any time instead of limiting access to a particular subset of needs, like specialist services. Primary health care often acts as the gatekeeper for other healthcare systems, responding first to needs initiated by individuals and then facilitating access to higher levels of healthcare services. At the first level of the healthcare system, primary health care is responsible for patient access to a wide range of services which are often broader than those provided by an individual specialist. As most of the problems appearing in primary care are common and less serious, the diagnostic process in primary care settings often consumes less testing and fewer complex procedures. In terms of management, primary health care holds comprehensive information about patients not only from current primary healthcare services but also

from other levels of care to support patient-centred care.

Overall, primary health care is recommended for effective chronic disease management as it is a ‘level of a health service system that provides entry into the system for all new needs and problems, provides person-focused (not disease-oriented) care over time, provides care for all but very uncommon or unusual conditions and co-ordinates or integrates care provided elsewhere by others’ (page 8 (72)). In many countries such as the UK, Australia, Canada, Germany and Scandinavian countries, GPs are the focal point of a successful primary healthcare system. GPs in these countries are the health professionals who act as the gatekeepers of the health care system, providing and leading patient-centred care (73-76).

2.3.2 Components of the primary healthcare system

Primary health care constitutes three main components, structure, process and outcomes, all of which have been examined and developed over decades (Figure 2.3) (72, 77-79). The structure of primary health care is anything related to governance, economic conditions, and workforce development (77, 79) that provides vision, direction and policy to facilitate performance and process of primary health care. Process of care highlights the importance of access, continuity, coordination and comprehensiveness (79). Outcomes of care are reflected through quality of care, efficiency of care and equity in community health provision (Figure 2.3). A systematic review found that structural components are associated with increasing access, continuity and coordination of care and promote the achievement of equity in health care (77).

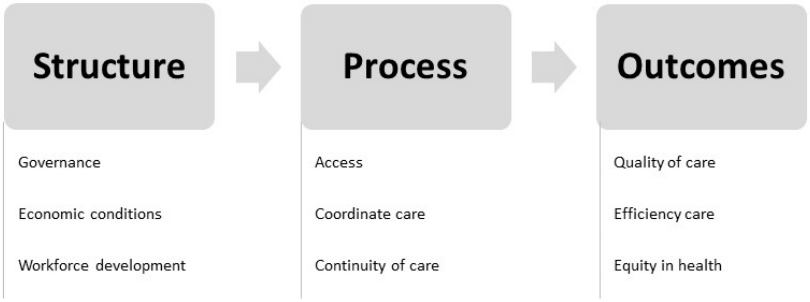


Figure 2.3. Framework of structure, process and outcomes

Source: *Modified from the work of Kringos, Boerma (77)*

The impact of the structural components on the outcome domain of primary care reflects changes in process of care, including in the areas of access, continuity, coordination and comprehensiveness. The subcomponents in the process of care are connected in a hierarchical order in which individuals start the process of care by gaining access to primary care and then enter the healthcare system in which care is provided in a coordinated manner and continuity base. The literature particularly highlights the importance of continuity of care as it is largely interrelated with coordination of care and associated with high quality of care, efficiency of services and patient satisfaction, especially for people with chronic conditions (26, 80, 81). Continuity of care also contributes to promoting preventive care and reducing hospitalisations and costs in a complex healthcare system (77, 79).

The outcomes of primary care have been measured in terms of quality, efficiency and equity of care. Potentially preventable hospitalisations (PPH) is a frequently used indicator to measure the efficiency of primary care, particularly for chronic conditions (82). Although it is widely used in research,

the indicator is not easy to define and measure (16). Thus, the concept of an admission for an ambulatory care-sensitive condition (ACSC) was introduced as a proxy measure of PPH (16). The implication of the indicator is that hospital admissions can be prevented through timely and effective management and early treatment provided in primary care settings (13). A broad range of conditions including vaccine-preventable, acute and chronic ACSCs have been identified in the literature and constantly revised to better reflect the performance of primary health care on the measure of avoidable hospitalisations (83, 84).

Although primary health care is a multidimensional domain, most studies only examined a single dimension, which is unable to fully reflect the complexity of the primary care. However, many systematic reviews have brought together multiple dimensions of primary care and drawn the focus towards development of integrated indicators (72, 77, 79). The ideal indicator should be able to capture the interrelation between access, coordination and continuity in the process of care. This facilitates understanding of the complexity of primary health care and provides opportunities for informed system change (72, 77, 79).

2.4 Continuity of primary health care

2.4.1 Continuity concepts

Continuity of care is an important element in the process of the primary care system to ensure high quality of care and patient satisfaction (27, 28, 85). The literature suggests two main perspectives of continuity of care – (i) interpersonal relationships and (ii) coordination of care. In terms of

interpersonal continuity of care, the American Academy of Family Physicians views continuity of care as the long-term relationship between identified physicians and patients that offers the opportunity to provide a high quality of care based on the known history of the disease and a holistic person perspective (23). This view particularly facilitates the leading role of the physician in a team-based approach to improve quality and safety of care, especially for people with complex and/or multiple chronic conditions (23). The perspective can be easily measured through the extent of care provided by a single (or specified group of) provider(s) (28). However, continuity of interpersonal relationships is becoming more difficult to sustain due to the changing nature of general practices over time and to the recent evolution of large multi-partner (or corporate) practices rather than the solo-practice model common in previous decades (26, 28).

In the current context of a high burden of complex and multiple chronic conditions, health care for people with complex needs is now hardly ever delivered by a single professional (28). Multi-disciplinary team care across a wide range of skills and settings is often employed to better manage chronic conditions. Thus, the other view of continuity of care is concerned with the extent of health care provided over time in a coordinated manner with appropriate response to patients' needs (86). It also focuses on patient-centeredness in which services are delivered in a respectful and responsive way to respond to patients' preferences and values and with more patient participation in clinical decisions (28). Coordination of care is believed to play a significant role to ensure adequate communication, sharing information and keeping records so that care can be delivered in order, uninterrupted and

consistently across disciplinary team members (28). Thus, most healthcare systems refer to continuity of care in terms of coordination of care to ensure that care meets the needs of patients, increases patient satisfaction, produces a high quality of clinical care and contains costs (28).

Multidimensional models of continuity of care proposed by Haggerty, Reid (26) have integrated both interpersonal continuity and coordination continuity. The model suggests continuity of care includes three main dimensions: relational continuity, management continuity and informational continuity. Relational continuity highlights a connection of past with current and future care. This model places great value on primary health care as it facilitates communication and building trust and relationships with multiple caregivers (26). Management continuity ensures that care delivered across providers is complementary and timely. Management continuity can be identified through activities such as regular contact or shared care plans. Regular contact with healthcare providers can offer opportunities to amend medication and facilitate accessibility to a broad range of services. The shared management plan can ensure care is delivered on time with less duplication (26). Information continuity is an important thread to connect care between healthcare providers. The information for sharing can provide a more comprehensive picture of disease status, preferences, values and context that is relevant to treatment and disease management (26).

Overall, continuity of care adds two main components to the existing models of chronic disease management in primary care settings: care over time and patient-centeredness (26, 28). High levels of continuity of care are associated

with positive patient experiences, patient satisfaction, increased treatment adherence (87), reduced number of hospitalisations (24) and fewer adverse health outcomes (27).

2.4.2 Challenges in measuring continuity

Many measures of continuity of care have been developed over recent decades (31, 88). The most commonly used measure of continuity is the usual provider of care index (UPC) which captures distribution of a health provider over a time period (31, 89). The UPC index measures the proportion of contacts with primary care practitioners that are the most frequently seen (90). The index shows a density of the most frequently visited provider - how often an individual visits the same healthcare provider over a given period (91). The advantage of the index is that it takes into account the total frequency of GP visits, thus, it can be adjusted for high frequency of visits due to disease burden (92). However, frequency in this sense is only recorded for a particular provider (31). Thus, it is unable to indicate a variation in frequency of visits changing across providers (91).

Another commonly used index which captures dispersion in continuity is the continuity of care index (COCI) (31). The COCI measures the degree of dispersion associated with visits to un-referred providers (93). As the COCI tracks multi-providers, it may reflect to some extent management perspectives but is still mainly used to measure continuity of care in terms of the interpersonal relationship between patients and providers (31). Similar to the COCI, the Herfindahl index measures the distribution of visits across providers, although it has a slightly different method of calculation (88). This

index is commonly used in economic analysis to measure concentration of providers (88).

The sequence index (SECON) of continuity of care measures the proportion of subsequent visits made to the same provider (52). It captures the total number of i^{th} visit and its subsequence $(i+1)^{th}$ visit that are from the same health care providers (91). However, this index may not be useful for non-sequential issues (91).

Literature indicates a high correlation between UPC, COCI, Herfindahl index and SECON, although it is slightly lower for SECON (88). Many studies have applied continuity indices such as UPC, COCI and SECON and found strong inverse associations with the number of PPHs (24), all-cause mortality (89) and a positive association with treatment adherence (87, 94).

Although continuity of care is a complex and multi-dimensional concept, the currently used continuity indices mostly reflect interpersonal continuity through quantifying the distribution of a single provider or multiple providers over a period of time (24, 27, 31, 32). With today's high burden of chronic disease, good management of care aims for comprehensive service delivery to give patients appropriate management plans and access to other healthcare services to meet patients' complex needs with less duplication (26). The literature suggests that robust ongoing management, rather than other aspects of continuity of care, contributes to patient satisfaction (30). There is no doubt about the importance of management continuity; however, limited measures are currently in place to support evaluation of the management of continuity of care. The development of measures that

capture the management aspects of continuity of care should be prioritised to encourage and evaluate effective continuity of care in the interests of efficient chronic disease management (27, 30).

Recent studies have included the element of time intervals between GP visits into the concept of regularity, capturing for the first time the degree of variation in the time intervals between GP contacts (33-35). Regularity index is measured using the equation: [1/(1+ SD)], in which SD is the standard deviation of time intervals between GP contacts. Studies suggest a strong association between regularity of GP contact and a reduction of number and costs of hospitalisations for selective conditions (37, 38). The regularity index may reflect to some extent management continuity of care, as high regularity suggests care that is planned and proactive, while visits on an irregular basis (even if frequent/numerous) are likely to indicate care that is unplanned or reactive and thus not indicative of effective ongoing management (36). Current evidence also shows that use of the Enhanced Primary Care Medicare Schedule items in Australia increases regular primary healthcare contact in the follow-up year (35, 38), suggesting that regularity is amenable to health policy intervention (35, 40). However, calculation of the regularity index using only the variation of time intervals between GP visits, is unable to differentiate if individuals with specific chronic conditions are receiving sufficient primary health care, as individuals with the same regularity score may have different time intervals between services. Although measuring for the time interval between services is relatively new in health service research, the concept has been used in measuring persistence of medication utilisation, which is capturing the time periods that people are receiving a

sufficient supply of a prescribed medication (41, 42). The time interval between services is also an important component in the framework of customer relationship management (43, 44) to evaluate the strength of the relationship between customers and service providers. Previous literature examining primary healthcare delivery incorporating a time interval component, such the annual cycle of care for people with diabetes, found its use was associated with a reduction in hospitalisations (4). Better understanding of time interval effects on health outcomes and health service utilisation would be useful for supporting both patients and GPs in planning for patient-centred care, ensuring the needs of patients are addressed proactively (9, 11). More knowledge of the effects of time intervals between GP services would offer opportunities to improve the effectiveness of chronic disease management and to measure the success of policies aimed at developing care strategies that are proactive , rather than relying on reactive approaches, which are expensive and ineffective (1, 47). Thus, development of an appropriate measure to capture continuity of care in terms of the time duration between GP services may offer benefits to optimising management of chronic conditions in the primary healthcare setting.

2.5 Chronic disease management in Australia

This section will set the scene for this research by contextualising the Australian healthcare system, especially primary health care and relevant chronic disease management policies. It demonstrates that GPs take a leading role in the primary care team to provide patient-centred care for the population, especially for people with chronic conditions. Given a strong

focus on GP roles in both policies and financial incentives pertaining to management of chronic disease, development of a measure that can assist in the comprehensive evaluation of GP performance would be useful for optimising primary healthcare service utilisation and allocating Australian healthcare resources wisely.

2.5.1 The Australian healthcare system

The healthcare system in Australia operates under a universally taxed or financed comprehensive health insurance (Medicare) scheme with both public and private provision and shared responsibilities between federal and state governments (95). The Australian (federal) Government retains most revenue-raising powers. Each state is responsible for its own healthcare and public health services but relies on financial transfers to support the delivery of services. For example, the states operate public hospitals but their funding comes from both state and federal governments. The Australian Government subsidises out-of-hospital services through Medicare via the Medicare Benefits Scheme (MBS) and prescription medicines via the Pharmaceutical Benefits Scheme (PBS) (95).

Medicare has operated through many different funding approaches. Prior to 1974, health care was funded by private insurance with public subsidies. It was changed to a national universal health insurance scheme between 1974 and 1976 and then returned to predominantly private insurance with public subsidies between 1976 and 1984. The national funding method then moved to publicly financed, universal health insurance between 1984 and 1996 to which publicly subsidised private health insurance was added from 1996 to

2013. From 2013 to the present, health funding takes the form of publicly financed universal health insurance with means testing for private insurance subsidies (95).

2.5.2 Australian primary health care

As in many European countries and Canada, primary health care is the first level of access (*i.e.* the gatekeeper) to the Australian healthcare system, mostly provided by private GPs and financed through Medicare subsidies and out-of-pocket payments. Although GPs act as the gatekeeper of the healthcare system, it is not required that individuals register with a single practitioner or general practice. People are free to visit any GP they wish and can visit multiple GPs and general practices simultaneously. The role of GPs has been emphasised in the Australian Medical Association (AMA) statement that GPs are the only physicians appropriate for taking the leading roles in the primary healthcare team and coordinating with other healthcare professionals to provide the best patient-centred care (20). The statement also indicates that, in the view of the AMA, GPs are the best primary healthcare professionals to perform patient-centred care, including diagnosis, treatment and management (20). The role of the GP and other primary care services in primary healthcare is presented in Figure 2.4.

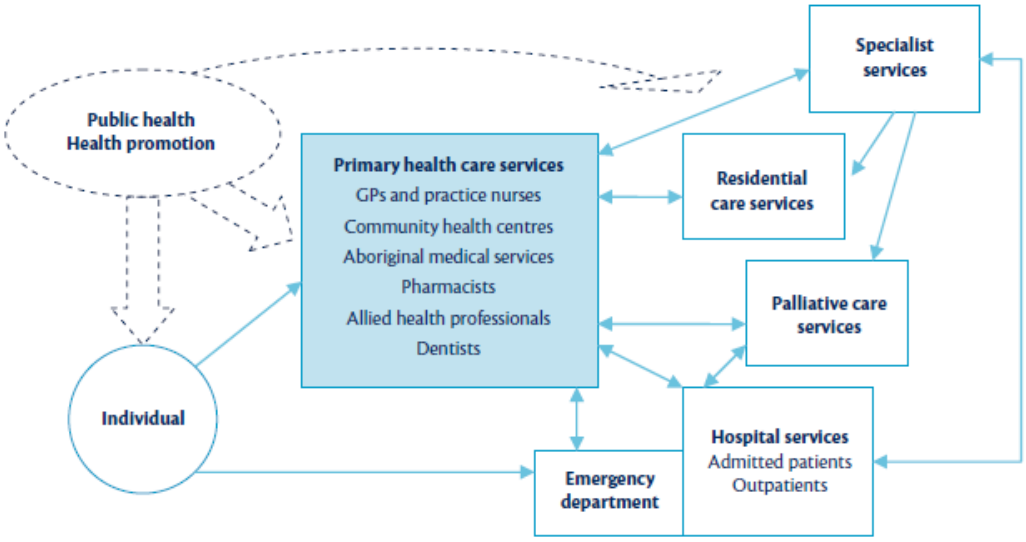


Figure 2.4. Framework for the roles of primary health care in Australia

Sources: AIHW (2008). *Review and evaluation of Australian information about primary health care: a focus on general practice* (96)

Medicare pays for GP services on a fee-for-service basis via MBS items listed on the Medicare Benefit Schedule and reimburses 85% of the MBS schedule fee. Since 2004–05, there has been an incentive to price-control the scheduled fee, known as 'bulk billing'; this provides direct reimbursement from Medicare to GPs and an increase in the reimbursement from 85% to 100% of the Medicare Benefit Schedule fee, provided the GP only charges the schedule fee (57).

According to a report from The Department of Health (97), there were a total of 34,632 GPs in 2015–16 (including GPs and other medical practitioners) who provided general practice services to about 24 million Australians (97). The national study, the Bettering the Evaluation and Care of Health (BEACH) program conducted in 2015–16, showed that GP services are the most frequently used health service in Australia, with 87% of the population having

made at least one Medicare Benefit Schedule claim from a GP consultation during that year (17). Within the 2015–16 financial year, Medicare claimed items for GP consultations made up about 143 million claims and cost almost A$6.8 billion (17). In terms of the problems managed, GP consultations accounted for a wide range of health problems, with an average of 154 problems per 100 encounters (17). In addition, GPs also frequently conducted integrating and coordinating care activities with higher levels of care, with about 10% of GP consultations referred to specialists and 6% referred to allied health services (17).

Primary health care in Australia, however, is faced with issues in equity of access to health care (98). While Medicare funding structures promote equity of access to primary health care for disadvantaged subpopulations, the lack of funding for other areas of primary health care, such as allied health and dental care are likely to increase inequity of access (98). In addition, disparity in access and utilisation of GP services were found between subpopulations, with relatively low use among those with low incomes or living in rural and remote areas (57). Moreover, individuals with lower socioeconomic status were more likely to have a higher prevalence of ambulatory care-sensitive conditions *i.e.* those conditions that could most benefit from more access to primary care. It has been suggested that the relatively recent trend of increasing involvement of the private health insurance industry in primary health care (due to major reforms of the private health sector in 2007 outlined in Broader Health Cover (BHC)) may impose a potential risk to equity in the sector (98). BHC for the first time allowed private health insurers to offer members programs which facilitate reduction of hospital use and support

chronic disease management (99). Since inpatient care is the traditional role of private health insurance in Australia, the limited availability of private inpatient care facilities in regional areas may reduce levels of private health insurance coverage in those areas and thus result in inequity of access to those chronic disease management programs provided by private health insurance (100). Inequity is also reflected in a substantially longer waiting time for access to surgery and specialist services among people without private health insurance compared with those with private health insurance (98, 100).

2.5.3 Chronic disease management in Australian primary health care

In Australia, primary health care has been integrated into the chronic disease management models, with an emphasis on GPs' roles. This commenced with the introduction of the Enhanced Primary Care (EPC) program in 1999 (101). The program comprised a wide range of Medicare Benefit Schedule fee-for-service items to encourage medical practitioners be become involved in ongoing management of chronic diseases for older people (102). The EPC items provided financial incentives for GPs to provide routine follow up, care plans and health assessments for the general population aged 65 years or older and Indigenous people aged 45 years and older. According to a preliminary evaluation of the EPC program in 2003, although the EPC items initiated positive changes in practices of GPs towards better integrating and planning care for older people with chronic conditions and complex needs, the EPC program only attracted a small number of practices to participate (103).

In 2004, the EPC program was expanded and re-packaged as the Medicare-Plus Chronic Disease Management (CDM) program, comprising additional MBS items. The CDM aimed to enhance multidisciplinary care for people with chronic or terminal medical conditions and in addition to the existing items provided funding for multidisciplinary team care planning incorporating a GP and at least two other health or care providers (101). Although no specific list of eligible conditions is presented, any chronic condition that requires ongoing and coordinated care over time, such as diabetes, asthma, cancer, cardiovascular disease and stroke, is under support of the CDM (104).

The new items allowed GPs to refer eligible patients to allied health professional services with costs subsidised by Medicare (102). The CDM program also initiated bulk billing incentive payments and incentives for GPs to undertake medication management reviews for older people. According to its financial report of 2008–09, Medicare spent about A$298.2 million on CDM items (105). Evidence showed that the CDM program helped to increase uptake of chronic disease management of MBS items (previously badged as EPC items) among GPs, especially items for GPs to refer their patients to allied health professionals (106). Literature also showed an increase in the regularity of GP visits (an indicator for proactive care) among people aged 65 years and older following use of chronic disease management MBS items (40). However, measurement in terms of number of care plans or team care management items per GP per year revealed that GP involvement in chronic disease management activities was still low, with only about 22 claims per year made per GP in 2008–09 (106). In addition, lower access to the CDM program was observed among males and those

living in rural areas, implying difficulty in the promotion and coordination of care for these groups (57).

In summary, the Australian Government has introduced policies and financial incentives to support the chronic disease management in the primary health care setting with a strong focus on GP roles. In addition, primary healthcare policies also orient CDM towards a patient-centred approach to ensure a high quality of care for people with chronic diseases. However, the system is still faced with challenges in finding efficient approaches to reduce the burden of costs related to health care service delivery for people with chronic diseases (57).

2.6 Data linkage for research

Linked data has been defined as multiple data collections linked at the individual level using data linkage techniques to provide powerful sources of information while maintaining individual privacy (107, 108). Dunn defined the original concept in 1946 as a ‘Book of Life’ which can provide comprehensive individual records from birth to death with information about an individual’s social and health events (109). As it utilises available administrative datasets, data linkage is often less intrusive and costly than other forms of data collection. The data often covers entire or large populations from multiple sources that are updated over time to provide a rich resource for research in a wide range of healthcare areas (110, 111).

This section describes the tremendous growth of Australian data linkage in both infrastructure and linkage capabilities which provide rich sources of information while conforming to the highest standards of ethical conduct. This

environment offers opportunities for health service research to improve efficiency in health service delivery and population health outcomes. However, there are challenges in using these data for research. Development of useful tools and approaches to address the challenges is needed to maximise the value and potential of the data and fully utilise the opportunities.

The following subsections will start with a brief overview of the infrastructure development of Australian data linkage, following by an assessment of its capabilities to ensure linkage accuracy and completeness, and privacy security. The section will conclude with a discussion regarding the opportunities and challenges of using linked administrative data for health services research.

2.6.1 Infrastructure development of Australian data linkage

Recognising the benefits of linked administrative health data, the Australian Government has made a large investment in establishing infrastructure of the data-linkage units throughout the nation and supporting implementation of secure data delivery (112).

The first initiative was the establishment of the Western Australian Data Linkage System (WADLS) in 1995 to facilitate development of research on aetiology, utilisation and health outcomes (109). Up to 2008 the WADLS had completed linkages for more than 40 administrative and research datasets (Figure 2.5) (110, 111). The WADLS has provided rich data sources for a range of users, including academic researchers, analysts, government and service agencies (109).

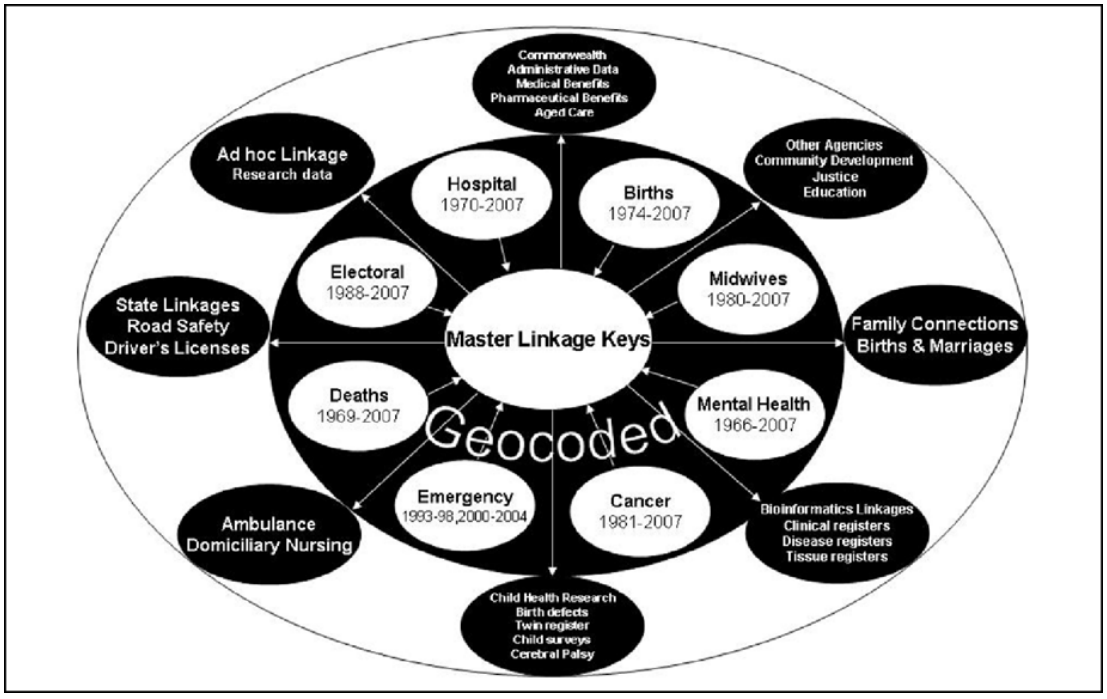


Figure 2.5. The Western Australia data linkage system 2007

Sources: *'Public good through data linkage: measuring research outputs from the Western Australian Data Linkage System', Volume: 32, Issue: 1, Pages: 19-23, DOI: (10.1111/j.1753-6405.2008.00160.x) (110).*

Following the success of the WA data linkage, a decade later the Centre for Health Record Linkage (CHeReL) was established in New South Wales (NSW) in 2006 (113). Although the CHeRel was formed later it has quickly developed and incorporated many core datasets for research. Currently, the CHeRel master linkages include 164 million records for 14.2 million people in NSW and the Australia Capital Territory (ACT) (114).

Based on the success of the two dedicated health record linkage units, WADLS and CHeRel, from 2009 the Australian Government has provided significant investment to form the Population Health Research Network which includes the establishment of data linkage units in all Australian states, the Centre for Data Linkage for links across Australian jurisdictions, the secure

remote access environment for researchers and the data delivery system (111). From this national initiative, many ‘Proof of Concept’ collaborative projects have been implemented that use cross-jurisdictional data linkage and further support research development (112, 115).

2.6.2 Capabilities of Australian data linkage

Accuracy and completeness

In Australia, because of the lack of a universal unique individual person identifying number, data linkage is conducted using probabilistic linkage methods to match individual demographic information (115). This is a process including two main steps: blocking and matching. The blocking step is carried out using a set of variables to identify those with a minimal level of agreement before implementing the matching step (115-117). The matching step is performed across demographic variables within a blocked pair of records. Based on levels of information agreement, a weighting is assigned to records and used for calculating a comparison score for each pair. The pair of records are deemed as a match if their comparison score exceeds a specific threshold (115). A systematic review shows that probabilistic linkage methods for linking health administrative databases achieved high sensitivity (74%–98%) and specificity (99%–100%) (118). The linkage systems in the states also have been reviewed intensively to make them consistent with international benchmarks (109, 115). In a recent study of cross-national data linkage, it was found that linkage using the jurisdictional keys achieved a very high matching efficiency (97%–99%) and extremely high accuracy (99.7%) (115).

Privacy security for data linkage

Privacy and security of the data linkage process in Australia has been maintained through implementing the best practice protocol based on the separation and multiple layer principle without compromising the quality of data (109, 111). Privacy is maintained as no single centre possesses both individual clinical information and linkage to programmatic contents (109, 111).

When accessing linked data, although each state can may have additional requirements in the approval process, there are well-documented guidelines for researchers to follow. In general, researchers need to obtain approvals from three stakeholders, including data linkage centres, data custodians and a human research ethics committee (119). With the increasing use of linked data, data privacy and protection has been protected through supporting data analysis carried out in the Secure Unified Research Environment (SURE) system. SURE provides a secure computing environment that allows researchers in Australia to access and analyse linked health data remotely (120).

Overall, data linkage in Australia has been established in accordance with the necessary safeguards to protect confidentiality and individual privacy to meet the highest standard of ethical conduct (119). This provides necessary infrastructure, laws and regulations to support research in many areas, such as health services utilisation, disease surveillance and methodologic development (109, 121).

2.6.3 Opportunities for health services research

Linked administrative data offers many opportunities for research due to its advantages in term of rich sources of information, comprehensive collection over time, across geographic areas, minimal bias due to loss follow up, and relatively low cost of collection (107, 122). Linked administrative data often contains information from various sources, such as hospital records, medical claims for reimbursement, prescriptions and diagnosis information (123). The multiple sources of information provide valuable clinical and demographic information about ongoing process of care and can act as a robust search tool to evaluate performance of health services (123). Systematic collection of data over time that allows researchers to conduct longitudinal design with low costs and accurately estimate incidence of health outcomes, especially for rare events which require large sample size and a long period of observation (122, 123). It offers opportunities to conduct large-scale studies in many fields of epidemiology, such as health services research, cancer research, clinical epidemiology and pharmacoepidemiology (107, 110, 121, 123, 124). In addition, the massive growth of computing power and infrastructure allows researchers to take further advantages of large linked administrative datasets to better understand latent patterns of service utilisation. Thus, application of advanced analytic approaches in linked administrative datasets will provide more opportunities to improve quality of health service research and support to address population health and health system issues (107, 122, 124).

2.6.4 Challenges in using linked data

Although linked administrative data has many advantages in terms of volume, variety and velocity, there are many challenges in using the data for health service research. One of the common challenges in using administrative data for research is that administrative data is not collected based on standard research designs (107, 124). Thus, to maximise the advantage of longitudinal data to answer specific research questions, researchers need to develop approaches that consider the data generation process (107, 124). Another common challenge of using data linkage is that not all required variables/conditions are captured in the datasets; thus proxy measures are required to enable full utilisation of the data (107). For example, traditional indicators to assess individual-level socioeconomic status, such as education, income, and employment status, do not often exist in the linked dataset. There is also a challenge in finding analytic approaches that can explore latent patterns of healthcare service utilisation to provide useful information and be readily interpretable for both policy makers and clinical users.

2.7 Summary of evidence in literature and focus of the research

2.7.1 Summary of evidence in literature

In the context of ageing population, chronic diseases have produced considerable pressures on healthcare systems, which are already strained. To address this, chronic disease management models have provided comprehensive strategies to organise and orient health care towards strengthening capabilities of the primary healthcare system. The models also

highlight the importance of shifting primary health care towards proactive care rather than costly and inefficient reactive care to better manage chronic diseases within stable delivery systems. The philosophy behind this is that primary health care, rather than other health professional sectors, has unique characteristics that significantly contribute to effective and affordable health care for populations with chronic conditions. The literature particularly points to continuity of care as an essential element of primary health care for people with chronic conditions, contributing to high quality of care, patient satisfaction and efficient use of resources. Three main dimensions identified in the continuity of care model include interpersonal continuity, management continuity and information continuity. Among these, management continuity of care is considered as an aspect that supports comprehensive service delivery and ensures care is provided on time and with less duplication. However, current measures of continuity of care mostly reflect interpersonal continuity of care through quantifying the distribution of providers. Thus, measures which can integrate management into the model would be useful to address the perceived challenges in measuring the continuity of care and thus to optimise efficiency in management of chronic diseases.

In the context of Australia, GPs are gatekeepers of the healthcare system and play a leading role in chronic disease management. The Government has made a large investment to enhance GPs' roles in management of chronic diseases through the provision of financial incentives under the Medicare scheme. Although preliminary evaluations following this suggest an improvement in GP participation in management of chronic conditions, the system is still faced with challenges to find more efficient strategies to reduce

costs related to healthcare service delivery, especially for people with chronic conditions.

Given the tremendous growth in the availability of large health administrative datasets for health services research in Australia, it is clear there are great opportunities to explore underlying patterns of service utilisation in large-scale datasets. Better understanding patterns of service utilisations would provide a powerful foundation to improve the efficiency of service delivery as well as quality of care and public health outcomes. However, there is to date a scarcity of useful tools that can maximise the power of the large linked health administrative datasets and make their data interpretable to policy makers and clinical users.

Overall, conceptual frameworks for chronic disease management emphasise that strengthening primary health care is crucial for addressing the burden of chronic disease, improving population health outcomes. One of the keys to success of primary health care for chronic disease management is continuity of care in terms of interpersonal relationships, information and management. Among these factors, management aspects should be prioritised to better support comprehensive chronic disease management. Development of measures that capture management continuity will facilitate the evaluation of multiple aspects of continuity of care and also be useful for policy development aiming at addressing the burden of chronic diseases. The Australian Government has made large investments in enhancing primary health care through promoting the leading role of GPs in chronic disease management. A comprehensive measure of continuity of care would provide

a useful tool for optimising service delivery and evaluating primary healthcare performance. In addition, given the increasing availability of big linked administrative data sets, development of a measure capturing the management aspects of continuity of care would maximise the value of this rich data environment and make a significant contribution to improving health service management.

2.7.2 Focus of the research

Evidence in the literature suggests that management of continuity of care is a crucial element in effective chronic disease management and patient satisfaction (24, 26, 30). Several recent studies have examined management continuity in terms of regularity of GP visits (33-35). Regularity is measured based on the degree of variation in the time intervals between GP visits, with high regularity suggesting a high level of planned and proactive care. High regularity was associated with lower number and costs of hospitalisations and has been suggested as a target area for health policy intervention (35, 40). However, based as it is on the variation of time intervals between GP visits, the regularity index does not capture whether individuals with a specific chronic condition are receiving a sufficient amount of primary health care. This is because regularity does not account for the actual intervals between GP visits (*i.e.* one visit every three months has a similar regularity score as one visit per year). A long interval between visits may suggest inadequate management of the patient's condition, as some of the protective effects of regular care to support self-management and treatment adherence may be lost over time. Measures that incorporate time intervals between services are relative new in health services research, but the concept has been widely

used in pharmaceutical studies to measure persistence of medication adherence (41, 42). It is also used as a key component in evaluating customer relationships with service providers (43). Integrating time intervals between GP services into the regularity measure would be useful to better measure the management aspects of continuity of care and evaluate sufficiency in the uptake of primary health care.

Hence, this research aimed to develop and test a new metric, the Cover Index which incorporates a time-duration component into regularity of contact with GPs. The study of a cohort of people with diabetes aims to capture management of continuity of care at the individual patient level using linked administrative data. The Cover Index measures the proportion of days within a fixed ascertainment period that a patient is considered to be under the 'protective effect' of their GP and thus potentially at lower risk of a PPH, as illustrated in Figure 2.6.

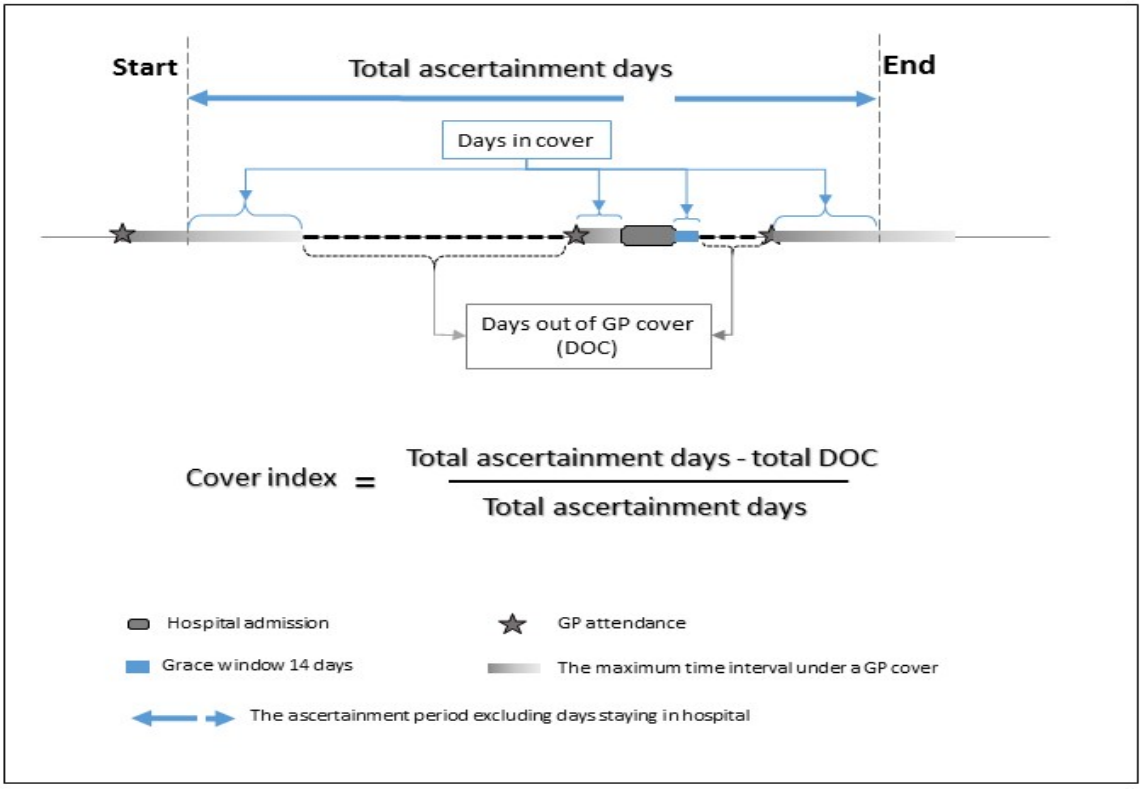


Figure 2.6. The Cover Index

The ascertainment period is preferably one year, since this is the time period on which current chronic disease management plans are based (48). In contrast to the persistence concept in drug utilisation studies, where the medication protective effect is usually clearly defined by the *in-vivo* half-life of the drug, in primary care no data exist to inform the most effective duration of a GP visit—that is, what duration has the maximum potential to protect a patient from an adverse event such as hospitalisation or medical complication. Thus, this research uses an empirical approach to estimate the protective effect – the cover period—in this operationalisation of the Cover Index. For the purpose of demonstrating this novel development of the index, studies were only conducted among people with diabetes, although a similar process could be applied to other chronic ambulatory care sensitive

conditions.

This chapter has presented the relevant conceptual frameworks and context of the healthcare system and linked data environment in Australia to set the scene and justify the overall aim of this research. The following chapter will focus on the data and key variables used in the research presented in this thesis.

Chapter 3 Data and key variables

This chapter provides an overview of the data sources, study populations, data structure, main measures and analytic approaches used in chapters 4 to 7. A summary of methods used in each chapter is presented in Table 3.1.

Overall, this thesis comprises two main stages. The exploration and development stage includes three studies, presented in chapters 4, 5 and 6. This stage used historical datasets obtained from the Western Australian Data Linkage System comprising whole-of-population linked administrative data from 1984 to 2004. These studies were conducted to: 1) classify diabetes severity; 2) explore patterns of GP utilisation using multiple attributes; and 3) develop the Cover Index.

The second main stage (application), is presented in Chapter 7, which reports on the use of the Cover Index in evaluating the impact of continuity of primary care on PPHs in the contemporary context. This stage used a longitudinal cohort and linked administrative data from The Sax Institute's 45 and Up Study carried out in New South Wales from 2005 to 2016.

Table 3.1. Summary of methods used in this thesis

Stage	Data sources	Chapter - Paper	Study population	Main predictors & outcomes	Analysis approach
Exploration & Development	WA datasets 1984-2004	**Chapter 4 - Paper 1** Diabetes severity classification	Annual panel data of people aged 18+ years old identified with diabetes on or before 1998/99	Diabetes severity complication Index Diabetes-related potentially preventable hospitalisations (PPH)	Threshold effects model
		Chapter 5 - Paper 2 Patterns of GP utilisations	Annual panel data of people aged 18+ years old identified with diabetes on or before 1998/99	GP utilisation: Maximum, Mean and Standard deviation of time intervals between GP visits Count number of GP visits Diabetes-related PPH	Cluster analysis Negative binomial model
		Chapter 6 - Paper 3 Development of the Cover Index	Annual panel data of people aged 45+ years old identified with diabetes on or before 1998/99	Maximum time interval Diabetes-related PPH	Threshold effects model
Application	NSW datasets 2005-2016	**Chapter 7 - Paper 4** Application of the Cover Index in evaluation of continuity of care	Annual panel data of people aged 45+ years old enrolled in the 45 and UP study identified with diabetes on or before 2008/09	The Cover Index Diabetes-related PPH Unplanned diabetes-related PPH Length of stay	Threshold effects model Generalised propensity score (GPS) in dose-response function

3.1 Data sources

This thesis used linked person-level data from Commonwealth MBS claims, PBS claims and comprehensive state administrative data from Western Australia (WA) and the 45 and Up Study in New South Wales (NSW). A summary of key information in each dataset is presented in Table 3.2.

For WA, the whole-of-population state or Commonwealth linked person-level data from 1984 to 2004 included data from the following datasets: (i) the WA Hospital Morbidity data system (HMDS); (ii) the WA Mortality data system; (iii) the MBS; and (iv) the WA Electoral roll. The data included all records pertaining to individuals aged 18+ years registered with Medicare in WA at some time during the study period. The WA data were linked using the Western Australian Data Linkage System (109) and the MBS data by the Commonwealth Department of Health. Further details of the datasets are also presented in chapters 4, 5 and 6.

For the 45 and Up Study, linked person-level data consisted of the following datasets (i) the NSW Admitted Patient Data Collection (APDC); (ii) the NSW Register of Births Deaths and Marriages (RBDM); (iii) the MBS; (iv) the Pharmaceutical Benefits Scheme (PBS); and (v) the 45 and Up Study baseline survey. The MBS and PBS data were linked deterministically. The linkage of the APDC, and RBDM to the survey data was conducted probabilistically by the NSW Centre for Health Record Linkage. MBS and PBS data were linked by the Sax Institute using a unique identifier provided by the Department of Human Services (125). Quality assurance data on the data linkage show false-positive and false-negative rates of <0.5 and <0.1%,

respectively (126). The data were accessed through SURE (120). Further details of these data are presented in Chapter 7.

Table 3.2. Summary of key information available in datasets used in this research

Databases	WA	NSW	Key information	Measures
Time period	1984-2004	2005-2015		
WA historical electoral roll	✓		Individuals' residential information in WA for each year of the study. Demographic characteristics	Dates of any migration in and out of WA, age, gender, postcode of residence in WA with dates, Accessibility/Remoteness Index of Australia (ARIA), and Socio-Economic Index for Areas (SEIFA) (ascertained from residential postcodes).
HMDS	✓		Date of admission Date of discharge Principal diagnosis and 21 additional diagnoses recorded in the ICD codes	Hospital outcomes Comorbidities Complications
APDC		✓	Principal diagnosis and 54 additional diagnoses recorded in ICD codes	Hospital outcomes Comorbidities Complications
The 45 and Up survey data		✓	Socio-demographic information among adults aged 45+ years (age, gender, Indigenous status, SEIFA, accessibility, income, housing status, and education) Self-report health status and conditions, smoking, alcohol consumption, BMI and physical limitation.	Identify people with diabetes Basic sociodemographic characteristics
MBS (Commonwealth)	✓	✓	Date of service, MBS item number. All claims for medical and diagnostic services subsidised through the MBS De-identified provider codes (only in NSW data)	Identify people with diabetes through HbA1c, diabetes cycles of care and Fructosamine quantitation Measure GP utilisation (Frequency of GP visits and time intervals between GP visits), UPC, Regularity and count number of specialist utilisations.
PBS (Commonwealth)		✓	Subsidised prescription medicines dispensed Item code, Anatomical Therapeutic Chemical (ATC) code, quantity and date supplied	Identify people with diabetes through ATC code of diabetes medications

3.2 Study population

Two algorithms were used to identify diabetes cohorts due to differences in available information in each dataset (Table 3.3). For the diabetes cohort identified from WA datasets, diabetes mellitus was determined if (i) at least one record in the HMDS included ICD codes in any diagnosis field indicative of diabetes; or (ii) MBS claims were indicative of the presence of diabetes. The algorithms were evaluated by the project clinical steering panel (which included researchers and GPs). Depending on the specific objective in each study of the thesis, the study population was further limited to certain age groups and selection criteria as described in each study.

For the diabetes cohort identified from the 45 and Up Study, diabetes mellitus was determined if (i) in the self-report survey, an individual answered yes to the question 'Has the doctor ever told you that you have diabetes?'; or (ii) if they had an APDC record with ICD-10-AM codes for diabetes, including E10, E11, E13 or E14 in any field of diagnosis; or (ii) a PBS claim indicating a dispensing between 2005 and 2009 using the ATC code of A10A (insulins and analogues) or A10B (blood glucose lowering drugs excluding insulins). The 45 and Up Study algorithm was based on previous published studies suggesting that a combination of self-reported diabetes, APDC and PBS data is the most useful combination to identify people living with diabetes, while MBS is less useful due to its low sensitivity (127, 128). However, since the WA data did not have either PBS or self-reported information, the MBS data were used as shown in Table 3.3, based on advice from the clinical project panel, to maximise sensitivity so that the WA cohort was not limited to those with a previous hospitalisation for diabetes (*i.e.* those with highest severity).

Table 3.3. Algorithms to identify people with diabetes

State	Data sources	Codes
WA	HMDS	ICD-9-CM: 250.xx ICD-10-AM: E10.xx, E11.xx, E13.xx, E14.xx
	MBS	Diabetes cycle care (2517, 2518, 2521, 2522, 2525, 2526, 2620, 2622, 2624, 2631, 2633, 2635) Fructosamine quantification (66557) Two HbA1c records within 18 months (66551, 66319, 66320, 2043, 2044, 1313, 1314)
NSW	APDC	ICD-10-AM: E10.xx, E11.xx, E13.xx, E14.xx
	PBS	ATC code of A10A (insulins and analogues) and A10B (blood glucose lowering drugs excluding insulins)
	Self-report	Response YES to this question 'Has a doctor ever told you that you have diabetes?'

3.3 Data structure

This research adopted a panel couplet structure for data analyses, depending on the specific objective of each study. Each couplet comprised pairs of years, where characteristics of the studied population (*i.e.* independent variables) were assessed in one year (initial year) and the outcomes (*i.e.* dependent variables) were measured in the follow-up year (Figure 3.1). These pairs of years (forming the couplet record) move forward through the time period of the data such that each follow-up year becomes the initial year of the next couplet. The couplet year design was developed by (129) for use in linked administrative data and has been applied in several recent studies (4, 130, 131).

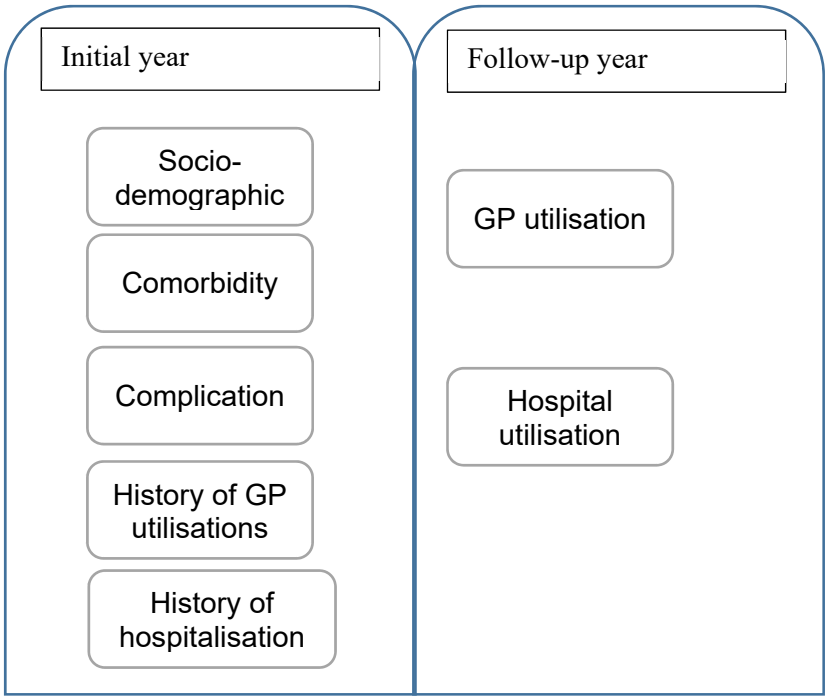


Figure 3.1. Structure of an individual couplet record

3.4 Main measures

3.4.1 Hospital outcomes

Potentially preventable hospitalisations (PPHs) have previously been used as an indicator to measure performance of primary health care in Australia, due to its simplicity and ability to be routinely ascertained via hospital morbidity datasets (132, 133). The rationale behind the indicator is that timely and effective provision of health care through early treatment, prevention and management of disease delivered in primary health care settings can prevent hospital admissions for ambulatory-sensitive conditions such as diabetes (132, 134). In this thesis, the primary outcome was specified diabetes-related PPHs. The diabetes related PPHs included diabetes PPH using ICD-9-CM and ICD-10-AM suggested by the National Health Performance Framework (135); and hospitalisations related to diabetes where the risk of

hospitalisation is significantly increased in people with diabetes as suggested by Davis et al (136). This method of assigning PPHs as diabetic-related was required because most diabetes complications are not specifically recorded as diabetes in the principal diagnosis in hospital records (137, 138). The inclusion of hospitalisations related to diabetes, as defined in this research, better captures the hospital burden of diabetes. Details of the ICD codes used to identify diabetes-related PPHs measured in this research are presented in Table 3.4.

Unplanned diabetes-related PPH was another outcome considered in Chapter 7. This was defined as diabetes-related PPH with admission through the Emergency Department.

Length of stay of diabetes-related PPHs and unplanned diabetes-related PPHs were also used as indicators in Chapter 7 and were defined as the number of days spent in hospital for admissions identified as diabetes-related PPHs, or unplanned diabetes-related PPHs, respectively.

Table 3.4. Identifying diabetes-related PPHs

Conditions	ICD-9-CM principal diagnosis and procedure codes	ICD-10-AM principal diagnosis and procedure codes
Diabetes/diabetes complications	250	E10-E14
Circulatory disorders		
Hypertension	401-405	I10-I13, I15
Ischemic heart disease	410-414	I20-I22, I24, I25
Cerebrovascular disease	430–438, 362.34, 784.3	I60-I67, I69, G45, H34.0, R47.0
Heart failure	428, 429.2–429.3, 429.9	I50.0-I50.1, I50.9, I51.6-I51.7, I51.9
Atherosclerosis	440	I70
Peripheral vascular disease	443, 459.8–459.9, 444, 447.1	I73, I87.2, I99, I74, I77.1
Visual disorders		
Glaucoma	365	H40, H42.8
Cataract	366	H25-H26, H28.0
Blindness	369	H54
Other disorders		
Nephropathy	580–586, V45.1, V56	N00, N01, N03-N05, N07, N08, N16-N19, Z49, Z99.2
Other renal complications		
Infections of kidney	590	N10, N11.8-N11.9, N12, N15.1, N15.9, N28.8
Cystitis, urinary tract infection	595, 599.0	N30, N39.0
Proteinuria	791.0	R80
Neuropathy/other neurologic symptoms	354, 355, 356.8, 729.2	G56-G57, G58.7, G60.8, M79.2, M54.10, M54.11, M54.19
Chronic skin ulcer	707	L89, L97, L98.4
Gangrene	785.4	R02
Non-traumatic lower-extremity amputation or revision	84.1, 84.3	44338–00, 44358–00, 44361-00, -01, 44364–00,-01, 44367–00, -01, -02, 44376–00
Other complications		
Candidiasis of vulva and vagina	112.1	B37.3 N77.1
Chronic osteomyelitis of the foot	730.17	M86.37, M86.47, M86.57, M86.67, M86.87
Cellulitis	681, 682	L03

3.4.2 Main predictors

Depending on the objective(s) of each chapter, the following predictors were constructed, as described in Table 3.5. Further details of each measure are also presented in the relevant methods section of the papers presented in chapters 4 to 7.

Table 3.5. Description of main predictors in this research

Chapter	Measure and description
Chapter 4 Diabetes severity classification	Diabetes complication severity index (DCSI) The DCSI was measured using a scale suggested by Young, Lin (139). The diabetes complication was identified using ICD codes recoded in HMDS data in WA and weighted with complication severity. The scale ranged from 0–13 to indicate severity level. In this study, DCSI was accumulated in each financial year from 1998/99 to 2003/04 with a retrospective period up to 1990 for any historical complication. Further details of ICD codes and weights are presented in Chapter 4.
Chapter 5 Patterns of GP utilisations	GP utilisation (including frequency and recency) was adapted from the framework for customer relationship management (140). The measures were captured using MBS data integrated with HMDS data. A brief description of each factor is as follows. Frequency of GP visits was the sum of number of GP visits within each financial year. The time intervals between GP visits was calculated in days between all GP visits in each financial year with special consideration for the start of the year such that time was calculated between the date of the first GP visit in the year and the date of the most recent previous GP visit, with a maximum lookback of 3 years. If there was a hospital admission during the ascertainment period, the time spent in hospital was excluded and calculation of the time interval was re-started either from the first GP visit, if it was within 14 days of discharge, or from the14th day after discharge, whichever came first. Annual recency was captured through three indicators regarding the time interval between GP visits, including (i) the average of time intervals between GP visits, (ii) the maximum time interval between GP visits and (iii) the standard deviation of time intervals between visits. Other alternative indicators, including the median of the time interval between GP visits and the median absolute deviation, were also considered. Further details of these measures are presented in Chapter 5.

Chapter	Measure and description
Chapter 6 Development of the Cover Index	The GP perspective on length of temporal protective effect following a GP consultation from the risk of hospitalisations and complications for people with diabetes was evaluated using a semi-structured survey among selective GPs currently practising in Australia. The maximum time interval between GP visits in each financial year was used as a key predictor to estimate the optimal maximum time interval under GP cover. The optimal maximum time interval was then used to operationalise the Cover Index. The Cover Index is defined as 'The proportion of time that an individual is under GP cover over a pre-specified ascertainment period'. The Cover Index for the study was calculated by (Sum of ascertainment days – Sum of days out of GP cover) / (Sum of ascertainment days). The Cover Index was calculated separately for each financial year over the period 1998/99–2003/04 in WA.
Chapter 7 Application of the Cover Index in evaluation of continuity of care	The maximum time interval between GP visits in each financial year between 2009/10 and 2015/16 from The Sax Institute's 45 and Up Study in NSW was used as a key predictor to estimate the optimal maximum time interval under GP cover and subsequently used for operationalising the Cover Index in this cohort. The Cover Index was calculated annually, and then the average of each three-year period (2009/10 to 2011/12 and 2012/13 to 2014/15) was used to measure the association of GP cover with diabetes-related PPH and LOS, controlling for other facets of continuity of care.

3.4.3 Other covariate measures

For this thesis, the covariates available for each individual study are described in Appendix G. In summary, the covariates include a number of demographic characteristics: age group (18–44, 45–59, 60–74 and ≥75 years); gender; Indigenous status; and ethnicity. Socioeconomic status was measured including quintile of the Census specific Socio-Economic Indexes for Areas (SEIFA) Index of Relative Socioeconomic Disadvantage (141), quintile of accessibility to services (ARIA) (142), household income, marital status, and education. Health behaviours and indicators included smoking status, alcohol consumption, physical activities, body mass index (BMI), psychological distress, level of limitation, social support, and a number of

comorbidities.

In addition, the number of comorbidities was also calculated from administrative hospital data (APDC and HMDS). This was summed from a list of comorbidities as suggested by Holman *et al*. (143, 144), excluding conditions classified as complications of diabetes.

The duration of diabetes was expressed in years from the date of a diabetes indicator first identified in any dataset, including MBS, PBS, self-reports in the 45 and Up Study and HMDS or APDC, depending on the availability of datasets in each state.

The frequency of GP usage was defined as the total number of GP visits within a financial year, excluding those GP visits occurring within 14 days of the previous GP visit. This exclusion was to minimise over-counting GP service utilisation, as visits within 14 days were thought by our expert primary care clinicians more likely to be associated with the existing episode of care rather than being indicative of a new episode (e.g. returning for the results of tests); this feature has also been noted in the literature (78).

The number of out-of-hospital specialist visits was identified using MBS claims data, amalgamated in each financial year.

The number of non-diabetes-related PPHs was a count of any hospitalisations which were not classified as diabetes-related PPH in either HMDS or APDC.

The regularity of GP visits was calculated using the standard deviation of time interval between GP visits in each financial year as [1/(1+standard deviation)] for each individual, described in detail elsewhere (33-35).

The usual provider continuity index (UPC), one of the most commonly used indexes to proxy interpersonal continuity of care, was measured using de-identified provider codes in the MBS which is however, only available in the MBS dataset in NSW.

The UPC measured the proportion of GP contacts within each financial year that was provided by the same provider (24, 31).

3.5 Analysis approach in this research

To optimise its use of large administrative data, this research applied data-driven analysis approaches, including threshold effect models and cluster analyses to explore the latent pattern of service utilisation. In addition, the generalised propensity score was used to control for any bias arising from the unbalanced distribution of observed covariates in estimating the dose-response function of the Cover Index on diabetes-related PPHs. An overview of each of these techniques is provided below, but also explained in greater detail in the relevant chapter.

3.5.1 Threshold effect approach

Threshold effect models were suggested by Gannon, Harris (145) to be used in the context of discrete data. Given a parametric model with conditional density function $f(y|\ x;\emptyset)$ and parameter vector $\emptyset$, the threshold effects model allows variation of $\emptyset$ values across subpopulations identified by threshold τ in an observed variable *r*. The simple form of the model is presented as follows.

$$fM(y|x,r,\emptyset,\tau) \quad = \sum_{m=1}^{M} f(y|x,\emptyset_m) \quad .r_m(\tau)$$

Where $r_m(\tau) = 1\{\tau_{m-1} < r \quad < \tau_m\}$ and 0 otherwise, *M* is the number of subpopulations which are determined by thresholds τ. Both *M* and τ are estimated from the data along with the process of searching for the preferred model through dimensions of both *M* and τ. The preferred model is the one with the least number of parameters but maximising log-likelihood value. Information criteria including Bayesian Information Criteria (BIC) and Akaike Information Criteria (AIC), were used for selecting the optimal model. Any parametric model estimated by maximum likelihood techniques can be expanded to include such threshold effects.

In essence this approach considers any discrete choice, or limited dependent variable model (such as a binary 0/1 logit), which embodies a covariate (or several) that has (have) an unknown nonlinear relationship with the outcome variable of interest. The technique assumes that this relationship is proxy, by a step-function approach, with an unknown number of breakpoints at unknown positions. It effectively considers thousands of trials with differing numbers and positions of such breakpoints, and simply selects the one that minimises the information criteria (AIC and BIC). In essence, this is simply a form of machine learning.

The threshold effect model was then applied to the random effects negative binomial model. The negative binomial model was chosen to take into account over-dispersion of the count outcome variable of interest, *i.e.* diabetes-related PPH. The random effects estimator was used as it is more efficient than the fixed-effect estimator in large datasets, as suggested by Cameron and Trivedi (146). The model also included Mundlak variables, (group means of time-varying variables) to allow for arbitrary correlation

between observed and unobserved heterogeneity terms in the model with panel data (147, 148). The initial condition (history of diabetes-related hospitalisations at the baseline year) was also included to allow for any endogeneity arising from the dynamic set-up of the approach (149). Details of the model specification specific to each analysis is presented in the methods section of chapters 4, 6 and 7.

3.5.2 K-mean cluster analysis

Another data-driven approach used in this thesis is K-mean cluster analysis which has been used previously to classify customers showing similarities among multiple attributes into appropriate clusters (150, 151). The philosophy of the approach is that it groups individuals into clusters that can help to maximise between cluster heterogeneity and within cluster homogeneity (150, 151). K-mean cluster analysis is one of the most common techniques used to stratify individuals into subpopulations as it is simple and quick to perform (151). This technique is also less susceptible to extreme values and is recommended for use in large datasets (150). In this study, the K-mean cluster analysis approach was used to combine multiple attributes of GP utilisation to better identify patterns of GP utilisation among people with diabetes. Details of the application is presented in the methods section of Chapter 5.

3.5.3 Generalised propensity score in estimating the dose-response function

This generalised propensity score (GPS) approach was used in Chapter 7 in order to achieve a better balance in the observed covariates between different levels of the Cover Index. The GPS was then used as a covariate in

estimating effects of the Cover Index on the number of diabetes-related PPHs, unplanned diabetes-related PPHs and length of stay, using the dose-response function.

The propensity score approach was introduced by (152) and has been widely used in the context of observational data to minimise bias caused by any imbalance in the distribution of confounding factors when estimating the effect of a treatment variable on health outcomes (153, 154). Although methods to estimate the propensity score have been well-established for binary treatment variables (154, 155), there is a paucity of practical guidelines for using GPS for continuous treatment variables or for fractional treatment variables such as the Cover Index.

In this study, the GPS was estimated through generalised linear modelling which accommodates different distribution functions, including fractional treatment data, by simply changing family and link function, developed in a Stata package (156). The GPS model included covariates that are theoretically associated with both the Cover Index and hospital outcomes (diabetes-related PPH and unplanned diabetes-related PPHs) or only hospital outcomes, as recommended in the literature (155, 157, 158).

Assessing covariate balance is an important step when using the GPS (159). The GPS balance diagnostics were conducted by comparing overlapping areas of GPSs between treatment intervals. Those having a GPS that were not comparable with any other treatment interval were removed. The remaining population was then further assessed for covariate balance using blocking on the quintiles of GPS, as suggested by (160). Both the standardised mean difference and t-test were used to evaluate covariate

balance achievement (156, 159). Following the literature, the GPS was then used as a covariate adjustment in the estimate of the dose-response function (156, 159). Covariate adjustment using the GPS is recommended when the extent of confounding is large as it produces lower variability and fewer mean-squared errors compared with GPS-based weighting approaches (161). Further details of the application of the GPS is presented in Chapter 7.

Chapter 4 Stratification Strategy for Diabetes Severity

Chapter 4 consists of a study developing a strategy to classify diabetes severity based on the association between the diabetes complication severity index and diabetes-related hospitalisations. This study used Western Australian linked administrative datasets for 40,624 individuals with diabetes aged 18 years or older. A 13-scale diabetes complication severity index was used as the main predictor of diabetes-related hospitalisation in threshold effect models to identify the homogeneity in the risk of hospitalisation across changes in the DCSI.

The results indicated that up to four subpopulations, comprising individuals with no complications, one complication, two complications and three or more complications, could be used to stratify diabetes severity. The finding was used to inform the next stage of the analysis, which needed to account for severity of diabetes in the context of linked data.

The following manuscript was accepted on 29 March 2017 and first published online on 5 April 2017.

Thi Ninh Ha, Mark Harris, Suzanne Robinson, David Preen & Rachael Moorin. (2017). Stratification strategy for evaluating the influence of diabetes complication severity index on the risk of hospitalization: a record linkage data in Western Australia. J Diabetes Complications, 31(7), 1175-1180. doi:10.1016/j.jdiacomp.2017.03.015

The PDF of the published paper can be found in Appendix B; however, for ease of reading, the paper is reproduced formatted for the thesis here.

4.1 Introduction

Diabetes is a serious chronic condition leading to complications in multiple body systems and high risk of premature mortality (162). It affected 422 million adults, equal to 8.5% of the global adult population in 2014 (162). The prevalence of diabetes in Australia was around one million in 2012, and is estimated to increase to three million Australians by the year 2025 (62, 163). Diabetes imposes a considerable economic burden both at the individual level and for healthcare systems (162, 164). It has been predicted that the burden will substantially increase in the next several decades as a result of an increase in prevalence, cost of health care and population ageing (162).

It has been estimated that only half of those with diabetes in both Australia and the US achieve adequately managed blood glucose control in the long term (62, 165). It is therefore unsurprising that rates of complications from diabetes are known to be high, with one study finding that approximately 27% of people with diabetes have some form of macrovascular-related complication and that 50% have microvascular-related complications (166). In addition to affecting an individual's health, complications from diabetes also have a large impact on hospitalisation rates and costs. People with diabetes who have multiple chronic complications tend to be hospitalised at a higher rate and stay in hospital longer than those with no complications (139, 167, 168). Costs of health care for people with diabetes with complications have been found to be substantially higher than for those without complications (167, 169, 170).

Recent studies have examined the effect of diabetic complications on health

care utilisation using the number of complications or DCSI as a continuous variable or a categorical (ordinal) factor in linear regression (139, 167, 170, 171). Although the linear approach is flexible enough to examine the overall pattern of the relationship between the number of complications or DCSI and health care utilisation, it may not reflect the underlying probability of the relationship given the conditional nature of subsequent events on prior complications (172). Our assumption is that if diabetic complications are treated as a continuous variable, the impact of subsequent complications may not be accurately characterised, since by definition the linear nature of the model treats each subsequent increment of one complication as having the same impact across the full range of number of complications. Alternatively, if the number of complications are categorised into subgroups, using appropriate cut-off points for stratification, then non-linear relationships between the cumulative number of complications and health care use could be included in models. This approach could provide a greater understanding of the impact of diabetic complications on health care utilisation and such a classification of the diabetic population would be more suitable for evaluating healthcare interventions and planning healthcare provision than current approaches.

The aim of this study was to examine if the relationship between prior complications from diabetes and the risk of subsequent diabetic-related hospitalisation is heterogeneous and how the relationship varies across different levels of complication, using individual-level linked whole-of-population administrative data in Western Australia (WA).

4.2 Methods

4.2.1 Data sources

The guidelines from the Reporting of Studies Conducted using Observational Routinely-collected Health Data Statement (173) were applied to present this study. The study used whole-of-population administrative health data that were linked at the individual level using the WA Data Linkage System (174). The linked data were limited to individuals aged ≥18 years who were enrolled to vote in WA at any time between 1 January 1988 and 31 December 2004. For each individual, the following person-level linked data were extracted:

- WA Hospital Morbidity Data System (HMDS) records (1980-2004) comprises diagnoses, dates of admission and discharge for all hospital separations in WA. Diagnoses are coded using International Classification of Disease (ICD) codes, including the principal and up to 21 additional diagnoses.
- Medicare Benefit Scheme (MBS) claim records originating in WA (1984 to 2004) includes all claims for medical (general practitioners), specialist, nursing and allied health care and diagnostic services provided to all Australian citizens. The data provide the date of service and Item Number of the claim.
- WA Electoral Roll records (1988-2004) include information indicating the dates individuals migrated in and out of WA and therefore time periods individuals were eligible for the study. As voting is compulsory for all Australian adults the Electoral Roll provides almost comprehensive population data (175) incorporating gender, date of

birth, and residential location; furthermore changes to address are actively captured (including emigration) (176, 177).

- WA mortality records (1988-2004) includes all deaths in WA registered in the WA Registry of Births, Deaths and Marriages. These data provided information to identify any individuals in the cohort died during the study period.

4.2.2 Study population

Eligibility for the study was based on (i) at least one previous record indicating diabetes in the HMDS or MBS data prior to the start of, or in the baseline financial year (1998/99); and (ii) at least two continuous years alive and resident in WA. Diabetes mellitus was determined using the International Classification of Disease, 9th edition-clinical modification (ICD-9-CM) codes in HMDS records (Table 4.1). MBS claims indicative of presence of diabetes (Table 4.1) were identified for each individual.

Table 4.1. ICD codes and MBS items indicating diabetes

	ICD-9-CM	ICD-10-AM	MBS items
Diabetes mellitus	250.xx 648.0	E10.xx, E11.xx, E13.xx, E14.xx O24.0, O24.1, O24.3,	
Diabetes cycle care			2517, 2518, 2521, 2522, 2525, 2526, 2620, 2622, 2624, 2631, 2633, 2635
Fructosamine quantification			66557
Two HbA1c within 18 months			66551, 66319, 66320, 2043, 2044, 1313, 1314

The study examined the relationship between complications of diabetes in one year (the exposure year), and hospitalisation in the following year (the

outcome year). Thus for each individual in the study population data pertaining to a series of pairs (or couplets) of eligible financial years, one being the exposure year and one being the outcome year formed the unit of evaluation. The couplet design has been applied in the recent publication (4). Periods of temporary exit and re-entry to the study cohort were captured via Electoral Roll records that indicated outward or inward state migration. These data were used to ascertain residence within WA. The individuals were observed from the baseline year to 30 June 2004 for any change in complications, hospitalisations or related characteristics.

Ethical approval was provided by The University of Western Australia and Curtin University Human Research Ethics Committees who exempted the study from obtaining individual patient consent.

4.2.3 Study outcome and predictors

Diabetes-related hospitalisations

Hospital separations classified as potentially preventable for diabetes by the National Health Performance Framework (135) and those where diabetes was identified as a significant risk factor by Davis *et al*. (136) were classified as diabetes-related hospital admissions using the primary or secondary diagnosis codes and all procedure codes on the HMDS separation record. The number of diabetes-related hospitalisations in each follow-up financial year over the study period was captured as a count variable.

Diabetes Complication Severity Index

The 13-point Diabetes Complication Severity Index (DCSI), developed by Young, Lin (139) and modified by Chang, Weiner (178), was used to

measure the severity level of diabetic complications. The DCSI has been validated and widely used, and has shown better performance than a simple count of the number of complications (139, 171, 178). The DCSI includes a severity score (0, 1, and 2) for seven categories of diabetic complication: cardiovascular disease, nephropathy, retinopathy, peripheral vascular disease, stroke, neuropathy, and metabolic. Scores indicating severity level range from zero to a maximum of 13. Complications were identified as suggested by Davis, Knuiman (136) and Young, Lin (139) and coded using ICD-9-CM mapped to the 10th Revision, Australian Modification ICD codes (ICD-10-AM) where appropriate (Appendix A). The DCSI in each financial year was an accumulation of the DCSI from the first ever record of the complication in the data for each individual.

Covariates

This study used the following covariates in the multivariate analysis: general demographic covariates (sex, age, and Indigenous status); quintiles of the census-specific Socio-Economic Indexes for Areas (SEIFA) Index for Relative Socio-economic Disadvantage, a relative classification of socioeconomic status by geographic area obtained from the Australian Census conducted every five years (141); accessibility to services using the Accessibility and Remoteness Index of Australia (ARIA+) derived from census-specific ARIA indices (142); quintile of frequency of general practice visits ascertained from MBS claims data (score categorised as 0 to 4); history of diabetic-related hospitalisation in the observed year (yes/no), ascertained using all prior HMDS records; duration of diabetes in years between the date of the first identification with diabetes in either MBS or HDMS and the date 30

June of each study year. Both socioeconomic status using, SIEFA and accessibility to services using ARIA+ were ascertained using the postcode of residence on the Electoral Roll data for each year of residency in WA.

4.2.4 Statistical analyses

The data in this study were constructed as a panel structure where individuals had multiple records indicating changes in exposure, outcomes and covariates over the study financial years. The panel was unbalanced and complex since individuals moved in and out the study population on multiple occasions or died prior the end of the study period. Descriptive and multivariate analyses were conducted to account for the unbalanced data. Threshold effects models were used to examine the non-linear relationship between the DCSI and the risk of hospitalisation. Threshold effects models were performed on a restricted panel dataset (restricted sub-population A), that excluded those who moved in and out of the state during the study period or who died prior to the end of the study period. This acted as an internal validation of the final threshold model. Another internal validation was also conducted on a subpopulation (restricted subpopulation B), excluding those who had diabetes with kidney dialysis, to examine if serious complications may cause bias in the models. STATA for Window version 14.1 was used for this analysis.

Descriptive analyses were performed to evaluate the distribution of hospitalisation and no hospitalisation in the baseline financial year 1998/99 across socio-demographic and clinical characteristics. The results were presented in mean, standard deviation (SD) and range for continuous variables and percentage for categorical variables.

Random effects negative binomial regression models for panel data were used to examine the relationship between the DCSI and hospitalisations in bivariate and multivariate analyses. The negative binomial regression model was chosen for use in this study because the outcome variable (the number of hospitalisations) was over-dispersed (179). Both the Bayes Information Criterion (BIC) and Akaike Information Criterion (AIC) statistics and a graph of observed versus predicted counts of hospitalisations indicated that a negative binomial model was preferable to a Poisson model (Figure 4.1). A random effects estimator was more efficient than the fixed effects estimator in our study as our study included a large number of observations (n=180 385 observations) (146). Mundlak variables were defined as group-means of time-varying variables. Mundlak variables were used in our models to relax the assumption in the random-effects estimator that observed variables were uncorrelated with the unobserved variables (147, 148). The Mundlak variables used in this study included the DCSI, duration of disease, hospitalisation status, SEIFA, accessibility to services, and quintile of frequency of general practitioner (GP) visits.

Threshold effect models were used to further examine the homogeneity in the impact of the DCSI on the risk of hospitalisations given the DCSI at each observed financial year. The model searched for sample homogeneity in the response of number of hospitalisations to variations in the complication severity index identified in each financial year. The approach was proposed in previous publications (145, 180) to determine both the number of subpopulations and their definition. The ‘true’ regression model was the one with minimum information criteria (AIC and BIC). A similar procedure for the

threshold models was also performed on the restricted panel data.

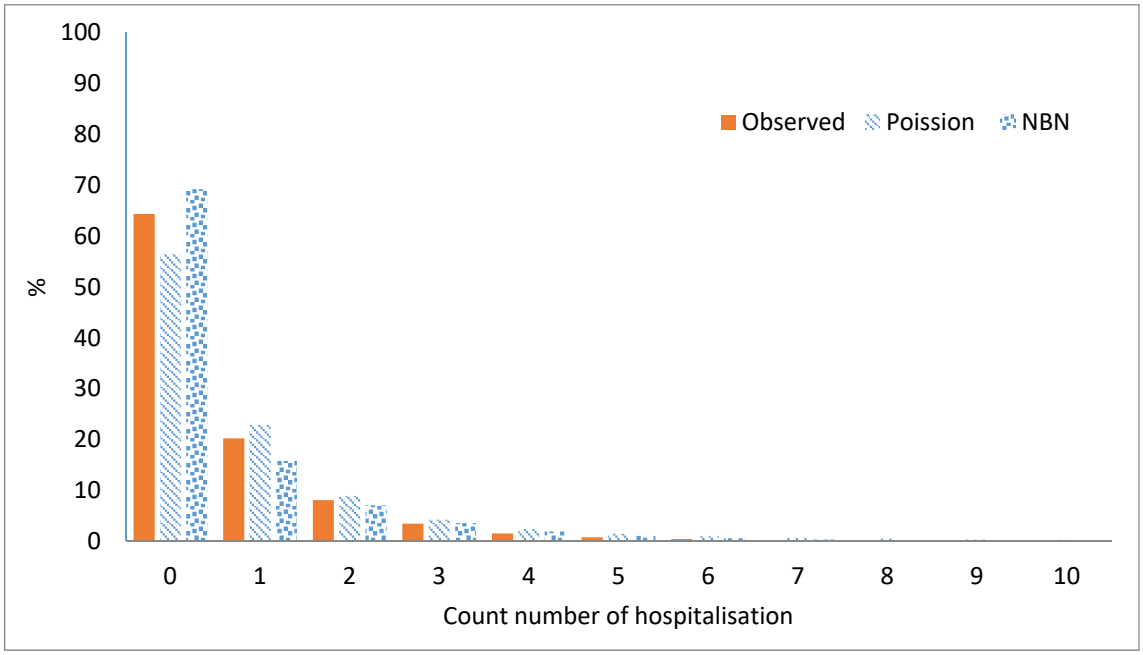


Figure 4.1. Observed versus predicted probabilities from Poisson and Negative binomial regression

The threshold effects model

The model endogenously searched for sample heterogeneity in the response of number of hospitalisation to variations in the DCSI identified for each financial year. This approach is based on finding the optimal number and position of breakpoints with regard to model selection criteria (the Bayes Information Criterion (BIC) and Akaike Information Criterion (AIC)), following Gannon, Harris (145) and Gonzalo and Pitarakis (180) which here determines both the number of subpopulations and their definition(s). We apply this general technique to a nonlinear panel data model (negative binomial, due to the count nature of our dependent variables). The approach is detailed below.

The standard random effects negative binomial regression for the

relationship between DCSI and hospitalisations (*HOSP*) is presented:

$$HOSP_{it} = \gamma DCSI_{i,t} + \beta_1 X_{i,t} + \beta_2 \bar{x}_{i,t} + \alpha_i + U_{i,t} + \beta_0$$

$$, i = 1,2 \dots N; t = 1,2 \dots, T$$

with $DCSI_{it}$ and X_{it} being DCSI and other explanatory variables of individual i at time t ; γ a vector of unknown coefficients; $\bar{x}_{i,t}$ being Munlak (148) variables; $U_{i,t}$ an error term and $HOSP_{it}$ is an observed count hospitalisations. The latent hospitalisation is assumed to be mapped into the observed dependent hospitalisations $HOSP_{it}$ by

$$HOSP_{it} = j.1\{\mu_{j-1} < HOSP_{it}^{*} \leq \mu_j\}, j = 0, 1, 2 \dots 273$$

with $\mu_0, \dots \mu_{273}$ are the boundary parameters to be estimated.
The constant-coefficient model was then extended to allow for the hypothesised differential effect of complications on hospitalisation with regard to an individual's position in terms of DCSI at each exposure year. Thus, the coefficient γ on DCSI in the threshold model is allowed to vary according to DCSI at each exposure year while the effects of other explanatory variables are assumed to be constant. The threshold model is presented with the following specification:

$$HOSP_{it} = \sum_{m=1}^{M} \gamma_m (DCSI_{it}.R_{m,i}) + \beta_1 X_{it} + \beta_2 \bar{x}_{i,t} + \alpha_i + U_{it} + \beta_0 ,$$

$$i = 1,2 \dots N; t = 1,2 \dots, T$$

Where $R_{m,i} = 1 \; if \; \{\tau_{m-1} < DCSI_i \leq \tau_m\}$, and 0 otherwise
with *m* as number of subpopulations and τ as the threshold parameters. These thresholds were estimated from the data, along with m.

The estimation process was running through all possible values for τ and m. All competing models can be simply compared using their AIC and BIC values. The preferred model is the one which minimises the appropriate information criteria (AIC and BIC).

4.3 Results

The baseline characteristics of the 40,625 individuals with diabetes included in the study are presented in Table 4.2. The mean (±SD) age of study population was 61.9±14.4 years: 51% were male, 7.3% were Indigenous, about 50% were classified as highest or highly disadvantaged, and 90% lived in moderately-to-highly accessible areas. The mean duration of their diabetes was 5.2 years, ranging from 0 to 18.5 years. The mean DCSI was 1.1, ranging from 0 to13 (out of a possible 13). Almost 60% of study population had zero of DCSI at the baseline year. Details of DCSI distribution was presented in Figure 4.2.

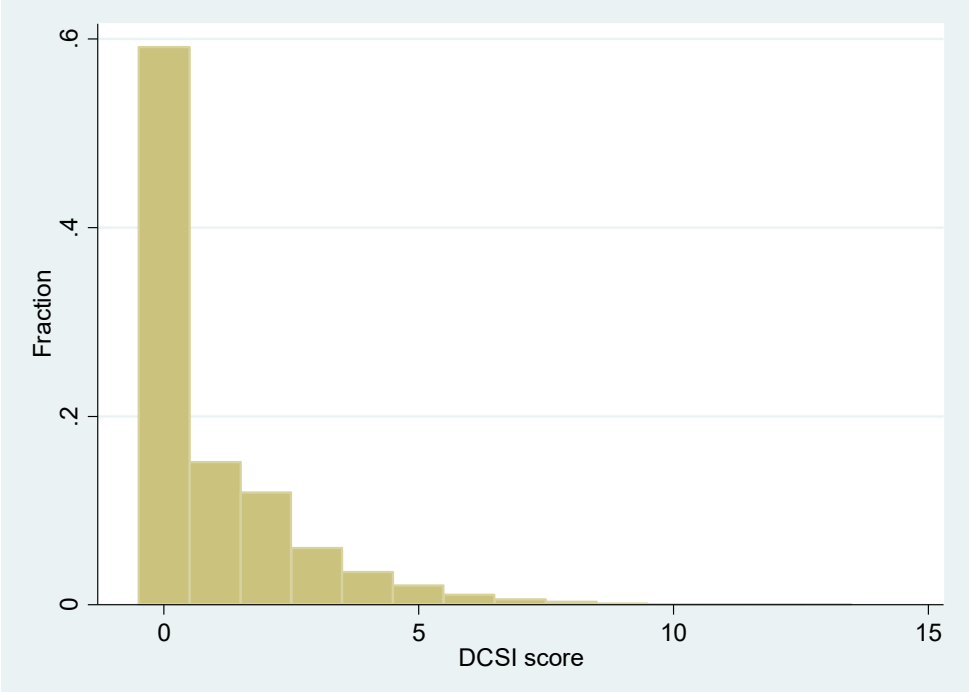


Figure 4.2. Distribution of DCSI score at the baseline year

Individuals having at least one hospitalisation at the baseline were significantly older (63.1 years vs. 61.2), more likely to be female (51.1% vs. 47.8%), Indigenous (9.4% vs. 6.0%), classified as disadvantaged or highly disadvantaged (51.1% vs. 48.8%), and living in very remote areas (6.7% vs. 3.1%), compared with those having no hospitalisations at the baseline year. The average duration of diabetes was shorter among those with hospitalisations than with no hospitalisation. The mean DCSI was higher among those with hospitalisations (1.6, SD 1.9) than those with no hospitalisation (0.8, SD 1.4).

Table 4.2. Baseline characteristics of study cohorts in 1998/99

Variables	No hospitalisation	≥1 hospitalisations	Total
N	25919 (63.8)	14706 (36.2)	40625 (100)
Age (mean ± SD)	61.2± 14.1)	63.1 ± 14.9)	61.9 ± 14.5)
Sex			
Female	12388 (47.8)	7512 (51.1)	19900 (49.0)
Male	13531 (52.2)	7194 (48.9)	20725 (51.0)
Indigenous			
Yes	1473 (6.0)	1369 (9.4)	2842 (7.3)
No	23013 (94.0)	13157 (90.6)	36170 (92.7)
SEIFA			
Highest disadvantage	4950 (20.9)	3172 (21.8)	8,122 (21.3)
High disadvantage	6604 (27.9)	4267 (29.3)	10,871 (28.5)
Moderate disadvantage	3283 (13.9)	2185 (15.0)	5,468 (14.3)
Less disadvantage	3778 (16.0)	2154 (14.8)	5,932 (15.5)
Least disadvantage	5032 (21.3)	2760 (18.9)	7,792 (20.4)
Accessibility			
Very remote	736 (3.1)	977 (6.7)	1,713 (4.5)
Remote	412 (1.8)	342 (2.4)	754 (2.0)
Moderate	1,109 (4.9)	888 (6.1)	1,997 (5.3)
Accessible	1,189 (5.1)	905 (6.2)	2,094 (5.5)
Highly accessible	20,203 (84.8)	11427 (78.6)	31,630 (82.5)
Frequency of GP visits (quintile)			
0	3,804 (16.0)	2,191 (14.9)	5,995 (15.6)
1	5,110 (21.5)	2,184 (14.8)	7,294 (18.9)
2	4,706 (19.7)	2,405 (16.3)	7,111 (18.5)
3	5,096 (21.4)	3,217 (21.8)	8,313 (21.6)
4	5,096 (21.4)	4,709 (32.0)	9,805 (25.5)
Duration of disease (mean ± SD)	5.5 ± 4.2	4.9 ±4.5	5.2 ± 4.3
DCSI (mean ± SD))	0.8 ±1.4	1.6 ± 1.9	1.1 ± 1.6

Table 4.3 shows the relationship between the DCSI and the risk of hospitalisations in the following year, presenting results from bivariate and multivariate analyses. Model performance was better in the third model controlling for all covariates and mean of time-variance variables with a smaller value of BIC and AIC. The model shows that the risk of hospitalisations in the following year increased by 55% for each unit increase in DCSI (Coefficient 0.44, 95%CI 0.43-0.45, p<0.001) after controlling other factors. Age (Coefficient 0.03, 95%CI 0.01-0.04), gender (Coefficient 0.00, 95%CI 0.00-0.00) and Indigenous status (Coefficient 0.08, 95%CI 0.04-0.13) had a minor impact on the risk of hospitalisation. While high number of GP visits (Coefficient 0.27, 95%CI 0.26-0.28) increased the risk of hospitalisations, duration of disease (Coefficient -0.10, 95%CI -0.10- -0.09) and history of hospitalisation in the previous year (Coefficient -0.43, 95%CI -0.44- -0.41) were negatively associated with the risk of hospitalisation. SEIFA and accessibility were not significantly associated with the risk of hospitalisation.

Table 4.3. Association of complication severity index and hospitalisations with and without adjustment for independent variables

	Model 1		Model 2		Model 3	
	Coef.	95%CI	Coef.	95%CI	Coef.	95%CI
DCSI	0.29***	(0.28,0.29)	0.27***	(0.26,0.27)	0.44***	(0.43,0.45)
Gender (Males)			-0.02*	(-0.05,-0.00)	0.03**	(0.01,0.04)
Age in years			0.00***	(0.00,0.00)	0.00***	(0.00,0.00)
Indigenous (Yes)			0.25***	(0.20,0.30)	0.08***	(0.04,0.13)
SEIFA						
Highest disadvantage			REF		REF	
High disadvantage			0.01	(-0.03,0.03)	-0.01	(-0.04,0.02)
Moderate disadvantage			-0.04*	(-0.07,-0.01)	-0.03	(-0.08,0.01)
Less disadvantage			0.01	(-0.02,0.04)	0.01	(-0.05,0.07)
Least disadvantage			-0.01	(-0.04,0.02)	-0.01	(-0.08,0.06)
Accessibility						
Very remote			REF		REF	
Remote			-0.13**	(-0.21,-0.05)	-0.02	(-0.10,0.06)
Moderate			-0.21***	(-0.28,-0.14)	-0.06	(-0.15,0.04)
Accessible			-0.16***	(-0.23,-0.09)	0.01	(-0.10,0.13)
Highly Accessible			-0.40***	(-0.46,-0.34)	-0.03	(-0.18,0.11)
Duration of disease			-0.03***	(-0.04,-0.03)	-0.10***	(-0.10,-0.09)
History of hospitalisation (Yes)			0.13***	(0.11,0.14)	-0.43***	(-0.44,-0.41)
Quintile of GP visits			0.22***	(0.21,0.23)	0.27***	(0.26,0.28)
Mean severity index					-0.39***	(-0.40,-0.38)
Mean duration of disease					0.10***	(0.09,0.10)
Mean hospitalisation status					3.08***	(3.04,3.12)
Mean SEIFA					-0.01	(-0.02,0.02)
Mean accessibility					-0.02	(-0.06,0.02)
Mean quintile of GP visits					-0.19***	(-0.21,-0.18)
AIC	382557.45		369081.20		344032.61	
BIC	382597.86		369262.17		344273.89	

Notes: *Result from random effects negative binomial regression*

** if p-values <0.05; ** if p-values<0.01; *** if p-value<0.001*

Table 4.4 presents the various information criteria along with the optimal model for each number of subpopulations. Considering the information

criteria, the model with the lowest value of BIC and AIC (representing the most parsimonious fit) was chosen with four subpopulations characterised by DCSI at 0, 1, 2 and ≥3 for both the full panel data and the restricted panel data. The results suggested that a DCSI score of zero had a negative effect on the risk of hospitalisation (Coef. -0.247, SE 0.03) while a DCSI of 1 or 2 had a significant positive effect on the risk of hospitalisation (Coef. 0.289, SE 0.01 and Coef. 0.339, SE 0.01, respectively). From a DCSI of 3 or more, the effect of DCSI on the risk of hospitalisation was highest (Coef. 0.381, SE 0.01) and there was no further classification into subpopulations. The results were consistent with the results from both sub-population A and sub-population B. The results of the model are further illustrated in Figure 4.3 to visualise the risk of hospitalisations varying by DCSI from 0 to 13, and show a marginal effect of DCSI on predicting number of hospitalisations across subpopulations.

Table 4.4. Threshold model estimation results

	Full population							**Restricted sub-population A**	**Restricted sub-population B**
Number of subpopulation	2	3	4	5	6	7	13	4	
BIC	342866.0	342827.1	342794.4	342804.2	342813.6	342824.8	342887.1	282988.9	335741.0
AIC	342584.5	342535.5	342492.4	342492.5	342492.9	342493.03	342494.9	282691.5	335439.5
Threshold parameters									
τ_1	0	0	0	0	0	0	-	0	0
τ_2		4	1	1	1	1	-	1	1
τ_3			2	2	2	2	-	2	2
τ_4				7	4	4	-		
τ_5					7	7	-		
τ_6						10			
Complications coefficients									
γ_1	-0.043*** (0.01)	0.047* (0.02)	-0.247*** (0.03)	-0.222*** (0.03)	-0.139*** (0.06)	-	-	-0.289*** (0.03)	-0.253*** (0.03)
γ_2	0.408*** (0.00)	0.442*** (0.01)	0.289*** (0.01)	0.302*** (0.02)	0.344*** (0.03)	-	-	0.270*** (0.01)	0.286*** (0.01)
γ_3		0.418*** (0.01)	0.339*** (0.01)	0.348*** (0.01)	0.376*** (0.02)	-	-	0.332 *** (0.01)	0.339*** (0.01)
γ_4			0.381*** (0.01)	0.387*** (0.01)	0.407*** (0.01)	-	-	0.376*** (0.01)	0.383*** (0.01)
γ_5				0.382*** (0.01)	0.398*** (0.01)	-	-		
γ_6					0.391** (0.01)	-	-		

*Notes: * if p-value <0.05; ** if p-value<0.01; *** if p-value<0.001*

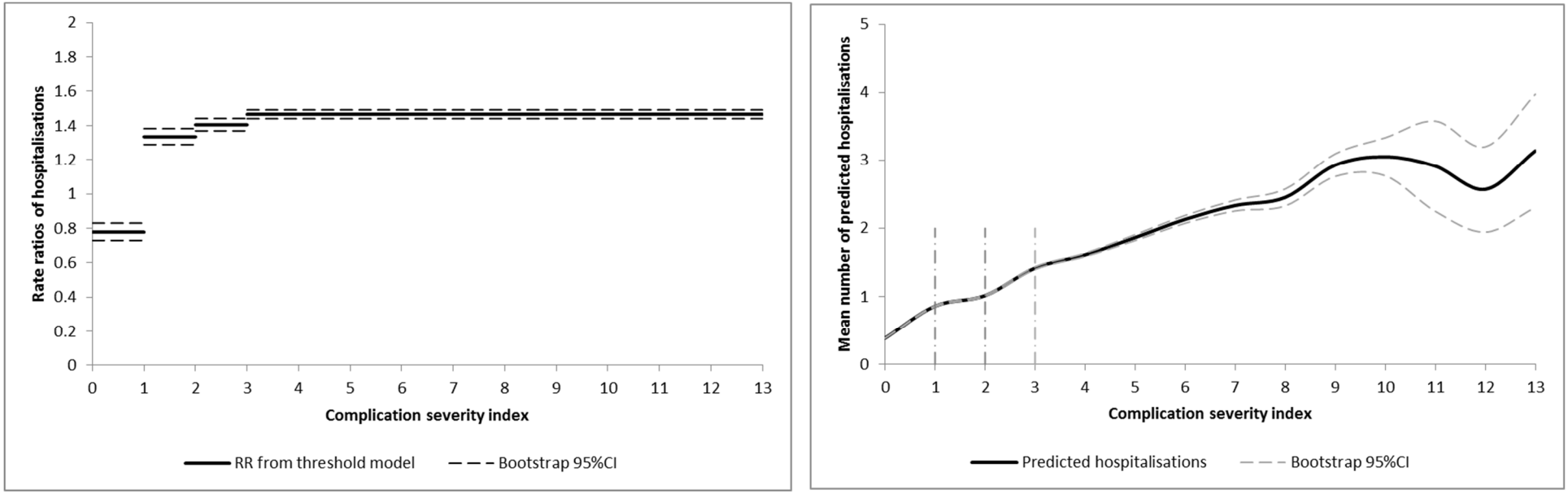


Figure 4.3. Estimated rate ratios under threshold model and predicted hospitalisation for each sub-population

4.4 Discussion

To our knowledge, this study is the first to examine the non-linear relationship between diabetes complication and the risk of related hospitalisations at the whole-population level. The results show that the risk of hospitalisations among diabetics without complication is different from those with complications. However, our results importantly indicate that diabetics with varying degrees of complication severity should be stratified into three subpopulations with one, two and three or more of the DCSI score, based on the homogeneity of the risk of hospitalisation in response to variation of the DCSI. These findings may contribute to a better understanding of diabetic risk stratification and therefore better risk adjustment for use in planning and evaluating healthcare provision strategies targeting high-risk populations to improve health outcomes.

The significant increase in hospitalisations in response to the increase in diabetes severity observed in the literature is consistent with our findings when examining the linear association between hospitalisations and the DCSI (139, 167, 181). The DCSI was stratified into six subgroups from 0 to ≥5 in studies examining the impact of complications on health care utilisation and costs and adjusting for their impact (171, 181, 182). Compared with all potential subpopulations derived from the observed DCSI range in this study, the optimal model indicated that from scores 3–13 the DCSI does not seem to be subject to any particular subpopulation, and hence it may not be necessary to refine the DSCI values when they exceed a score of 3. While recent studies used the six subgroup stratification suggested by Young, Lin (139), our study suggests that stratification into four subgroups (0,1,2 and 3

or more) may be a better approach to reduce over parameterisation of models and more accurately reflect the homogeneous impact of the DCSI on healthcare utilisation.

Our findings have major implications for planning and targeting healthcare provision. Previous studies suggested that DCSI is an important indicator to predict healthcare costs and resource uses (167, 169, 181). Our study supports those findings and adds further that four sub-populations with particular DCSI scores had different effects on predicting the risk of hospitalisation after controlling for clinical and sociodemographic characteristics. This result highlighted a substantial increase in hospital use among those with DCSI 3+ that would not have been indicated by specifying the association in a linear manner. Our model aids in estimating future resource use and healthcare provision, by providing a method to more accurately reflect real world settings. In addition, with a considerable gap in the risk of hospitalisation between people with diabetes who do or do not have diabetes-related complications, as observed in our study, proactive provision of primary care and interventions targeted to avoiding existing or newly diagnosed diabetics progressing to their first complication would appear to offer the greatest reduction in hospitalisations and healthcare savings.

Strengths and limitations

The strength of our study was the use of linked administrative data at the individual level which covered the whole population diagnosed with diabetes for assessing exposure and outcomes. Use of whole-of-population data provides strong external validity. The linked data provided accurate access to

both baseline and follow-up participant characteristics and trends over the studied period, reducing loss to follow up. The data also enabled us to include a range of covariates in the regression models. The study used a panel data structure that contained information on both within and between individual variations, allowing us to control for the effect of unobserved covariates (183). In addition, our study applied the recent advanced analytic approach 'the threshold effects model' (145) that enabled us to capture the most flexible relationship between complications and the risk of hospitalisation and suggest the most appropriate subpopulations in which the relationship is constant.

However, this study also has limitations which should be considered when interpreting the results. The severity of complications was obtained using DCSI, which is an unweighted index that did not independently examine the association between the adverse outcome and each complication (139). Use of this index may cause some potential bias due to the atypical impact of some serious conditions, like kidney failure requiring dialysis. However, since the analysis of the sub-population without serious complications showed results consistent with the analysis without this exclusion, it was evident that the presence of serious conditions did not drive the results. Individuals with undiagnosed diabetes or those who did not use healthcare services for diabetes in WA during the study period could not be captured by the data. This limitation was somewhat mitigated by the fact that we had access to data gathered over almost 20 years; this enabled us to look back to identify use of health services over an extended period of time. However, the data could not capture people with diabetes in the community unless they had

accessed a primary care provider for diabetes-related care or been hospitalised previously, either for diabetes or been hospitalised for another reason where pre-existing diabetes was recorded on the hospital record as a comorbidity. Using the administrative datasets, the duration of diabetes was less likely to be under-represented, as the actual date of the onset would likely have been before the first date of using healthcare services recorded in datasets. In addition, while we could accurately identify person-time resident in WA and therefore accurately capture health service use in WA, we could not capture health service use or prior diagnosis of diabetes that occurred outside of WA. This limitation was partially offset by the use of a validation 'restricted panel' dataset that only included those individuals who had been resident in WA for the entire study period. These limitations are common and well known in administrative data. They did not affect our examination of the homogeneous impact of diabetic complication on the risk of hospitalisations but they do limit the generalisability of our findings to diabetics who have had at least one interaction with the health system.

4.5 Conclusion

The homogeneous impact of diabetes DCSI on the risk of hospitalisation varied significantly across four subpopulations. This stratification strategy may serve as an efficient tool for the classification of diabetes severity in management programs and population-based studies and interventions. Disease severity level is a strong predictor of healthcare service utilisation at both primary level and in relation to hospitalisations. Thus, an effective stratification of condition severity is necessary to minimise the bias due to disease severity in examining the relationship between primary health care

and hospitalisations. This study served as an initial step to explore how to stratify diabetes cohorts in a way that can effectively capture the severity level of the condition. The stratification strategy in this study was used to inform classification of diabetes cohorts in the context of linked data, as described in chapters 6 and 7.

Chapter 5 Exploration of patterns of GP utilisation

Chapter 5 presents a study that explored latent patterns of GP utilisation through simultaneously examining multiple attributes of GP utilisation among people with diabetes, then examining the association between the patterns of GP utilisation and the risk of diabetes-related potentially preventable hospitalisations. Using the cohort of 40,625 individuals with diabetes in WA administrative linked data, a data-driven approach using cluster analysis was conducted. The cluster analysis took into account multiple dimensions of GP utilisation, including frequency of GP visits, maximum time intervals, mean time intervals and standard deviation of time interval between GP visits, to classify people into different levels of utilisation. The results from the cluster analysis indicated that GP utilisation among people with diabetes was stratified into three main groups: moderate, high and very high usage, each having distinct patient characteristics. Interestingly, compared with no GP usage, those with moderate GP usage had the lowest risk of diabetes-related hospitalisation as opposed to the high or very high GP usage groups. Exploration of the pattern of GP utilisation also suggests that the time interval between services would be an underlying factor associated with reduction of diabetes-related potentially preventable hospitalisation. This paper therefore suggested that further exploration regarding the time intervals between GP visits would be helpful to reduce PPHs and hospital resource use.

This study was presented in:

- Mark Liveris Seminar, Health Science Faculty, Curtin University, 27 September 2017
- The Health Services and Policy Research Australian & New Zealand Conference, 1-3 November 2017.

The following manuscript was accepted on 26 January 2018 and first published online on 9 February 2018 (Appendix C):

Thi Ninh Ha, Mark Harris, David Preen, Suzanne Robinson & Rachael Moorin. (2018). Identifying patterns of general practitioner service utilisation and their relationship with potentially preventable hospitalisations in people with diabetes: The utility of a cluster analysis approach. Diabetes Research and Clinical Practice. doi: https://doi.org/10.1016/j.diabres.2018.01.027

The paper is reproduced here as follows.

5.1 Introduction

Diabetes is an increasing public health issue causing a substantial burden on healthcare systems around the world (184). In Europe, the number of people with diabetes was nearly 60 million in 2013, and is estimated to increase to 70 million by the early 2030s (185). Similarly, in the United States the prevalence of diabetes was estimated at 29.1 million in a national report in 2014 (186). In Australia, a country of approximately 24 million people, the prevalence of diabetes was about 1.2 million in 2014/15 (60) and is estimated to increase to 3.4 million by the early 2030s (187).The condition costs the Australian health system more than $A6.5 billion each year (187). Diabetes is considered an ambulatory care-sensitive condition (187), and consequently enhancing primary health care to better manage diabetes has been a major strategic approach in the healthcare system of Australia (4, 187).

The literature suggests that better primary health care delivery reduces the risk of hospitalisations for ambulatory care-sensitive conditions in general (34, 188, 189). With respect to diabetes, a recent systematic review indicated that regular primary care was associated with reduced risk of hospitalisation (190). However, other aspects such as frequency of visits or access to primary health care show inconsistent results (190).

In Australia, primary care services, mainly provided by general practitioners (GP), are subsidised through a universal health insurance scheme, Medicare, on a fee-for-service basis (4). Dedicated financial incentives have been provided under Medicare for GPs to provide comprehensive care for diabetes (4). However, to our knowledge, limited research has evaluated patterns of

utilisation of primary health care services for people with diabetes and their impact on health outcomes. Current studies are limited to examining the utilisation of primary health care based on single indicators, such as frequency (4) or regularity of services used (40).

Since patterns of primary health care utilisation are likely to be complex, more advanced approaches that account for multiple factors are required to more accurately classify and discover meaningful patterns of primary health care utilisation by people with diabetes. K-mean cluster analysis, a data-driven approach, is capable of taking into account multiple dimensions simultaneously and is suitable for use with large datasets (150). The technique can classify individuals with similar characteristics into homogeneous groups which can also maximise heterogeneity between groups (150). The technique has been applied to a variety of settings, for example, health behaviour (191); health psychology (192); healthcare cost analysis (150) and genetic classification (193).

Thus, our study aims to apply K-mean cluster analysis to identify GP utilisation patterns using multiple attributes of GP usage among people with diabetes. We will also examine the impact of identified GP utilisation patterns on the risk of potentially preventable hospitalisations (PPHs). Understanding patterns of GP utilisation and how they impact on health outcomes is useful for planning health care provision targeted to encouraging particular patterns in utilisation and enhancing the relationship between patients and their primary health care provider.

5.2 Methods

5.2.1 Data sources

The Western Australian (WA) linked data used for this study comprised whole-of-population administrative health data linked at the individual level, for residents of WA aged 18 years or older who were registered at any time on the WA Electoral Roll (174). The data included a complete set of WA Hospital Morbidity Data System (HMDS) records; Medicare Benefit Scheme (MBS) claim records; WA Electoral Roll (ER) records; and WA mortality records for each individual subsequent to their first ever WA ER record. Details of each dataset have been described previously (130). In brief, the datasets provide statutory information on all hospitalisations (HMDS), claims for medical services out-of-hospital including GP visits (MBS), dates individuals migrated in and out of WA or changed address while living in WA and date/cause of death.

5.2.2 Study population

Annual panel data from 1998/1999 to 2003/2004 were constructed, consisting of individuals with diabetes identified via HMDS or MBS data prior to the start of or in the baseline financial year (1998/99). Diabetes mellitus was determined using the International Classification of Disease (ICD), 9th edition-clinical modification (ICD-9-CM) codes in HMDS records and MBS claims indicative of the presence of diabetes, as described elsewhere (130). All individuals were observed annually from the baseline year to 30 June 2004, their last year living in WA or death (whichever occurred first) for any change in GP utilisation, hospitalisations, and clinical and demographic characteristics. GP utilisation and demographic and clinical characteristics

were measured in the exposure year, and PPH outcomes measured in the following year. Only individuals who were alive and resident in WA for at least two consecutive years were included in the study. The couplet design (*i.e.* comprising pairs of years, the exposure year followed by an outcome year) has been applied in other recent publications (4, 130). Annual data was measured in financial year from 1 July to 30 June.

Ethical approval was provided by The University of Western Australia and Curtin University Human Research Ethics Committees who exempted the study from obtaining individual patient consent.

5.2.3 Study outcome and predictors

Diabetes-related potentially preventable hospitalisations

The primary outcome measure was diabetes-related potentially preventable hospitalisations (PPHs) during the follow-up year of each couplet. Hospitalisations were deemed PPHs based on either their principal diagnosis being identified by the National Health Performance Framework (135) as a diabetes-related PPH or identification by Davis *et al.* (136) as associated with increased risk for people with diabetes. Principal diagnoses were captured using ICD-9-CM and Australian Modification ICD codes 10th revision (ICD-10-AM) codes included in the HMDS records (Table 3.4).

Variables for GP usage clustering

The goal of these cluster analyses was to identify patterns of GP service utilisation among people with diabetes. Candidate variables included in the cluster analyses were adapted from the customer relationship management framework proposed by Hughes (2005) (140) that capture both level of usage

and strength of the relationship between patients acting as customers and GPs acting as primary care providers. Three main components suggested from the framework were Recency, Frequency and Monetary (140) which have been applied to healthcare data previously (46). Since healthcare costs for Australia are covered by Medicare, with limited out of pocket payment from patients, the monetary component was not considered in our analyses. However, recency and frequency are useful indicators of how well the relationship between patients with diabetes (acting in the role of a customer) and primary healthcare provider (GP) (acting in the role of service provider) has been maintained (46).

In our study recency of GP usage consisted of three factors including: (i) the average time interval between access of healthcare service capturing the overall interaction between patients and GPs, (ii) the standard deviation from the average time interval capturing the extent of consistency in service utilisation, and (iii) the longest time interval between services, capturing the extent that patients were out of coverage of primary care. Since the mean and standard deviation values may be driven by extreme values, two alternatives to the recency variable group were also considered in the cluster analyses, including (A) mean time interval, mean absolute deviation from the mean and the longest time interval and (B) median time interval, median absolute deviation from median, and the longest time interval. The results of cluster analysis of the three groups of variables are compared in Table 5.1. The time interval was determined between the date of a GP visit and the date of the previous healthcare service provided either from a GP or hospitalisation.

Frequency of GP usage was defined as the number of GP visits in a financial year. Those GP visits occurring within 14 days of the previous GP visit were counted as one GP usage to minimise over-counting GP service utilisation, as those within 14 days of each other are likely to be associated with a single episode of care: for example, people may need to return to a GP to receive laboratory test results, rather than to receive an additional discrete GP service (as suggested in discussion with our GP experts), this feature has also been noted in the literature (78).

All indicators were measured within financial years. However, a three-year look-back period was used, where necessary, to calculate the time interval between the first GP service in that year and the previous service. Three years was found to be the tie period that maximised capturing recency of GP utilisation for the cohort. Individuals having only one GP visit within a financial year were included in the cluster analysis if they had a previous healthcare service within the look-back period to enable the calculation of recency of GP usage.

Covariates

For this study, a number of individual characteristics were included to control for potential confounders in the relationship between GP usage cluster and PPHs. Demographic characteristics included were age group (18–44, 45–59, 60–74 and ≥75 years), gender, Indigenous status, quintile of the Census specific Socio-Economic Indexes for Areas (SEIFA) Index of Relative Socioeconomic Disadvantage (141) and quintile of accessibility to services (142). Diabetes complications were identified using ICD codes as suggested

by Young, Lin (139) and classified into four groups (0, 1, 2 and 3 or more complications) according to our previously published methods (130). The number of comorbidities was summed from a list of comorbidities suggested by Holman *et al.* (143), excluding conditions classified as complications of diabetes. Regularity of GP visits was calculated as [1/(1+variance)] (34), where variance is a variance of the time interval between GP visits occurring within the financial year and classified into four quantiles. Number of specialist visits, and non-diabetes-related hospitalisation were calculated within a financial year. Duration of diabetes was calculated in years.

5.2.4 Statistical analyses

Cluster analyses were conducted using different alternative combinations of recency and frequency of GP usage among those with at least one GP visit in a financial year. First, the values of the mean/median time interval, the standard deviation/absolute deviation of mean/median time intervals, longest time interval and frequency of GP visits were normalised by subtracting the minimum of each value and dividing that difference by the range of all values (150). K-mean cluster analyses were then conducted on normalised values of recency and frequency of GP visits. The K-mean cluster approach was preferred as it is less susceptible to outliers in the data and is appropriate for use with large datasets (150). The number of clusters was indicated using Calinski-Harabasz stopping rules for the options of 2 to 6 clusters, the large values of the Calinski-Harabasz pseudo-F index indicating distinct clustering (194). Characteristics of final GP usage clusters were described using a box plot.

Both descriptive bivariate and multivariate analyses were performed.

Descriptive analyses were used to summarise characteristics of participants among no GP usage and for each GP usage cluster in the baseline year. The results were presented as the mean and standard deviation (SD) for continuous variables and percentage for categorical variables. Multivariate analyses were conducted using the random-effects negative binomial regression model (NB) for panel data and the zero-inflated negative binomial regression model (ZINB) with the inflated component contained in the intercept only. Bayes Information Criterion (BIC) and Akaike Information Criterion (AIC) statistics were used to assess the fit of the model where NB with random effects was the preferred model compared to ZINB. We included Mundlak variables, defined as group-means of time-varying variables, to relax the assumption in the random-effects estimator that observed covariates were uncorrelated with the unobserved covariates (147, 148). The group mean variables used were number of specialist visits and non-diabetes-related hospitalisation. All analyses were conducted using STATA for Windows version 14.1.

5.3 Results

Clustering results

Table 5.1 presents summary results of cluster analyses with different groups of recency variables. The candidate group included mean time interval, mean absolute deviation from the mean, longest time to GP visit and frequency of GP visits; alternative A group included mean, standard deviation, the longest time interval and frequency; alternative B group included median, median absolute deviation from median, the longest time interval to GP visit and frequency of GP visits. Using the Calinski cluster stopping rule, all three

groups identified three clusters. Compared with the candidate group, the other alternative groups had a very high percentage of agreement in term of grouping subjects into a cluster, with 99.3% in the alternative A group and 95.5% in the alternative B group. The candidate group also had the highest Calinski F index value. Thus, the results of the candidate group were kept to present in this paper.

Table 5.1. Cluster analysis outputs with different groups of recency variables

	Group of Indicators used in K-mean cluster		
	Candidate group	Alternative A group	Alternative B group
Mean	*Yes*	*Yes*	
Median			*Yes*
Mean absolute deviation from the mean		*Yes*	
Median absolute deviation from median			*Yes*
Standard deviation	*Yes*		
The longest time to GP visit	*Yes*	*Yes*	*Yes*
Frequency of GP visits	*Yes*	*Yes*	*Yes*
Cluster stopping (Calinski rule)	133805	132616	129095
Number of clusters	3	3	3
% of agreement vs. group 1 (Kappa values)	-	99.3%	95.5%

Table 5.2 and Figure 5.1 summarise the GP usage clusters from K-mean analyses. Three clusters were identified, including 1) moderate GP usage with mean time interval of approximately 10 months (296 days), standard deviation of about four months (115 days), the longest time interval being 14 months (404 days) and frequency of about two times a year; 2) high GP usage with mean time interval for GP visits of three months (88 days),

standard deviation of 1.5 months (48 days), the longest time interval of 5 months (147 days) and frequency of 3.7 times a year; and 3) very high usage with mean time interval of 1.5 months (40 days), deviation of 0.5 months (20 days), the longest time interval being two months (76 days) and frequency of visit approximately 7.8 times a year.

Table 5.2. GP usage clusters summary

Clusters	**Mean** (days)	**SD** (days)	**The longest** (days)	**Frequency of GP visits**
Moderate usage				
Min	75.0	0.0	225.0	1.0
Mean	296.8	115.0	404.0	1.9
Max	1093.0	744.5	1095.0	8.0
High usage				
Min	1.0	0.0	1.0	1.0
Mean	88.1	48.8	147.0	3.7
Max	230.0	178.1	387.0	7.0
Very high usage				
Min	5.2	0.0	9.0	5.0
Mean	39.7	20.8	76.1	7.8
Max	124.7	273.0	947.0	17.0

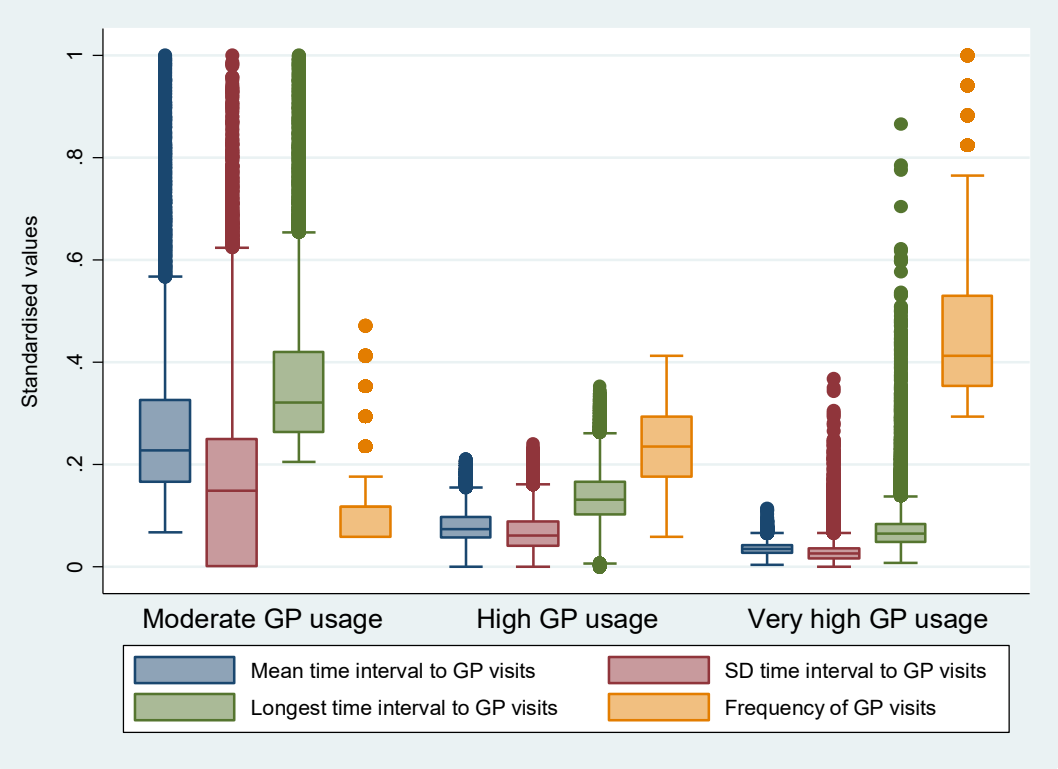


Figure 5.1. GP usage by clusters

Characteristics of study population by GP usage cluster at the baseline year

Basic demographic and clinical characteristics of the study population are described in Table 5.3 by no GP usage and each GP usage cluster. The majority of the study population had high (n=17 077, 42.0%) and very high (n=15 858, 39.0%) GP usage, were aged 45 years or older (86.2%), and were more likely to be male (51%), non-Indigenous (92.7%), moderate to least disadvantaged (51.6%), and living in areas with moderate-to-high accessibility to services (93.4%). Those with complications accounted for 43.3% in the study population, higher in the very high GP usage cluster (51.5%). The average number of comorbidities was 4.5 (SD 3.6), the highest in those with very high GP usage cluster (mean 5.6; SD 3.5), followed by high GP usage cluster (mean 4.1, SD 3.5), no GP usage cluster (mean 3.5; SD 4.4) and moderate GP usage cluster (mean 3.2; SD 2.9). The average

duration of their diabetes was 6.4 (SD 4.3) years, with similar duration across GP usage clusters and the no GP usage group. No regularity and low regularity of GP visits were observed across GP usage clusters, except in the very high GP usage cluster. High numbers of hospitalisations were observed among those with no GP usage (average of 3.4 admissions), followed by the very high GP usage cluster (0.8 admissions), high GP usage cluster (0.7 admissions) and moderate GP usage cluster (0.2 admissions).

Overall, the moderate GP usage cluster tended to be younger (25.1% aged 18–44 years, and 37.7% aged 45–60 years), male (62.6%), Indigenous (10.1%), live in less accessible areas (25.7%), compared with both the high and very high GP usage cluster, as shown in Table 5.3. The moderate GP usage cluster was less likely to have complications (27.2%); had a lower number of comorbidities (3.2 (SD 2.9)); was less likely to have regular GP visits (20.5%) and had a lower number of hospitalisations (0.2 (SD 0.8)) compared with both high and very high GP usage clusters. The no GP usage group was quite comparable to other GP usage clusters in term of age, gender, complications and comorbidity distribution. However, the no GP usage group had a higher proportion of individuals who were Indigenous (23.7%), in the highest disadvantage SEIFA quintiles (31.1%) and resided in very remote areas (20.1%).

Table 5.3. Characteristics of study population by GP usage cluster

Characteristics	No GP usage	Moderate GP usage	High GP usage	Very high GP usage
	(N, (%))	(N, (%))	(N, (%))	(N, (%))
N (%)	4 198 (10.3)	3 492 (8.6)	17 077 (42.0)	15 858 (39.0)
Age group (years)				
18-44	781 (18.6)	877 (25.1)	2,668 (15.6)	1178 (7.4)
45-59	1059 (25.2)	1316 (37.7)	5,649 (33.1)	3543 (22.3)
60-74	1183 (28.2)	1,016 (29.1)	6,655 (38.9)	7465 (47.1)
≥75	1175 (28.0)	283 (8.1)	2,105 (12.3)	3672 (23.2)
Gender				
Female	1679 (40.0)	1307 (37.4)	7,912(46.3)	9002 (56.8)
Male	2519 (60.0)	2185 (62.6)	9,165 (53.7)	6856 (43.2)
Indigenous status				
No	3084 (76.3)	2911 (89.8)	15,197 (93.8)	14978 (96.5)
Yes	961 (23.7)	329 (10.1)	1,003 (6.2)	549 (3.5)
SEIFA				
Highest disadvantage	1285 (31.4)	631 (18.4)	23,240 (19.2)	3435 (21.8)
High disadvantaged	1037 (25.3)	918 (26.7)	4,797 (28.4)	4558 (28.9)
Moderate disadvantage	573 (14.0)	593 (17.3)	2,381 (14.1)	2185(13.8)
Less disadvantage	544 (13.5)	561 (16.3)	2,754 (16.3)	2416(15.3)
Least disadvantage	645 (15.7)	728 (21.2)	3,691 (21.8)	3158 (20.0)
Accessibility				
Very remote	825 (20.1)	251 (7.3)	611 (3.6)	79 (1.2)
Remote	172 (4.0)	90 (2.6)	355 (2.1)	184 (1.1)
Moderate	268 (6.5)	265 (7.7)	946 (5.6)	659 (4.2)
Accessible	210 (5.1)	273 (7.9)	1,027 (6.1)	695 (4.4)
Highly accessible	2619 (63.9)	2,552 (74.3)	13,926 (82.6)	14036 (89.1)
Complication severity level				
No complication	1957 (46.6)	2,543 (72.8)	10,845 (63.5)	7694 (48.5)
1 complication	746 (17.8)	385 (11.0)	2,372 (13.9)	2638 (16.6)
2 complications	577 (13.7)	322 (9.2)	1,804 (10.5)	2266 (14.3)
3+ complications	918 (21.9)	242 (6.9)	2,056 (12.0)	3260 (20.6)
Number of comorbidity				
Mean (SD)	3.5 (4.4)	3.2 (2.9)	4.1 (3.4)	5.6 (3.5)
Duration of diabetes (years)				
Mean (SD);	6.7 (4.4)	6.3 (4.2)	6.1 (4.2)	6.5 (4.4)
Regularity quantiles				
No regularity	4,198 (100.0)	2,776(79.5)	3,315 (19.4)	0
Quantile 1		716 (20.5)	6,684 (39.1)	287 (1.8)
Quantile 2			4,719 (27.6)	2,972 (18.7)
Quantile 3			1,497 (8.8)	5,917 (37.3)
Quantile 4			862 (5.0)	6,682 (42.1)
Diabetes-related PPH				
Mean (SD)	2.5 (17.5)	0.07 (0.38)	0.25 (2.6)	0.25 (1.02)

Association between GP usage and the risk of hospitalisations

The preferred model was the panel negative binomial regression model based on information criterion (AIC and BIC) (Table 5.4). The results show that GP usage across all clusters had a protective effect against the risk of PPH in the following year, after adjusting for all covariates. However, the greatest protective effect was observed for individuals in the moderate GP usage cluster (IRR=0.67 (95%CI: 0.62-0.71). The average adjusted predictions indicate that on average 0.25 PPHs per year (95%CI: 0.24-0.27) can be expected for those in the moderate GP cluster; 0.26 per year (95%CI 0.259-0.27) for those in the high GP usage cluster and 0.29 per year (95%CI: 0.28-0.30) for those in the very high GP usage cluster, while those with no GP usage are estimated to have on average 0.38 hospitalisations per year (95%CI: 0.36-0.40) (Figure 5.2).

Table 5.4. Association of GP usage pattern and diabetes-related PPH with and without adjustment for other covariates

	Multivariate NB		Adjusted multivariate NB		ZINB	
	IRR	(95%CI)	IRR	(95%CI)	IRR	(95%CI)
GP cluster usage						
No usage	1	(1; 1)	1	(1; 1)	1	(1; 1)
Moderate usage	0.62***	(0.57; 0.66)	0.67***	(0.62; 0.72)	0.41***	(0.33; 0.50)
High usage	0.67***	(0.64; 0.71)	0.70***	(0.66; 0.73)	0.40***	(0.35; 0.46)
Very high usage	0.76***	(0.72; 0.79)	0.76***	(0.72; 0.80)	0.39***	(0.34; 0.45)
Gender						
Males vs. females	1.06***	(1.03; 1.10)	1.07***	(1.04; 1.11)	1.24***	(1.13; 1.36)
Age (years)						
18–44	1	(1; 1)	1	(1; 1)	1	(1; 1)
45–59	1.20***	(1.12; 1.28)	1.21***	(1.14; 1.29)	1.10	(0.91; 1.32)
60–74	1.74***	(1.64; 1.86)	1.73***	(1.62; 1.84)	1.44***	(1.20; 1.73)
75+	2.30***	(2.15; 2.46)	2.31***	(2.16; 2.47)	1.42***	(1.18; 1.71)
Indigenous status						
Yes vs. No	1.47***	(1.37; 1.59)	1.50***	(1.39; 1.61)	2.18***	(1.79; 2.67)
SEIFA						
Highest disadvantage	1	(1; 1)	1	(1; 1)	1	(1; 1)
High disadvantaged	0.95*	(0.91; 1.00)	0.95*	(0.91; 0.99)	0.96	(0.84; 1.09)
Moderate disadvantage	0.95	(0.90; 1.00)	0.94*	(0.89; 0.99)	0.86*	(0.76; 0.97)
Less disadvantage	0.98	(0.93; 1.03)	0.97	(0.92; 1.02)	0.95	(0.82; 1.10)
Least disadvantage	0.93**	(0.88; 0.98)	0.90***	(0.86; 0.95)	0.94	(0.81; 1.09)
Accessibility						
Very remote	1	(1; 1)	1	(1; 1)	1	(1; 1)
Remote	1.00	(0.87; 1.13)	1.00	(0.88; 1.13)	0.76*	(0.59; 0.96)
Moderate	0.97	(0.88; 1.08)	0.98	(0.88; 1.08)	0.84	(0.64; 1.09)
Accessible	0.92	(0.83; 1.03)	0.92	(0.82; 1.02)	0.73*	(0.57; 0.95)
Highly accessible	0.89*	(0.82; 0.98)	0.90*	(0.83; 0.99)	0.97	(0.78; 1.21)
Duration of diabetes (years)	1.03***	(1.03; 1.04)	1.04***	(1.03; 1.04)	1.05***	(1.04; 1.06)
Complication severity level						
No complication	1	(1; 1)	1	(1; 1)	1	(1; 1)
1 complication	1.33***	(1.27; 1.40)	1.27***	(1.21; 1.33)	1.05	(0.94; 1.18)
2 complications	1.68***	(1.60; 1.77)	1.58***	(1.51; 1.66)	1.57***	(1.37; 1.80)
3+ complications	2.12***	(2.02; 2.22)	1.90***	(1.81; 2.00)	2.72***	(2.34; 3.15)
Number of comorbidities	1.07***	(1.06; 1.07)	1.04***	(1.03; 1.04)	1.07***	(1.05; 1.09)
Number of specialist services	1.01***	(1.01; 1.01)	0.99***	(0.98; 0.99)	0.97***	(0.96; 0.98)
Non-diabetes-related hospitalisation	1.05***	(1.02; 1.09)	0.99	(0.96; 1.02)	0.99	(0.90; 1.10)
Diabetes-related hospitalisation lag1			1.36***	(1.31; 1.40)	4.65***	(3.94; 5.49)
Diabetes-related hospitalisation baseline			1.11***	(1.07; 1.14)	1.14*	(1.02; 1.27)

Group mean number of specialist visits		1.04***	(1.04; 1.05)	1.06***	(1.05; 1.08)
Group mean non-diabetes-related hospitalisations		1.60***	(1.50; 1.72)	1.89***	(1.52; 2.36)
AIC	191782.6	190686.5		202182.5	
BIC	192075.6	191019.9		202515.9	

Notes: * if p-values <0.05; ** if p-values<0.01; *** if p-values <0.001"

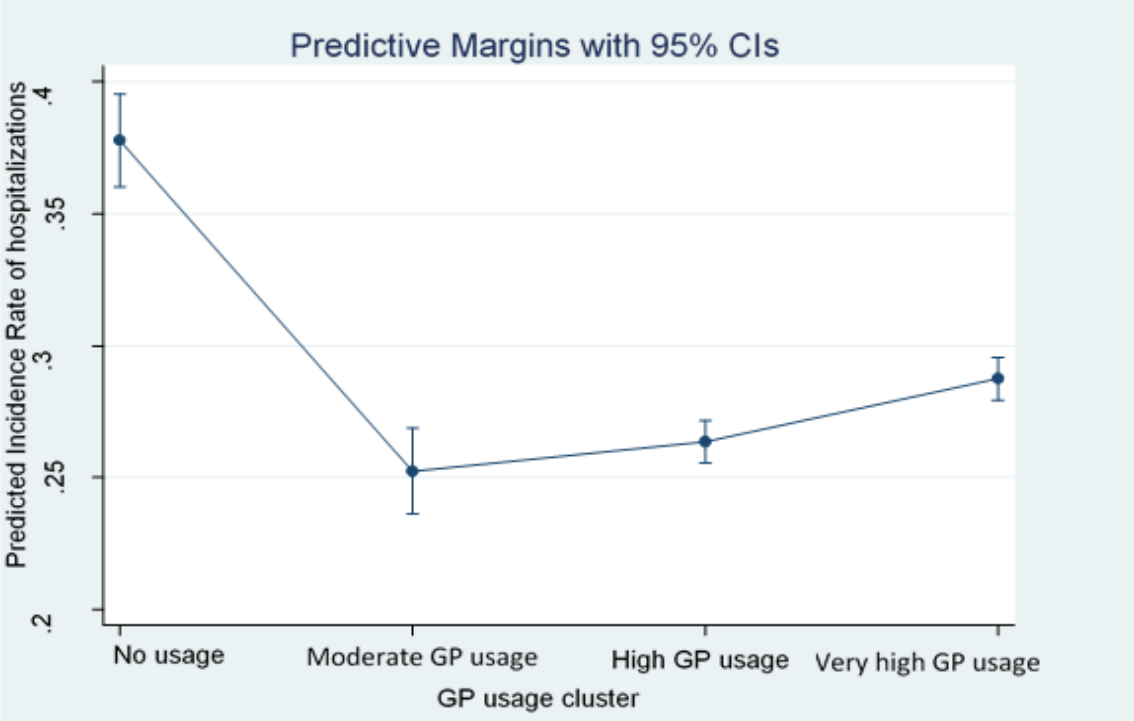


Figure 5.2. Predictive margins for the incident rate of diabetes-related PPH

5.4 Discussion

This study aimed to reveal the latent pattern of GP contact using K-mean cluster analysis, a novel statistical technique, which overcomes many of the limitations associated with current studies by examining GP service use simultaneously across multiple attributes. Importantly, we were able to include time intervals between service utilisations, including average time interval, deviation of the time intervals, and the longest time interval, in assessing patterns of GP service use; this improved the accuracy of

classification.

The rationale behind our exploration of incorporating multiple attributes to categorise GP use was our hypothesis that using frequency or regularity of GP contact alone may be too simplistic, since individuals that have the same number of visits or the same regularity in a year may have differences in the temporal distribution of visits. Shorter time intervals between services in combination with more regularity may reflect ‘proactive care’ and the strength of the relationship between patient and GP. In turn, more proactive care may allow the opportunity for continuous improvement in self-management skills and health literacy, factors that may assist in the prevention and early treatment strategies in the primary healthcare care setting (4, 195). Such characterisation of GP utilisation, based on multiple domains, has not to our knowledge been previously reported and, we argue, represents an advance on current single-domain methods of analysis.

In our study, although the no GP usage group was comparable to other GP usage clusters in term of age and gender and disease severity, the group comprised a higher proportion of disadvantaged population (Indigenous status, highest disadvantage SEIFA, and very remote). These findings highlight the existence of inequity in access to primary care for people with diabetes, in particular for subpopulations, as has been previously reported in the literature (196, 197) .The majority of individuals with diabetes were categorised in high or very high GP usage clusters. Those in the high and very high usage clusters also had high and very high recency and frequency of GP usage, respectively, while those in the moderate GP usage cluster had

lower recency and also lower frequency of contact. The clinical characteristics of each cluster differed significantly, with those in the high or very high GP usage clusters more likely to have a higher number of complications and comorbidities compared with the moderate GP usage cluster. These results were in line with literature that showed higher healthcare service utilisation was observed among diabetes with multiple comorbidities and complications (6, 198, 199). Thus, the multidimensional GP usage clusters identified in our study may be an indicator of clinical characteristics that are driving patients' healthcare needs. This represents an improvement on other more simplistic measures, such as frequency, that do not correlate well with health outcomes (4, 190).

The literature does not show a consistent relationship between the level of primary health care and the risk of hospitalisation (188, 190). While Comino *et al*. found that a higher number of GP visits increased the risk of hospitalisation (4), other authors found an inverse relationship between the frequency of GP visits and hospitalisation (200). Discordant results in the literature may be due to the complexity of the mechanism in the relationship between primary health care and hospitalisation, which may not be adequately captured by the number of GP visits (4). Thus, use of a more complex measure of GP use, such as that developed in our study, which incorporates several dimensions, may be better suited to understand the risk of hospitalisation and help predict and contain the costs of health care for diabetes.

Our findings support the hypothesis that GP contact reduces the risk of

hospitalisation. However, the effect was not linear for each additional level of GP usage, with the highest effect observed among those with moderate GP usage cluster. This may be explained by characteristics of GP usage cluster: those with moderate usage were likely to be younger, have fewer complications and comorbidities than those with high and very high GP usage. The results were also supported by the health demand model of Grossman, where health is considered as a durable capital stock that depreciates with age and can be increased through investment in health care (201). Thus, a finite lifetime increase in the depreciation rate of health may lead to an increase in demand for both preventive care and curative care (201, 202). However, if primary health care can provide early treatment and prevention of illness, it would still be a substitute for hospital care in some instances (202).

Strengths and limitations of the study

The major strength of our study is that it was based on a large set of linked administrative data at the individual level that encompassed the whole population and a comprehensive range of healthcare services. The linked whole-of-population data allowed us to assess changes in both exposure and outcomes at the individual level over the follow-up period. The panel data structure contained information on both within and between individual variations, enabling us to control for the effect of unobserved covariates (183). Our study also applied a novel advanced analytic approach, cluster analysis, and adapted a customer relationship management framework to reveal previously hidden patterns of primary health care utilisation. These

approaches allowed us to examine primary health care utilisation across multiple attributes simultaneously, and thus characterise a measure of GP utilisation that may facilitate a better understanding of the influence of primary health care in reducing the risk of hospitalisations among people with diabetes.

Our study has some limitations. Comorbidity was accessed by a simple count of conditions, which may not well capture actual healthcare needs although the measure is frequently used in the literature (4, 6, 203). The analyses were limited to Australian citizens in one Australian state, due to reliance on the WA Electoral Roll, and those with a previous diagnosis of diabetes as captured in the data. Thus, the result may not be fully generalisable to all individuals living with diabetes, since the Electoral Roll is known to under-represent some groups, such as Indigenous Australians and those aged under 21 years of age (131). However, the use of longitudinal Electoral Roll data provided the ability to accurately capture person-time at risk, due to capturing movement in and out of the state (131). Limiting the study to a single Australian state is unlikely to have significantly influenced the findings, since Australia has a single public health system, Medicare. Similarly, our reliance on linked administrative health data to identify those diagnosed with diabetes limited the study to those who had previously accessed health services pathognomonic of diabetes; thus people living with diabetes who have never accessed diabetes-related health services are not represented. Individuals not included in our data are likely to be the lower severity patients who are less likely to need hospital care. These limitations are common and well-known in administrative datasets and, because of the features of the

excluded patients, are likely to have a limited effect on our examination of the pattern of primary care utilisation and the relationship between the patterns of utilisation on the risk of hospitalisation in previously diagnosed diabetes.

Through combining both temporal factors with measures of frequency of use of GP services our study revealed a latent pattern of primary health care utilisation. Incorporation of multiple attributes that go beyond a simplistic frequency-based approach may better characterise the complex relationship between use of GP services and diabetes-related hospitalisation. The study has demonstrated the ability of cluster analyses to provide a systematic formalised approach for exploring complex patterns of health service utilisation in large administrative datasets. Application of the cluster analysis approach to other chronic conditions would be useful for better understanding of patterns of service utilisation. Future studies should further examine temporal factors in the provision of primary health care and evaluate what combination of time between visits, regularity and frequency of access to primary care would best improve health outcome and contain costs.

5.5 Conclusion

The combination of temporal factors with measures of frequency of use of GP services has revealed patterns of primary health care utilisation associated with different underlying patient characteristics. Incorporation of multiple attributes that go beyond frequency-based approaches, may better characterise the complex relationship between use of GP services and diabetes-related hospitalisation. The results of this study provided evidence to support the thesis hypothesis that the time interval between services would

be an underlying factor associated with reduction of diabetes-related PPH. This was the foundation for a further exploration to examine whether there is an optimal time duration for GP consultations—when ongoing GP care would help to minimise hospitalisation for people with diabetes. These results are presented in the following chapter.

Chapter 6 Development of the Cover Index

This chapter is a study using a mixed methods approach in the setting of diabetes to demonstrate the development of the Cover Index. The Cover Index is defined for these purposes as 'the proportion of time an individual is under the potentially protective effect of GP contact'. In this study, a semi-structured survey was first conducted to explore GPs' perspectives on the temporal protective effect of a GP consultation for people with diabetes to inform the direction of the empirical analysis. A threshold effect model, extended from the random effects negative binomial model for panel data, was then developed, using the WA whole-of-population linked administrative data from 1998/99 to 2003/04. The models empirically estimated the 'optimal maximum time interval' as a proxy reflection of the duration of the protective effect of GP contacts. This was defined as the maximum time interval between GP contacts observed over the ascertainment period that provided the greatest reduction of diabetes-related PPHs for diabetes cohorts across different severity levels. The appropriate optimal maximum time interval was then used to calculate a Cover Index score for each individual in the cohort. Finally, face validity of the Cover Index score was performed by evaluating the score relative to sociodemographic characteristics known to be associated with access and utilisation of GP services. Although the semi-structured survey only served as an exploration of GPs' opinions, the results lend support to a hypothesis that GP consultation provides a protective effect against the risk of hospitalisation for people with diabetes. Results from the empirical analysis found that the Cover Index was observed to be lowest among people aged 75+ years, males, those with the lowest socioeconomic

status, and those living in very remote areas. These results align with other studies on access and use of GP services, suggesting that the Cover Index has good face validity. A further evaluation of the relationship between the Cover Index of GP visits and diabetes-related PPH using contemporaneous data is the subject of Chapter 7.

Results from the empirical analysis of this study was presented as:

- A poster and short oral presentation at the Australian Epidemiology Association conference, 23–24 October 2018, Fremantle, WA, and
- An oral presentation at the International Population Data Linkage Network conference, 11–15 September 2018, Banff, Canada.

A manuscript has been submitted and is currently under review with BMC Health Services Research (Appendix D):

Thi Ninh Ha, Mark Harris, David Preen, Suzanne Robinson & Rachael Moorin. A time-duration measure of continuity of care to optimise utilisation of primary healthcare: A threshold effects approach among people with diabetes.

6.1 Introduction

Given current pressures experienced by most health systems, improvements in care delivery are needed to make the system more effective, efficient and sustainable. Over recent years the focus in many countries has been the enhancement of primary health care to reduce PPHs, which are often costly and undesirable for patients (189). The rationale behind this is that timely access and effective treatment in primary care settings for people with chronic conditions could afford a protective effect in preventing complications and adverse health events (204, 205). For common chronic conditions such as diabetes, heart failure and asthma, a shift in focus from acute to primary care has the potential to delay or even prevent the onset of complications and reduce PPH. This theory, applied to ambulatory care-sensitive chronic conditions, has been the driver of many policies aimed at increasing long-term, ongoing, rather than sporadic or episodic contact with a GP.

The Australian Government has set a focus on strengthening the primary health care system to address inequities and future challenges of chronic diseases (206). One of the ways this is being undertaken is by providing financial incentives to drive aspects of primary health care and GPs' behaviour: these include the introduction of Primary Health Networks, Integrated Care Models, Service/Practice Incentive Payments, the Healthcare Homes program, Chronic Disease Management Medicare Benefits Scheme items, and Home Medication Reviews (22). Payment systems incentivise behaviours that are key to determining where and how health care is delivered as well as its level of accessibility, and are particularly influential given the Australian fee-for-service primary health care

business model (22).

Continuity of care is an important component of high-quality primary health care, as it is associated with increased patient satisfaction and quality of life (80). New models of care often rely on the theoretical link between continuity of care and better health outcomes. A well-known conceptual framework of continuity of care has proposed three essential components of continuity: interpersonal (or relational) continuity, management continuity and informational continuity (26). Interpersonal continuity is defined as an ongoing relationship between a patient and the same provider. It is also considered as a longitudinal continuity where the relationship between patients and providers is strengthened through mutual familiarity and personal trust. Informational continuity is a link between providers to share comprehensive information about patients' history of care and circumstances that helps to reduce duplicative and wasteful use of resources. Management continuity is a collaboration between providers to ensure services are delivered promptly and are complementary; this is especially important in chronic and complex conditions which require management from multiple providers (26). A sufficient continuity of care requires the presence of both individually-oriented care and care delivered over time (24, 26).

However, the importance of timely utilisation to primary care, where people with a chronic condition are less likely to have an adverse event resulting in a PPH, has not been fully captured in most current continuity of care indexes. Previous studies have examined the concept of 'care regularity', capturing the degree of regular contact with primary health care providers (33-35).

Recent studies reported that regularity of contact is more important than the frequency of contact for reducing number and costs of hospitalisations (37, 38). Greater regularity of visits more likely indicates care which is planned and proactive, while visits on an irregular basis (even if frequent/numerous) likely indicate care which is unplanned or reactive and thus not indicative of good ongoing management (36). Current evidence also shows that use of Enhanced Primary Care Medicare items increases regular primary health care contact in the following year (35, 38), suggesting that regularity is suitable as a target for health policy intervention (35, 40).

This study expands on the concept of regularity by adding a time component to develop a new measure, namely the Cover Index. This is important as care can be regular if a patient sees their GP once per year, but this might not be sufficient (*i.e.* the time-duration may be too long between visits) to provide adequate management of the patient's condition and therefore some of the protective effects of regular care may be lost. The concept is analogous to 'persistence', a term that has been widely used in drug utilisation research to capture the proportion of days that a patient has an available supply of medication (41, 42). The Cover Index is the proportion of days, within a fixed ascertainment period (preferably one year since this is the time period on which current chronic disease management plans are based (48)) that a patient is considered under the 'protective effect' of their primary health care contact and at reduced risk of PPH. In contrast to drug utilisation studies, where the protective effect of medication is well defined, in primary care, no data exist to recommend the duration over which a GP visit has the potential to protect a patient from an adverse event or complication of

their chronic disease.

This study hypothesises that GPs' interaction may offer a protective effect for people with chronic condition such as diabetes from experiencing a diabetes-related PPH and that this protective effect may be maintained within an optimal time interval (*i.e.* does not exceed this time). This study aimed to develop a new time-duration protective effect measure, named the Cover Index, in order to capture the proportion of time that an individual is under the potentially protective effect of primary health care (via contact with their GP) over a pre-specified ascertainment period.

The aim was achieved through two main steps. It started with exploring GP perspectives on a time-limited protective effect/ temporal protective effect of a GP consultation for people with diabetes using a semi-structured survey. This was followed by devising a methodology for determining the Cover Index of primary care using individual-level linked administrative data: this involved (i) estimating the optimal maximum time interval over which primary care affords an increased protection from PPH, using threshold effects models; and (ii) using the derived optimal time period to operationalise 'cover' at the individual level. Ethical approval was provided by The University of Western Australia and Curtin University Human Research Ethics Committees.

6.2 Methods

6.2.1 Definition of the Cover Index

The proposed time-duration index, named the Cover Index, is defined as 'the proportion of time that an individual is under the potentially protective effect

via contact with their GP over a pre-specified ascertainment period'. Construction of the index relies on first determining a period of time between GP visits that a patient with a stated set of sociodemographic and clinical characteristics has a reduced probability of PPH. We term the potentially temporal protective effect as the 'optimal maximum time interval'. Once this optimal time period has been determined, cover can be calculated, as shown in Figure 6.1.

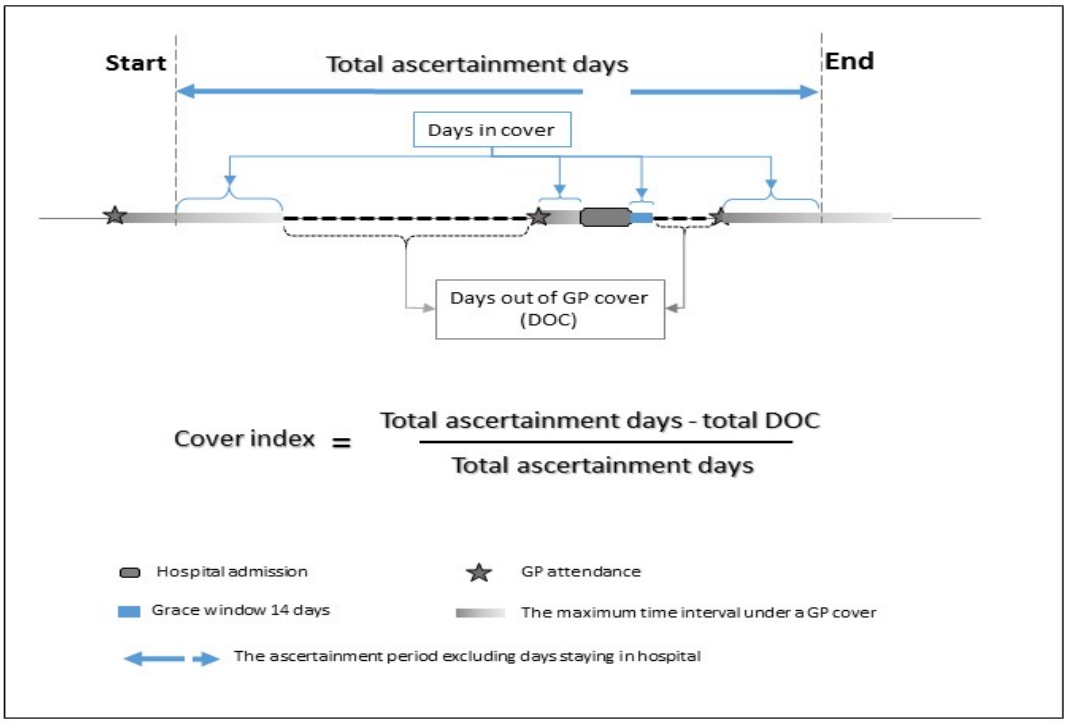


Figure 6.1. The Cover Index

Briefly, the actual time interval (in days) between each GP attendance within the ascertainment period is first determined. This time is then compartmentalised as within or outside of the pre-defined optimal maximum time interval for persons with pre-defined characteristics in that year. The number of days within the optimal maximum time interval (*i.e.* days covered) are then aggregated over an ascertainment period for each individual in the cohort and the proportion of the total number of days eligible for cover over

the ascertainment period is calculated. This provides the Cover Index, which has a value between 0 and 1, for each individual in each year in our scenario (or some other time period chosen based on specific clinical or policy-based rationale). A higher score reflects a greater proportion of time under cover.

Although methods used to calculate the cover score in this study were devised in cohorts of people with diabetes, the methods are applicable to other ambulatory care sensitive conditions.

6.2.2 Semi-structured survey

A semi-structured survey was used to explore the opinions of GPs on the existence and duration of the temporal protective effect of a GP consultation. The protective effect was defined as the duration of time following a GP consultation that people with diabetes would be expected to have a lower risk of hospitalisations and complications. The results were used to inform the empirical analysis.

6.2.2.1 Participants and recruitment procedures

This study used a cross-sectional survey design conducted among a convenience sample of GPs currently practising in Australia between September 2017 and April 2018.

Participants were primarily recruited through key contacts from the project steering panel and Western Australian Primary Health Alliance. Additional recruitment was carried out at GP panel meeting events. To be eligible for the study the participants had to be currently practising GPs with experience of diabetes management.

The participants were offered the choice of answering the survey either

online using the Curtin Qualtrics platform or via a paper version. Information about the study and a consent form were included with the survey, as shown in Appendix F. All surveys were coded and were free of identifying personal information to maintain confidentiality for participants.

6.2.2.2 Measures

Prior to conducting the survey, the questionnaire was piloted by a separate cohort of GPs and researchers in the field and revised according to their feedback. The questionnaire is presented as Appendix F. This survey consisted of four main parts including:

1) Participants' practice experience with patients with diabetes which collected information regarding years in practice, frequency of encounters with patients with diabetes, and experience with diabetes management.

2) Self-ratings on belief in the time protective effect following a GP consultation for people with diabetes.

3) GP ratings on key factors, including comorbidities, duration of diabetes, age, gender, Indigenous status, smoking, obesity, history of hospitalisation and other factors suggested by participants that may influence the duration of the temporal protective effect.

4) Estimations of the duration of the protective effects of a GP consultation for people with diabetes exhibiting several different characteristics; *i.e.* types of complications (macrovascular complications and microvascular complications), and complication status (no complication, one or two complications or multiple complications).

All the questions were designed on a six-point Likert scale with open-ended possibilities for participants to add comments.

6.2.2.3 Data management and analysis

Responses to the online survey were saved via the Qualtrics program and then downloaded and saved as an Excel file. The responses to the paper-based version were also entered into Excel. All data were stored and handled according to Curtin University guidelines.

A simple descriptive analysis was conducted to provide a summary of frequency of GPs' responses to the options for each section. Any responses entered in the open-ended sections were entered in separate columns and presented in quote marks. These results were then used to inform the empirical analyses.

6.2.3 Empirical analysis

6.2.3.1 Estimating the optimal time interval for GP services among people with diabetes

Data sources

Western Australia (WA) whole-of-population administrative health data linked at the individual level for adults aged 18 years or older enrolled to vote in WA at any time between 1 July 1990 and 30 June 2004 were used for this study. The data included four datasets: WA Hospital Morbidity Data System (HMDS); Medicare Benefits Scheme (MBS) claim records; WA Electoral Roll (ER) records and WA mortality records. The HMDS provided information on diagnosis, date of admission and date of separation from all WA hospitals. The MBS provided information on services provided outside the hospital (for

example GP services) and included the date of service and type of medical service. The ER provided information on dates of migration in and out of WA or changes in a residential address while living in WA. Mortality records provided date and cause of death. WA data were linked and extracted via the WA Data Linkage System (WADLS)(174) and MBS data by the Commonwealth Department of Health and Ageing using a linkage key provided by the WADLS.

Study population

The study population consisted of people living with diabetes aged 45 years and older in WA for the years 1998/99 to 2003/04. Individuals with diabetes mellitus were identified using the International Classification of Disease, 9th edition-clinical modification (ICD-9-CM) codes in HMDS records and MBS claims indicative of the presence of diabetes, using all the available data, as described previously (130). Three diabetes cohorts were constructed for this study, based on their level of disease at each observed year: *i.e.* no diabetes complications, 1 to 2 complications, and 3+ complications. The complication severity level was assessed using the complication severity index suggested by Young, Lin (139) and stratified into three groups as outlined previously (130).

All individuals were observed annually from the baseline year to 30 June 2004, or their last year living in WA, or death, with the data constructed as a panel (with years nested within an individual). Only individuals who were alive and resident in WA for at least two consecutive years were included in the study. Individuals could move to a higher complication cohort if their

complication status changed, as ascertained at the end of each observed year. Within each cohort, we measured individual characteristics, including GP utilisation, hospitalisations, complications, comorbidities and sociodemographic characteristics in each observed year, and GP utilisation and hospitalisations in the following year. A similar design has been applied in other studies (4, 130).

Dependent variable

Identification of the number of diabetes-related PPHs during each follow-up year was the main outcome of the study. Diabetes-related hospitalisations were identified using ICD-9-CM and ICD-10-AM codes suggested by the National Health Performance Framework (135) and hospitalisations where diabetes was identified as a significant risk factor suggested by Davis *et al.* (136).

Independent variables

GP utilisation, including frequency of GP services and the time interval between GP services, were focal measures in this study. For each individual, the date of GP services within a financial year was identified in MBS data. The time between GP visits was determined by number of days: (1) between GP visits within a financial year; and (2) between the date of first GP visit of a financial year and the date of the last GP visit in the previous financial year(s) looking back up to three financial years. In the case where a hospitalisation was observed, time was counted either to the first GP visit post-hospitalisation, provided that the GP visit was within 14 days of discharge, or from day 14 after hospital discharge date and the next GP visit. The 14-day

rule was applied based on a large-scale study which suggested that timely follow-up within 14 days of discharge may be considered to reduce the risk of readmission for patient with multiple complex chronic conditions, such as diabetes, heart disease and chronic obstructive pulmonary disease (207) and that time in excess of that would be deemed ‘out of cover’. The time intervals within a financial year were used to calculate the mean time interval for a GP visit, the variance of the time intervals and maximum time interval to a GP visit in months (or part thereof) of the financial year for each individual.

As mean time interval reflects the central tendency of time intervals between services, two individuals can have the same mean time interval but their maximum time interval may be entirely different. In addition, the maximum time interval is more likely to capture the period of time that people were not covered by any protective effect of GP service contact than the mean time interval. Thus, the maximum time interval to a GP visit in the following year was used as the main predictor of hospitalisations in all analyses, while mean time interval, frequency and regularity in the same year as well as mean time interval and regularity in the last year, comprised the covariates.

The variance of the time intervals was used to calculate the annual regularity of GP visits as [1/(1+ standard deviation)] for each individual, described in detail elsewhere (33-35). This regularity score was then converted into quintiles for each cohort. The frequency of GP usage was defined as the total number of GP visits within a financial year, excluding those GP visits occurring within 14 days of the previous GP visit. This exclusion was to minimise over-counting GP service utilisation, as visits within 14 days were

thought by our expert primary care clinicians more likely to be associated with the existing episode of care rather than being indicative of a new episode (e.g. returning for the results of tests); this feature has also been noted in the literature (78).

A number of individual sociodemographic and clinical characteristics were also measured. Demographic characteristics included were age groups (45–59 years, 60–74 years and ≥75 years), gender, and Indigenous status. Socioeconomic status was assessed annually using quintiles of the Census-specific Socio-Economic Indexes for Areas (SEIFA) Index of Relative Socioeconomic Disadvantage (141). Service accessibility was measured annually, classified as very remote, remote, moderate, accessible and highly accessible (142). The number of comorbidities was summed using the MACSS index (143), excluding conditions classified as complications of diabetes. Duration of diabetes was calculated in years from the first identification in WA-linked data. Other use of health services was accounted for by capturing the number of specialist visits and the number of non-diabetes-related hospitalisations in each financial year.

Average cost per hospitalisation was calculated and used to describe the characteristics of each cohort but not used as a controlling variable in regression models. Costs were assigned using Australian Refined Diagnostic Related Group costs from the National Hospital Cost Data collection and the National Efficient Price set by the Independent Hospital Pricing Authority (208). All costs were adjusted to the 2014 Australian dollar using the Consumer Price Index.

Statistical analyses

The data for each cohort were constructed as a panel data structure with multiple measures for each individual, such that response and control variables could vary over the study period. Panel data were complex and unbalanced as individuals could move in and out of WA, die or move to a higher complication level cohort during the study period. Characteristics of the population were described for each cohort at the time of entry to the cohort.

To estimate the optimal maximum time interval we employed the threshold effects model proposed by (145) to examine how the relationship between GP service and diabetes-related potentially PPH varies with the length of the time interval (the maximum time interval) between GP services. The model proceeded by searching for sample heterogeneity in the response of diabetes-related PPH to variation in the time intervals between GP services across populations in each cohort. The information criteria approach used the Bayes Information Criterion (BIC) and Akaike Information Criterion (AIC) statistics to select the optimal model. The selected model was used to identify a number of subpopulations, defined in terms of length of the time interval between GP services. The optimal model was used to suggest the maximum optimal time interval between GP services where the number of diabetes-related PPHs was minimal. The threshold effects model evaluates all subpopulations simultaneously rather than sequentially and therefore extends towards a non-linear model (145) that allows more flexibility in examining the relationship between GP service and the risk of diabetes-

related PPH. This approach has been applied in previous studies (130, 209).

The threshold effects model in our study was an extension of the random effects negative binomial model for panel data which accounts for time-variant factors and imbalance in the data structure. The general form of the model for individual *i* in year t is presented as follows:

$$HOSP_{it} = \sum_{m=1}^{M} \gamma_m [R_{m,i} * TInt_{i,t} \,|\, (GPsvc_{i,t} = 1 \,\&\, TInt_{i,t} \leq 18)]$$
$$+ \beta_1 (D1 = 1 \,|\, GPsvc_{i,t} = 0) + \beta_2 (D2 = 1 \,|\, TInt_{i,t} > 18) * Tint_{i,t}$$
$$+ \beta_1 X_{i,t} + \beta_2 \bar{x}_{i,t} + \alpha_i + HOSP_{t0} + U_{i,t} + \beta_0$$

$$, i = 1,2 \ldots N; t = 1,2 \ldots, T$$

The equation is the hypothesised differential effect of GP services ($GPsvc_{i,t}$) on diabetes-related PPH ($HOSP_{it}$) with respect to an individual's position with regard to the maximum time interval ($TInt_{i,t}$) to the next GP service. The threshold model allows the coefficient γ_m on GP service to vary according to the time interval to a GP service (in month) indicated by subpopulation indicators: $R_{m,i} = 1 \; if \; \{\tau_{m-1} < Tint_{i,t} \leq \tau_m\}$, and 0 otherwise, where m is the number of the subpopulation and τ is the threshold parameter. The number of subpopulation m (1, 2, 3 … M) and the threshold parameters τ were estimated from the data. The M = 1 setting gives a standard negative binomial model.

The threshold variable R_i only took values from 1 to 18 for two reasons: 1) 99% of the population in each cohort had a maximum time interval to a GP service ≤18 months, and so the sample size for the time interval >18 months

was relatively small (about 90 or less records for each time interval); 2) it was more computationally feasible with reduced searching time. However, we still included those cases with the time interval >18 months as a controlling variable (D2), with value of 1 if the maximum time interval >18 months, and 0 otherwise.

The threshold effects model included a dummy variable (D1) for any observation with no GP service in a financial year to control for, rather than exclude, the observation. The model also included demographic and clinical characteristics in the observed years and GP utilisation in both observed and follow-up years in the notation $X_{i,t}$ to control for any confounding. Endogeneity due to a correlation between the error term and the maximum time interval has been minimised by adding Mundlak variables $\bar{x}_{i,t}$, which are group means of time-varied variables, including frequency of GP visits, regularity of GP visits and comorbidities. The group mean of time-varied variables relax the assumption of the random-effects estimator that unobserved factors were independent from the observed factors (147, 148). In addition, the model also included initial conditions (history of hospitalisation at the baseline year, and GP utilisations in the previous years) to adjust for effects of unobserved heterogeneity (149).

All competing models were compared using their BIC and AIC statistics. The preferred model was the one which minimised the appropriate information criteria (AIC and BIC) (145). Within each diabetes cohort, the preferred model indicated the optimal maximum time interval between GP services which offered minimal risk of diabetes-related PPHs. This information was

subsequently used to operationalise the Cover Index.

All analyses were conducted using STATA for Window version SE14.1.

6.2.3.2 Operationalising the Cover Index in the diabetes cohort

In this process, the Cover Index was calculated for each financial year (1 July to 30 June) for the study period of 1998 to 2004, date of death or date of leaving WA, whichever came first. For each financial year, the ascertainment days were the total number of days that people were living in the community (*i.e.* not in hospital).

Days out of GP cover (DOC) were calculated by subtraction of the pre-defined optimal maximum time interval (updated according to diabetes severity level) from the actual time interval between a GP service and the next healthcare service (either via GP or hospital admission). Thus, by definition DOC values were positive. Any time interval that was shorter than the optimal maximum time interval was deemed as 'under cover', and thus given a DOC of zero.

The Cover Index= [∑ascertainment days - ∑DOC] / ∑ascertainment days] was calculated for each individual annually. As the optimal maximum time interval was identified as a range of values from the threshold effects model, the Cover Index was calculated with low, middle and upper value bounds corresponding to low, middle and upper values of the optimal maximum time interval identified for each diabetes severity cohort.

Values of cover were reported by sociodemographic characteristics of the cohort to explore the range of scores and serve to evaluate the face validity

of the Cover Index in capturing vulnerable groups which traditionally have poor continuity of primary health care.

6.3 Results

6.3.1 Semi-structured survey results

A total of 16 out of 42 potential participants (38%) responded to the survey. Each respondent had been practising as a GP for an average of 17 years, with 14 practising in Australia for at least five years and only two practising for two or three years. Most participants reported providing services frequently for people with diabetes. Eight out of 16 GPs reported every day; 4 out of 16 reported once a week; 3 out of 16 reported once a month and none reported rarely or never. GPs reported that they sometimes (2/16); often (6/16) or always (8/16) discussed care plans with diabetes patients. The majority of GPs (13/16) rated that proactively planning follow-up care for patients with diabetes would be extremely important or very important, while others rated it moderately important or slightly important (3/16) and none responded with low or not important ratings (Table 6.1).

Most (15/16) respondents believed that a GP consultation would have a temporary protective effect against the risk of hospitalisations or development of complications for people living with diabetes (Table 6.2). However, this was rated from very true (3/16) to true (6/16) and somewhat true (6/16). One participant who replied ‘somewhat true’ expanded in a comment: ‘*Depending if it was a routine surveillance consult which would give a longer temporal potential effect or an emergency consult for cellulitis which might mean that I refer them [to] hospital immediately’.*

Table 6.1. GP practising experience with diabetes patients

Characteristics	Frequency (N=16)	Percentage (%)
How many years have you been practising as a GP?		
Under 5 years	2	12.5
5 years or more	14	87.5
How often do you see patients with diabetes in the last two years?		
Every day	8	50.0
Every week	4	25.0
Every month	3	17.7
Rarely	1	6.3
Do you discuss a care plan with patients with diabetes?		
Always	7	43.7
Very often	6	37.5
Sometimes	3	18.7
How do you rate the importance of proactively planning follow-up care for patients with diabetes in maintaining their health and well-being?		
Extremely important	11	68.7
Very important	2	12.5
Moderately important	2	12.5
Slightly important	1	6.3

Table 6.2. GP's beliefs regarding the temporal protective effect of a GP consultation

GPs' believe	Do you believe that GP consultation would have 'time limited/temporal protective effect' following GP consultation on reducing potentially preventable hospitalisation for people with diabetes					
	Very true	True	Somewhat true	Somewhat untrue	Untrue	Not what I believe
N (%)	3 (18.7)	6 (37.5)	6 (37.5)	1 (6.2)	0 (0.0)	0 (0.0)

GPs' opinions on the relative importance of factors which may influence the temporal protective effect of a GP consultation are presented in Table 6.3. Overall, clinical characteristics, such as diabetes complications, comorbidities and history of hospitalisations, were mostly rated with moderate to extreme influence for predicting the temporal protective effect of a GP consultation. Factors such as sociodemographic characteristics, smoking and obesity were also highly rated with moderate to extreme importance: gender was the exception. The participants also suggested additional factors, such as living in rural and remote areas, patients' compliance with treatment and intellectual ability.

Table 6.3. Factors influencing prediction of the temporal protective effects of a GP consultation

Factors	Level of influence/importance of each factor					
	Extremely	Very	Moderate	Slightly	Low	Not at all
	N (%)	N (%)	N (%)	N (%)	N (%)	N (%)
Macrovascular complications	6 (37.5)	5 (31.3)	2 (12.5)	3 (18.7)	0 (0.0)	0 (0.0)
Microvascular complications	3 (18.7)	6 (37.5)	4 (25.0)	3 (18.8)	0 (0.0)	0 (0.0)
Count number of complications	5 (31.2)	5 (31.3)	5 (31.2)	1 (6.3)	0 (0.0)	0 (0.0)
Comorbidities	7 (43.8)	8 (50.0)	1 (6.2)	0 (0.0)	0 (0.0)	0 (0.0)
Duration of diabetes	0 (0.0)	8 (50.0)	7 (43.8)	1 (6.2)	0 (0.0)	0 (0.0)
Age	1 (6.2)	9 (56.3)	6 (37.5)	0 (0.0)	0 (0.0)	0 (0.0)
Gender	2 (12.5)	2 (12.5)	2 (12.5)	6 (37.5)	4 (25.0)	0 (0.0)
Indigenous status	4 (25.0)	7 (43.8)	3 (18.8)	1 (6.2)	1 (6.2)	0 (0.0)
Low social economic status	3 (18.8)	6 (37.5)	4 (25.0)	2 (12.5)	1 (6.2)	0 (0.0)
Smoking	6 (37.5)	4 (25.0)	3 (18.8)	3 (18.8)	0 (0.0)	0 (0.0)
Obesity	3 (18.8)	5 (31.3)	5 (31.2)	3 (18.8)	0 (0.0)	0 (0.0)
History of hospitalisation	3 (18.8)	9 (56.3)	3 (18.8)	0 (0.0)	1 (6.2)	0 (0.0)

Fifty percent of GPs (8/16) believed that the temporal protective effect following a GP consultation would be about 10 to 12 months for diabetes without complication, while the other 50% of participants believed it would be shorter (varying between 1 to 7 months). For diabetes with one or two complications, GPs' responses were less consistent. Among 16 participants, three estimated about 8 to 9 months, 5 estimated 6 to 7 months, 4 estimated

2 to 3 months, while 4 respondents believed that the protective effect would be less than a month. For diabetes with three or more complications, the majority (9/16) believed that the temporal protective effect would be one month or less, others believed it would be 2 to 7 months (6/16) and 8 to 9 months (1/16) (Table 6.4).

Table 6.4. GPs' estimation of the temporal protective effect by clinical conditions

GP's estimation	Length of the temporal protective effect of a GP consultation					
	1 month or less	2 - 3 months	4-5 months	6-7 months	8-9 months	10-12 months
	N (%)	N (%)	N (%)	N (%)	N (%)	N (%)
Diabetes with some sort of macrovascular complications	5 (31.3)	6 (37.5)	3 (18.8)	1 (6.2))	0 (0.0)	1 (6.2)
Diabetes with some sort of microvascular complications	2 (12.5)	5 (31.3)	2 (12.5)	4 (25.0)	1 (6.2)	2 (12.5)
Diabetes with NO complication	4 (25.0)	1 (6.2)	2 (12.5)	1 (6.2)	0 (0.0)	8 (50.0)
Diabetes with 1 or 2 complications	3 (18.8)	5 (31.2)	0 (0.0)	5 (31.2)	3 (18.8)	0 (0)
Diabetes with 3 or more complications	8 (50.0)	2 (12.5)	2 (12.5)	2 (12.5)	1 (6.2)	1 (6.2)
Diabetes with other comorbidities	5 (31.3)	6 (37.5)	1 (6.3)	1 (6.2)	1 (6.2)	2 (12.5)

6.3.2 Empirical analysis results

Characteristics of diabetes cohorts at the time of entering the cohort

A total of 36,667 individuals aged 45 years or older were classified as living with diabetes in WA in this study. Since individuals could change cohorts (*i.e.* move to a higher complication group) throughout the study the total number of individuals shown in Table 6.5 reflects the number of individuals who were

classified in that particular cohort at any time and is thus larger than the total number of individuals in the study. The cohorts are not mutually exclusive over the entire study period but are mutually exclusive within individual years (*i.e.* an individual cannot be in more than one cohort in the same financial year). During the study period, 8,968 individuals changed cohorts.

Characteristics of the individuals at the time of entry into each cohort is presented in Table 6.5. Compared with individuals in the cohort with no complication, individuals in cohorts with more complications were older (38.7% of those in three complication cohort and 25.8% of those in one or two complication cohort were aged 75 years or older vs. 10.8% among those with no complication); had a higher number of comorbidities (average of 8.3 and 5.7 vs. 3.0 comorbidities, respectively); a longer duration of diabetes (9.2 years and 7.2 years vs. 5.4 years, respectively), a higher number of hospitalisations (1.8 and 0.53 hospitalisations per year vs. 0.03 hospitalisations per year, respectively) and higher average cost per hospitalisation (A$7756.2 and A$5637.4 per hospitalisation vs. A$3993.2). However, other characteristics such as gender, socioeconomic status and accessibility to services and GP usage did not vary between cohorts.

Table 6.5. Characteristics of studied population at the time of entering each complication cohort

Characteristics	No complication	One or two complications	Three complications or more
	(N, (%))	(N, (%))	(N, (%))
N	20 039	14 866	10 730
Age group (years)			
45-59	9 223 (46.0)	3849 (25.9)	1,869 (17.4)
60-74	8 650 (43.2)	7178 (48.3)	4,708 (43.9)
≥75	2 166 (10.8)	3839 (25.8)	4,153 (38.7)
Gender			
Female	9 741 (48.6)	7263 (48.8)	5000 (46.6)
Male	10 298 (51.4)	7603 (51.1)	5,730 (53.4)
Indigenous status			
No	17 911 (95.9)	13,937(93.7)	9,880 (92.1)
Yes	771 (4.1)	929 (6.2)	850 (7.9)
SEIFA			
Highest disadvantage	3 951 (19.8)	3,232 (21.9)	2,445 (22.9)
High disadvantaged	5 540 (27.8)	4,302(29.1)	3,128 (29.3)
Moderate disadvantage	2 792 (14.0)	2,126 (14.4	1,496 (14.0)
Less disadvantage	3 205 (16.1)	2,226 (15.1)	1,582 (14.8)
Least disadvantage	4 412 (22.2)	2876 (19.5)	2,005 (18.8)
Accessibility			
Very remote	553 (2.8)	606 (4.1)	525 (4.9)
Remote	359 (1.8)	277 (2.0)	186 (1.7)
Moderate	945 (4.7)	772 (5.2)	603 (5.6)
Accessible	1 039 (5.2)	843 (5.7)	627 (5.9)
Highly accessible	17 004 (85.4)	12265 (83.0)	8,716 (81.9)
Number of comorbidity			
Mean (SD)	3.0 (2.9)	5.7 (3.1)	8.3 (3.1)
Duration of diabetes (years)			
Mean (SD);	5.4 (3.8)	7.2 (4.2)	9.2 (4.7)
Regularity quantiles			
No regularity	4 765 (23.8)	3,150 (21.2)	2,382 (22.2)
Quantile 1	3 833 (19.1)	2,776 (18.7)	2,082 (19.4)
Quantile 2	3 850 (19.2)	2,873(19.3)	2,070 (19.3)
Quantile 3	3 772 (18.8)	2,975 (20.0)	2,116 (19.7)
Quantile 4	3 819 (19.0)	3,092 (20.8)	2,080 (19.4)
Average time to a GP visit (months) Mean (SD)	3.6 (3.2)	2.8 (2.5)	2.4 (2.1)
Frequency of GP visits Mean (SD)	4.7 (2.8)	5.1 (3.0)	5.2 (3.2)
Number of specialist visits Mean (SD)	2.4 (4.1)	4.5 (6.5)	5.5 (9.2)
Number of non-diabetes-related hospitalisation	0.35 (1.57)	0.72 (2.3)	1.04 (1.85)
Number of diabetes-related hospitalisation	0.03 (1.06)	0.53 (1.7)	1.8 (10.8)

Average costs per diabetes-related hospitalisations (2014 A$) (Mean (SD))	4 381.2 (3 828.7)	5 185.5 (5 492.7)	8 192.7 (8 992.6)
Min-Max	800.8-38 842.4	748.8-128 552.6	598.2-144 061.3
Average costs per non-diabetes-related hospitalisations (2014 A$) (Mean (SD))	3 993.3 (4 132.2)	5 637.4 (7 964.4)	7 756.2 (12 172.2)
Min-Max	393.4-61 680.1	393.4-142 694.4	662.2 -227 080.1

Estimation of the optimal maximum time intervals for each diabetes cohort

Table 6.6 shows the results of the threshold effects model, which presents how the relationship between GP service and the risk of diabetes-related PPH varies across the length of the maximum time interval between GP services by complication cohort. Based on both BIC and AIC, the preferred models indicate a non-linear relationship between maximum time interval between GP visits and the number of hospitalisations, with five subpopulations in both no complication cohort and one or two complication cohort, and four subpopulations in three or more complication cohorts. Overall, the expected number of diabetes related PPH was observed lowest in a maximum time interval between GP visits of 9 months to 13 months for diabetes with no complication; 5 months to 11months for diabetes with one or two complications; and 4 months to 9 months for diabetes with three or more complications (Table 6.6).

For no complication cohort, the average number of predicted diabetes related PPHs within the optimal maximum time interval was 0.044 (95%CI, 0.043-0.045) admissions while the number was significantly higher among the sub-optimal time intervals (0.127 (95%CI, 0.126-0.128)). For one or two complication cohort, the average number of predicted diabetes related PPHs within the optimal maximum time interval was 0.159 (95%CI, 0.158-0.160) admissions while the number of hospitalisation was significantly higher

among sub-optimal time interval (0.314 (95%CI, 0.311-0.316)). For three or more complication cohort, the predicted number of diabetes related PPH within the optimal maximum time interval was 0.589 (95%CI, 0.583-0.595) admissions while the number of hospitalisations was significantly higher among the sub-optimal time interval (1.15, 95%CI 1.14-1.16). The change in the number of predicted diabetes-related PPH across the maximum time interval between GP visits using spline function is also presented in Figure 6.2.

Cover Index and its distributions

Table 6.7 shows the annual average Cover Index score overall for the whole studied population and by sociodemographic characteristics. Overall, the average cover score was 0.85 (upper bound) (95% CI 0.80 to 0.85), indicating that on average, in this cohort, 85% of the year people with diabetes were under the protective effect from PPH via contact with their GP. However, only 83% of the time period was covered if the lower boundary of the optimal maximum time interval was considered, rising to 84% of the time interval covered if the middle bound of the optimal maximum time interval was considered. The Cover Index score changed according to sociodemographic characteristics. The lowest average Cover Index scores across low, middle and upper bounds was observed among those aged 75 years or older (0.77, 0.78 and 0.79, respectively), males (0.80, 0.82 and 0.83, respectively), Indigenous (0.60, 0.63 and 0.64, respectively), those with the highest disadvantage (0.81, 0.82 and 0.83, respectively) and living in very remote areas (0.48. 0.51 and 0.52, respectively).

Table 6.6. Threshold search for max time to GP visits by complications for people aged 45 years or older

Complication cohorts	No complication [a]						One or two complications [b]						Three or more complications [c]				
Number of subpopulations	2	3	4	5	6	18	2	3	4	5	6	18	2	3	4	5	18
AIC	45169.0	45091.2	45049.5	45020.4	45017.6	45018.7	53464.2	53413.6	53360.2	53346.5	53408.3	53340.3	69875.6	69812.3	69774.9	69769.4	69777.3
BIC	45398.5	45329.9	45297.3	45277.4	45283.8	45450.1	53683.6	53641.8	53597.2	53592.3	53662.8	53752.9	70086.1	70031.2	70002.3	70005.2	70173.0
Threshold parameters																	
τ_1	8	8	2	2	2	-	10	2	2	2	3	-	9	2	2	2	-
τ_2		13	8	3	3	-		10	3	3	6	-		3	3	3	-
τ_3			13	8	8	-			11	4	7	-			9	9	-
τ_4				13	10	-				11	9	-				13	-
τ_5					13	-					11	-					
Coefficients																	
γ_1	-0.229***	-0.249***	-0.040	0.134**	0.123**	-	-0.194***	-0.015	0.194***	0.323***	-0.165***	-	-0.128***	0.289***	0.196***	0.190***	-
	(0.01)	(0.01)	(0.03)	(0.05)	(0.05)	-	(0.01)	(0.03)	(0.04)	(0.05)	(0.03)	-	(0.01)	(0.03)	(0.03)	(0.03)	-
γ_2	-0.083***	-0.126***	-0.199***	-0.057	-0.064*	-	-0.053***	-0.157***	0.006	0.087**	-0.216***	-	-0.014	0.115***	0.054*	0.050*	-
	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)	-	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	-	(0.01)	(0.02)	(0.02)	(0.02)	-
γ_3		-0.013	-0.101***	-0.148***	-0.152***	-		-0.039**	-0.099***	-0.023	-0.188***	-		-0.001	-0.046**	-0.048**	-
		(0.01)	(0.01)	(0.02)	(0.02)	-		(0.01)	(0.01)	(0.02)	(0.02)	-		(0.01)	(0.02)	(0.02)	-
γ_4			0.004	-0.072***	-0.089***	-			-0.000	-0.071***	-0.162***	-			0.028*	0.013	-
			(0.01)	(0.01)	(0.02)	-			(0.01)	(0.02)	(0.02)	-			(0.01)	(0.01)	-
γ_5				0.024	-0.057***	-				0.016	-0.116***	-				0.062***	-
				(0.01)	(0.02)	-				(0.01)	(0.02)	-				(0.02)	-
γ_6					0.022	-					-0.039**	-					
					(0.01)	-					(0.01)	-					

*Notes: * if p-values<0.05; ** if p-values<0.01; *** if p-values<0.001*

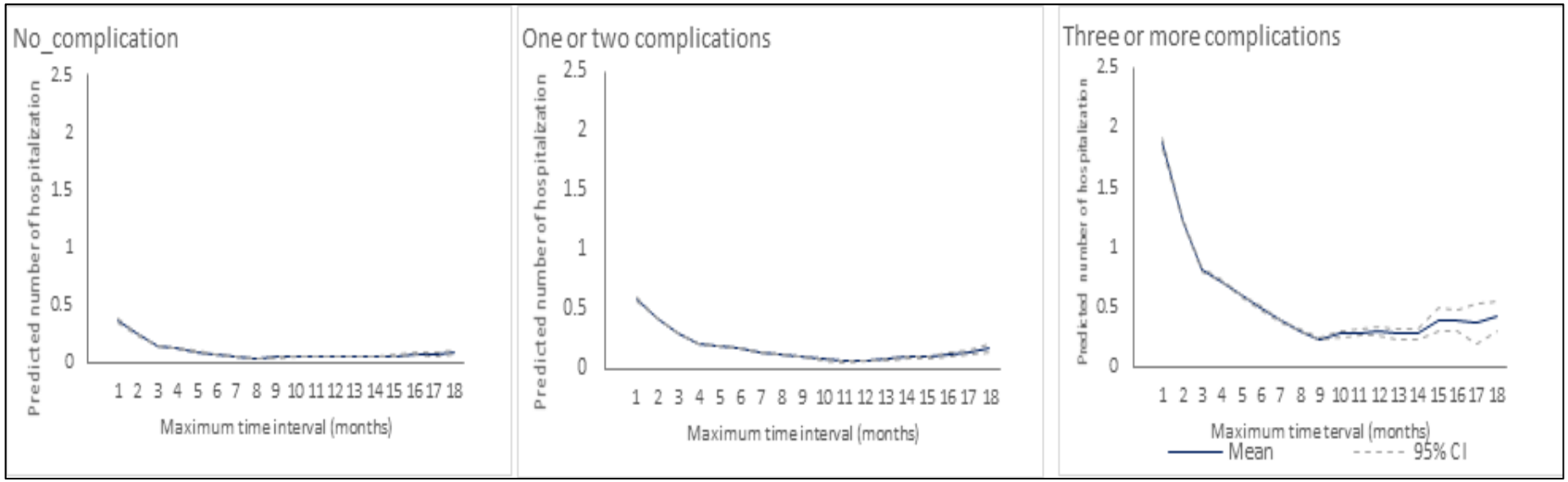


Figure 6.2. Changes in number of hospitalisations across maximum time interval between GP visits by cohorts

Table 6.7. Average yearly cover score across maximal optimal time interval boundary over the studied period

Characteristics	Low bound cover		Middle bound cover		Upper bound cover	
	mean	95% CI	mean	95% CI	mean	95% CI
Overall						
Mean	0.83	(0.83 - 0.83)	0.84	(0.84 - 0.85)	0.85	(0.80 - 0.85)
Median (IQR)	0.98	(0.81 - 1.00)	1.00	(0.86 - 1.00)	1.00	(0.87 - 1.00)
Age group (years)						
45-59	0.82	(0.81 - 0.82)	0.84	(0.83 - 0.84)	0.85	(0.84 - 0.85)
60-74	0.87	(0.87 - 0.87)	0.88	(0.88 - 0.89)	0.89	(0.89 - 0.89)
≥75	0.77	(0.77 - 0.77)	0.78	(0.78 - 0.79)	0.79	(0.78 - 0.79)
Gender						
Female	0.86	(0.86 - 0.86)	0.87	(0.87 - 0.87)	0.88	(0.88 - 0.88)
Male	0.80	(0.80 - 0.80)	0.82	(0.82 - 0.82)	0.83	(0.83 - 0.83)
Indigenous status						
No	0.84	(0.84 - 0.84)	0.86	(0.86 - 0.86)	0.86	(0.86 - 0.86)
Yes	0.60	(0.59 - 0.61)	0.63	(0.62 - 0.64)	0.64	(0.63 - 0.65)
SEIFA						
Highest disadvantaged	0.81	(0.80 - 0.81)	0.82	(0.82 - 0.83)	0.83	(0.83 - 0.83)
High disadvantaged	0.83	(0.83 - 0.84)	0.85	(0.85 - 0.85)	0.86	(0.85 - 0.86)
Moderate disadvantaged	0.83	(0.83 - 0.84)	0.85	(0.85 - 0.85)	0.86	(0.85 - 0.86)
Less disadvantaged	0.84	(0.84 - 0.84)	0.86	(0.85 - 0.86)	0.86	(0.86 - 0.87)
Least disadvantaged	0.84	(0.84 - 0.84)	0.86	(0.85 - 0.86)	0.86	(0.86 - 0.87)
Accessibility						
Very remote	0.48	(0.47 - 0.49)	0.51	(0.50 - 0.52)	0.52	(0.51 - 0.53)
Remote	0.74	(0.73 - 0.76)	0.77	(0.76 - 0.78)	0.78	(0.77 - 0.79)
Moderate	0.79	(0.79 - 0.80)	0.82	(0.81 - 0.82)	0.82	(0.82 - 0.83)
Accessible	0.81	(0.81 - 0.82)	0.83	(0.83 - 0.84)	0.84	(0.84 - 0.85)
Highly accessible	0.85	(0.85 - 0.85)	0.86	(0.86 - 0.87)	0.87	(0.87 - 0.87)

6.4 Discussion

This was the first study seeking to develop and operationalise the Cover Index, a novel measurement of continuity of primary care that represents an improvement to existing measurements of regularity of primary care, through examining the idea that a time-limited protective effect can be achieved from interactions with a GP. This study used a mixed method approach, which combined a semi-structured survey and empirical analysis in the development process of the Cover Index. A semi-structured survey allowed an exploration among GPs about their opinions, to test the hypothesis that a GP consultation may have a temporal protective effect which minimises the risk of PPH and subsequent complications for people with diabetes. Although the result of the survey provided a limited confirmation of GPs' estimations of the temporal protective effect of a GP consultation, the survey provides a strong sense of the duration of the protective effect and that the duration would be likely to change according to diabetes severity. Most participants suggested that the temporal protective effect would be 10 to 12 months for diabetes with no complications, 8 to 9 months for diabetes with one or two complications and one month or less for diabetes with three or more complications.

In trying to estimate how long a temporal protective effect would persist among people with diabetes, empirical analysis was performed to estimate a proxy measure of a temporal protective effect, that is, the optimal maximum time interval associated with the least number of diabetes-related PPH among diabetes cohorts. The empirical analyses indicated that the optimal maximum time interval where the risk of hospitalisation was least was 9 to13

months for diabetes without complication, 5 to 11 months for one or two complications and 4 to 9 months for three or more complications. Given the different approaches taken to estimate the temporal protective effect, some disparity in results between the survey and the empirical analysis was expected. Nevertheless, the empirical results were quite consistent with the result of the survey, except for diabetes with three or more complications where GPs estimated a much shorter period of protective effect. The finding is in line with the recommendation in primary care guidelines for diabetes (210, 211) which suggest people with diabetes should receive primary care at regular intervals of 3 to 12 months, depending on the complexity of their individual needs. In addition, the findings are consistent with growing evidence that optimised primary care may improve health outcomes and reduce pressure on resources (212, 213). However, current evidence does not clearly indicate specific time intervals for different disease severity levels, which may limit our present ability to effectively measure primary care performance and utilisation. In addition to facilitating the operationalisation of cover, the findings of this study have provided an important insight into primary care needs of people with diabetes corresponding to their severity level; this may provide further evidence for the improvement of primary care.

In this study, the empirical results were presented in order to demonstrate operationalisation of the Cover Index. The Cover Index could also be flexibly operationalised with a range of *a priori* optimal time periods, such as those based on expert opinion or clinical guidelines, if applicable, to aid in both the development and evaluation of policies incentivising provider–patient interactions. Differences in the Cover Index score operationalised in this way

could be used as to evaluate the impact of such opinion, guidelines or policy on PPHs. With the tremendous growth in the availability and range of whole-of-population administrative health datasets, empirical approaches are more than ever able to measure the performance of health systems and evaluate the impact of health policy. However, currently available metrics are limited in their sophistication regarding the domains they are able to capture (25, 28, 31, 80). The Cover Index and the empirical approach developed in this study would significantly contribute to the advancement of available methods for the analysis of these data.

Recent studies in health care demonstrate various approaches, such as counting a number of GP services in the short term or long term prior to hospitalisation (214); or visualising the density of GP services (215); or examining the utilisation of GP services. In countries where GPs are the gatekeepers to access for most medical services, using these approaches may not capture under-utilisation of GP services. This study suggests that using the maximum time interval instead of average time interval between healthcare services or frequency of services would be useful criteria to examine in relation to the risk of hospitalisation. The maximum time interval drives attention towards the ‘long overdue period’ likely to reflect discontinuity of GP care and lost opportunities for providing early treatment and reinforcement of healthy behaviours in the primary care setting.

Results of the variation in the average Cover Index show disparities in GP cover that are associated with socioeconomic disadvantage, even though the results are only exploratory. The results are consistent with the literature

showing poor access to primary care services among people from a low socioeconomic background, Indigenous people or those living in remote areas (196, 216) and thus provide some face validity that the Cover Index performs in the way expected. The results also provide a quantification of disparities in GP cover, which is important information to target healthcare resources; and provide a tool to accurately quantify the improvement in primary care resulting from interventions. Given the high burden of hospitalisation, improvement in GP cover would offer a cost-effective opportunity to reduce the costs of hospitalisation, especially among those with multiple complications. While not explored in this study, in addition to capturing periods that are not covered, the metric could also be adapted to capture periods of 'over cover' and thus be used to measure over- as well as under-servicing.

Strengths and limitations of the study

The major strength of this study was using a mixed approach which combined both the semi-structured survey and the empirical analysis; this added multiple dimensions to estimation of the time protective effect of a GP consultation for people with diabetes. This study used a threshold effects model, a powerful and flexible tool, to comprehensively estimate the optimal time interval for a GP visit. A further strength of this study is the large population and extensive range of linked databases used in the empirical analysis that allowed us to measure and control any changes in both outcomes and exposures over the studied period.

The Cover Index developed in this paper does not incorporate the number of

GPs or GP practices visited. Since the purpose of the metric is to determine the influence of the intervals between visits, it was judged that adjusting for other dimensions of continuity (*e.g.* the usual provider index, the frequency of visits and the number of practices visited) in models would be preferable to incorporating these dimensions of continuity in the metric. Therefore, the study's inclusive measure of time duration in the design of the Cover Index can be seen as a strength, since using the cover metric with separate adjustment for other dimensions of continuity allows the time duration component to be separated from other components; this makes the impact of time duration clearer. This feature will be more valuable to practitioners and policy makers than a metric that reports on a combination of features. Interaction terms could be added for evaluating various combinations of dimensions if required.

This study has some limitations to consider when interpreting its results. The major limitation of this study was that the GP survey included only a small number of participants. In addition, although the survey had open-ended options included in the questionnaire, this option did not effectively collect comments from the participants. A better designed semi-structured qualitative survey with a more generous sample size would provide more useful information in exploring and evaluating the temporal protective effects of a GP consultation. However, the survey results do provide a preliminary sense of the temporal protective effects following a GP consultation for people with diabetes and this aligns with the findings of the empirical analysis.

The empirical analyses were conducted using data from 1990 to 2004; hence it cannot provide evidence regarding current utilisation of GP services. However, for the purposes of this paper, which sought to develop and operationalise the cover metric, the lack of contemporaneous data is unimportant. In addition, the use of these historical data could be considered a strength because this particular time period incorporates a period in Australia when there were few policy interventions aimed at increasing the provision of primary care for people with chronic conditions. Thus, the data in this period could, with appropriate control of confounding factors, provide the baseline needed to identify the incremental impact of recent policies aimed at supporting the continuity of primary care, if it is used to measure changes in the Cover Index and associated impact on PPHs. The empirical study was also supported by the result of a survey of GPs; although this was small in scale, it did provide an exploration of current practices and beliefs regarding the duration of the GP protective effect for people with diabetes.

Administrative data are not collected for research purposes; hence, they do not include some clinical details about severity of disease. Data in this study also did not supply information about whether individuals visited the same or different GPs, information that may have improved the threshold modelling of estimation of the optimal maximum time duration. As using the same provider is a potential indicator for a holistic approach to continuity of care, future work may wish to expand on the current metric by including such data. The empirical results were limited to those who were clinically diagnosed with diabetes and who also have used healthcare resources through hospital admissions or Medicare claims: this limited cohort may affect any

generalisation about the optimal maximum time durations. Although the covered time duration estimated in this study relates only to diabetes at particular severity levels, the Cover Index has an obvious application to other ambulatory care sensitive chronic conditions.

6.5 Conclusions

By combining results from both a semi-structured survey and subsequent empirical analysis, this study provides evidence that there is a temporal protective effect following GP consultation, such that people with diabetes could be expected to have reduced risk of hospitalisations and developing complications. This study adds to the current literature by developing and operationalising a new measurement of continuity of primary care that recognises and incorporates its time-duration protective effects. This study also offers an application of the novel threshold effects model in estimating the optimal maximum time interval between GP services.

A further evaluation of the relationship between the Cover Index of GP visits and diabetes-related PPH, using contemporaneous data, is the subject of the next study in Chapter 7. This next study operationalises the Cover Index in a different study population and re-evaluates the previous estimation of the optimal maximum time interval of GP cover.

Chapter 7 Application of the Cover Index in evaluating continuity of care

This chapter presents a study which aimed to apply the Cover Index to contemporary data to examine the relationship between the Cover Index and diabetes-related PPHs, controlling for other continuity of care indexes, including the usual provider index and regularity index. This study used data from participants of the New South Wales 45 and Up Study (2005–2016) who were ascertained to have been previously diagnosed with diabetes and were aged 45 years and older. Using the same methodology as described in Chapter 6, the threshold effect model was used to empirically estimate the optimal maximum time interval between GP visits associated with the largest reduction in diabetes-related PPH for each diabetes complication cohort. The appropriate value was then used to calculate a Cover Index score for each individual. In addition to the standard negative binomial covariate adjusted model, the generalised propensity score approach was also used to estimate the dose-response function of the Cover Index on the number of diabetes-related PPHs and associated length of hospital stay. Given the availability of indicators for identifying unplanned diabetes-related PPHs, this study also examined the relationship of the Cover Index to unplanned diabetes-related PPHs and length of hospital stay. After controlling for other continuity of care index and individual socioeconomic and clinical characteristics, this study suggested that individuals with higher GP cover had a significantly lower number of diabetes-related PPHs, fewer unplanned diabetes-related PPHs and shorter lengths of stay. Incrementally increasing GP cover was associated with reduction in the number of diabetes-related PPHs, unplanned

diabetes-related PPHs and also length of hospital stay. This is the first study evaluating effects of continuity of care in terms of the time protective effect of GP contact on diabetes-related PPH independently from effects of regularity of GP contacts and consistency of providers. It also suggests that the Cover Index may be a useful tool to measure the existing performance and new policies aimed at the optimisation of primary care for people with chronic conditions, specifically diabetes.

A manuscript was submitted to the Sax Institute and the Department of Human Services on 20 November 2018 for technical review as required for all papers using the 45 and Up cohort data before submission to a peer-reviewed journal. The submitted manuscript is included as Appendix E:

Thi Ninh Ha, Mark Harris, David Preen & Rachael Moorin. The Cover Index: Evaluating continuity of care incorporating the time-duration effect of general practitioner care on diabetic-related potentially preventable hospitalisations

The study is described fully below, using the format of this thesis.

7.1 Introduction

Primary health care has become a cornerstone of health systems in many countries due to its contribution to optimise population health and minimise inequity across subpopulations (19, 217). In Australia, approximately 85% of the general population received at least one consultation per year from a general practitioner (GP) (217). In many countries GPs are responsible for the first contact of care, gatekeeping access to other parts of the health system, and coordinating and integrating primary and community care with services provided in secondary care settings, including specialists, allied health and hospital care (217). The growing proportion of elderly due to ageing of the population has resulted in an increase in the number of people living with chronic and complex conditions. Care offered by GPs has therefore been identified as vitally important for the management of chronic conditions (50). GPs are able to provide long-term and comprehensive care that is not solely focused on a single condition but rather focuses on the condition within the context of a patient's other health issues and social conditions (10, 19). Thus, GPs make an important contribution to high-quality care and efficient use of scarce healthcare resources (19).

Continuity of care is the centrepiece of high-quality primary care, especially for people living with long-term and complex conditions who are often faced with a wide range of challenges, such as medical crises, uncontrolled symptoms and social isolation (218). The connection of care from past to current and future, in which GPs play a central role, is essential to ensure sufficient provision of care, to minimise unnecessary or harmful care and to promote self-management for people with chronic health conditions (64, 85).

Continuity of care has been described as incorporating three main dimensions, including interpersonal relationships, information and management (81, 85). Previous studies have found that more continuity of care in terms of more continuity with the same provider (24, 219), greater regularity of GP visits (33, 35, 37) or greater density of visits (31) is associated with better patient satisfaction, and fewer avoidable hospitalisations.

For people with ambulatory care sensitive conditions (ACSC), early disease management and treatment provided in primary care settings has been shown to reduce potentially preventable hospitalisation (PPH) (13, 220). To be efficient in managing a chronic ACSC such as diabetes, shifting care to a proactive or predictive approach instead of reactive care, which is both expensive and ineffective, can be an effective strategy (47). Proactive care offers an opportunity for early and sufficient action to be taken to prevent the onset and delay progression of degenerative diseases (47). Recent evidence examining patterns of GP utilisation has suggested that the time interval between GP visits was associated with a reduction in PPHs (212, 221). The importance of the element of time duration between services has been suggested in customer relationship management frameworks (43), and used in a similar form to measure medication persistence (41, 42) and continuity of medication management (222). This concept is now integrated into a new continuity of care metric named the Cover Index, capturing the proportion of time people are under the potentially protective effect of GP care (221). To aid in the development of policies and behaviours that support proactive care by GPs, it is useful to examine the GP–patient relationship in terms of GP

protective cover, accounting for other facets of continuity of care including continuity of provider, regularity and frequency of GP contact. This study aimed to assess the amount of time people with diabetes spend under the protective effect of GP care, measured by the Cover Index; to highlight its relationship with diabetes-related PPH, while simultaneously incorporating other continuity of care measures, including usual provider index and regularity of GP contacts.

7.2 Methods

7.2.1 Data sources

This was a retrospective observational study using data from the Sax Institute's 45 and Up Study in New South Wales; details of the cohort profile have been previously reported (125). The Sax Institute's 45 and Up Study was sampled from the Department of Humans Services (formerly Medicare Australia) enrolment database. The study cohort comprised over 267,000 people aged 45 years and over with individual information on demographics, socioeconomic status, lifestyle factors, health status and wellbeing collected from the survey carried out between 2006 and 2009. Survey data were linked with administrative health records from i) the New South Wales Admitted Patient Data Collection (APDC) (2005 to 2015), ii) the Medicare Benefits Scheme (MBS) (2005 to 2015), iii) the Pharmaceutical Benefits Scheme (PBS) (2005 to 2015), and (iv) the NSW Register of Births Deaths and Marriages (RBDM) (2006 to 2015). The NSW Centre for Health Record Linkage (CHeReL) conducted the linkage for APDC and RBDM. CHeReL linkages are probabilistic. The MBS and PBS data were linked

deterministically by the Sax Institute using a unique identifier provided by the Australian Government Department of Human Services. The privacy of individual patients was conserved using a probabilistically linked technique with very low false-positive and false-negative rates of <0.5 and <0.1%, respectively (126). All individual data were de-identified and assigned a unique project person number.

The APDC data comprised dates of admission and separation, diagnoses (primary and secondary), procedures performed and other details of individual episodes of hospitalisation, such as type of admission, transfer and discharged status from all private and public hospitals in NSW. Details of diagnoses were recorded using 10th revision Australian Modification Codes (ICD-10-AM) in the principal diagnosis and up to 54 additional diagnoses (4). The MBS records consisted of the items claimed, date of service and de-identified unique provider codes for medical and diagnostic services provided out of hospital under Australia's universal health insurance scheme. The PBS records comprised claims for subsidised prescription medicines and included the item code Anatomical Therapeutic Chemical (ATC) code, quantity and date supplied. The deaths registry had information on the date and cause of death and was used to identify participants in the study population who had died during the study period.

7.2.2 Study population

The study population included people aged 45 years and older identified with diabetes between 2005 and 2009 using information from self-report, APDC and PBS data. People were identified as having diabetes if they answered

yes to the question ‘Has the doctor ever told you that you have diabetes?’; or if they had an APDC record with ICD-10-AM codes for diabetes (E10, E11, E13, E14) in any field of diagnosis and/or a PBS claim indicating a dispensing between 2005 and 2009 using the ATC code of A10A (insulins and analogues) or A10B (blood glucose-lowering drugs, excluding insulins. A total of 29,007 individuals were identified with diabetes by 1 July 2009. We then excluded those who died within two years after the baseline year (2009) (n=2 310, 7.9%) to allow a minimum of two-year follow up for every individual. As the main study interest is the relationship between primary health care and hospitalisation, individuals who did not have any hospitalisations or GP encounters in the whole study period from 1 July 2009 to 30 June 2016 were also excluded (n=95, 0.3 %). Finally, we excluded a small number (n=1 755, 6.0 %) of individuals without supplied details of age, sex, and/or socioeconomic characteristics.

Ethical approval was obtained from Curtin University Human Research Ethics Committee (RD-42-14) and the NSW Population and Health Services Research Ethics Committee (HREC/17/CIPHS/37). Consent was given by all participants in the Sax Institute’s 45 and Up Study for their information to be used in approved studies, and for follow up and data linkage. The conduct of 45 and Up Study was approved by the University of NSW Human Research Ethics Committee.

7.2.3 Outcome measures

The main outcome was the number of diabetes-related PPHs measured in each financial year using ICD-10-AM codes suggested by the National Health Performance Framework (135) and hospitalisations where diabetes was

identified as a significant risk factor (136). We excluded routine hospitalisations for kidney dialysis and inter-hospital transfers were counted as a single episode of care. We also measured unplanned diabetes-related PPHs which included only those diabetes-related PPHs with emergency admission status recorded on the APDC record.

Annual and three-year period total lengths of stay (LOS) were calculated for diabetes-related PPHs and unplanned diabetes-related PPHs, with same day episodes counted as one day.

7.2.4 Independent measures

The Cover Index

The main predictor was the estimated Cover Index, which is a metric that captures the proportion of time over the ascertainment period in which an individual is considered under the 'protective effect' (*i.e.* cover) of a GP contact, as developed in the previous study (221) (Figure 7.1).

The time under GP cover was determined using the optimal maximum time interval following a GP consultation during which people with diabetes were found to have the lowest number of diabetes-related PPHs. In this study, the optimal maximum time interval was estimated as the maximum time interval between GP visits, using threshold effect modelling stratified by severity level of the diabetes. Further details of estimation using threshold effects models are presented in the statistical analysis section below and have been previously reported (221).

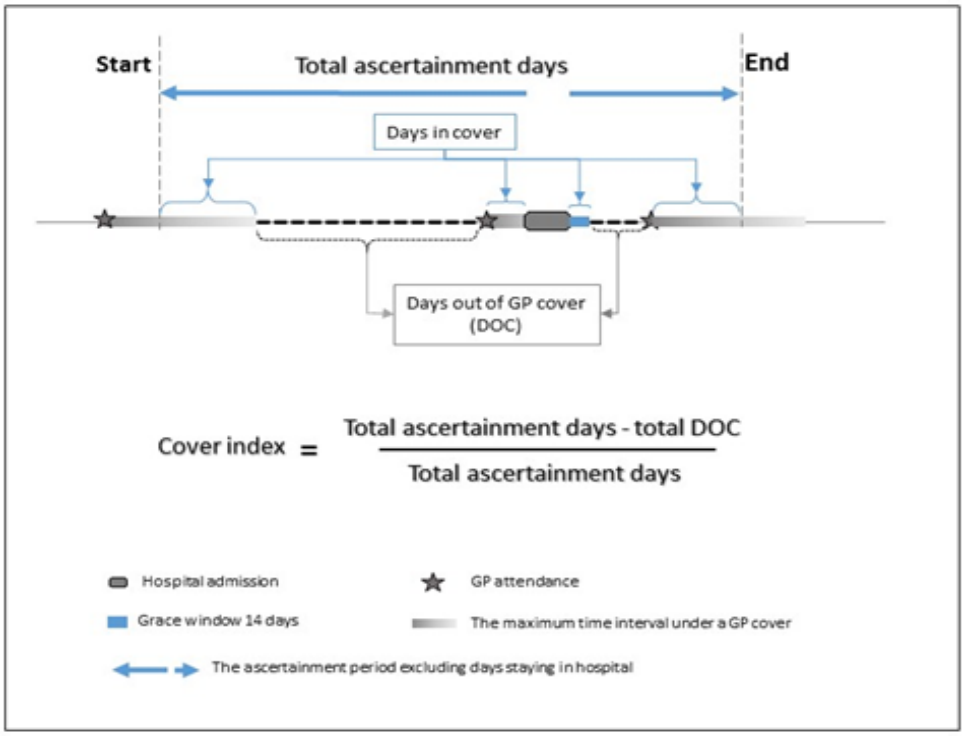


Figure 7.1. Calculation of the Cover Index

Note: The maximum time period for the calculation of the days out of cover was 6 months for three-complications or more; 8 months for one/two complications; and 13 months for non-complication. Following a hospital admission, a 14 day-period of grace was given before requiring a post-discharge GP visit. Calculation of days out of cover was re-started either at day 15 (if no GP contact was observed) or on the date of the GP visit (if a GP visit was observed prior to day 15).

The Cover Index was calculated for each financial year (*i.e.* 1 July to 30 June) ascertained from the number of days within each year that the individual remained alive and not in hospital (*i.e.* was living in the community and therefore eligible for a GP visit). The annual number of days under GP cover was the number of days following each GP visit that fell within the defined optimal maximum time interval, with special consideration given to the start of each year and time following a hospitalisation, as follows. For the start of each year the days from the last GP visit in the preceding year that were within the optimal maximum time period and fell within the financial year of interest were counted. Following a hospitalisation, determination of cover re-started on the earliest of either the 15th day post-separation date or the

date of the first GP visit. A three-year Cover Index was then calculated using the average of the annual Cover Index over the three-year exposure ascertainment period.

Other indices of continuity of care by a GP

Frequency of GP contact was calculated as the number of GP contacts within each financial year, excluding visits within 14 days of the previous visit to avoid over-counting GP episodes of care (78). The regularity index was used to measure the distribution of GP visits over each year and was calculated annually as [1/(1+standard deviation of the days between visits)], described in detail elsewhere (33-35). The regularity index ranges from 0 to 1 with 1 representing perfect regularity. Continuity of provider was measured using the usual provider of care index, which measures the proportion of GP contacts within the ascertainment period that were provided by the same GP (24). All indices were aggregated into the three-year ascertainment period when examining the association with the hospitalisation.

Covariates

Potential covariates considered for use in this study are presented in Appendix G. Demographic characteristics were assigned as gender (males or females), age (classified as 45–54, 55–64, 65–74, 75–84 or 85+ years), and Indigenous status (yes/no). Socio-economic characteristics included quintiles of the census-specific SEIFA index of relative socioeconomic disadvantage (141); residential remoteness classified according to the ARIA index (223); household income (classified as <$20,000, $20,000–$39,999, $40,000–$69,999, ≥ $70,00 and unknown); married status (classified as

married if married or living with a partner and no, otherwise); education (classified as below secondary school, secondary school graduation, higher education level). Smoking status was classified as never, current and past smokers). Weekly alcohol consumptions (classified as none, 1–14; ≥15 alcoholic drinks per week). Physical activity was measured using the Active Australian Survey standards and classified as sedentary, low active, sufficiently active, highly active and very highly active (224). BMI was calculated using self-reported weight and height and categorised as underweight (<18.50 kg/m2), normal weight (18.50–24.99 kg/m2), overweight (25.00–29.99 kg/m2) and obese (≥30.00 kg/m2) (224). Levels of limitation in terms of the ability to perform daily activities such as walking, bending, dressing and bathing were measured using the Medical Outcome Study Physical Function Scale (225), and classified into four groups: no limitation, minor limitation, mild limitation and severe limitation. The number of self-reported comorbidities was the sum of all self-reported conditions, including cancers, heart disease, high blood pressure, stroke, blood clot, asthma or hay fever, depression and anxiety, and Parkinson's disease. Anxiety and depression was measured with the Kessler scale, and classified as low (score 0–15), moderate (16–21), high (22–29) and very high (30 or higher) psychological distress (226). Social support was evaluated using the Duke Social Support subscale with a scale of 12 points (227). The number of self-reported comorbidities was the sum of all self-reported conditions, including cancers, heart disease, high blood pressure, stroke, blood clot, asthma or hay fever, depression and anxiety, and Parkinson's disease. The number of comorbidities was also counted in the APDC using the Multipurpose

Australian Comorbidity Scoring System (MACSS) with a five-year look-back period (143, 144). Diabetes complications were identified using ICD-10-AM codes in the APDC data and classified into three severity level groups: no complication, 1 to 2 complications and 3+ complications as used elsewhere (130, 139). The number of out-of-hospital specialist visits were identified using MBS claims data, counted in each financial year and then aggregated over a three-year period. The number of any hospitalisations was measured in each financial year using the APDC.

7.2.5 Statistical methods

Estimating the optimal maximum time interval using the threshold effect model

Descriptive analyses were conducted for key characteristics of the study population at the baseline year, followed by analyses on annual panel data to calculate the cover of primary care. Multivariable analyses were conducted to assess covariates associated with diabetes-related PPH and formed the basis for processing the threshold effects model. Time variant covariates such as BMI, social support and alcohol consumption were collected only once at the baseline survey of the 45 and Up Study between February 2006 and the end of 2009 (125). However, the study period chosen in this thesis was the most contemporary period between 1 July 2009 and 30 June 2016. Thus, to facilitate convergence of the models, the models of further analyses excluded covariates that were highly time variant and/or not significantly associated with diabetes-related PPHs. However, important covariates, including education and ARIA, were still included. The model including all covariates and the final model for processing threshold effects is presented in Appendix H.

The study population was stratified into three cohorts: (i) individuals with no complications of diabetes, (ii) those with one or two complications of diabetes and (iii) those with three or more complications of diabetes in categorising levels of disease severity (130). The data in each complication cohort were constructed in a panel structure, including annual measures of the following: maximum time interval to GP visits, average time intervals between GP visits, GP regularity, GP frequency and GP usual provider index, diabetes-related PPHs, and comorbidities between financial years 2009/2010 to 2015/2016. Threshold effects based on random negative binomial models were conducted to identify the optimal maximum time intervals between GP visits for which the number of diabetes-related PPHs were minimal for each complication-based cohort. This approach was proposed by Gannon, Harris (145) and applied previously (130, 209). Briefly, the model searched for subpopulations in which the association between diabetes-related PPHs and the maximum time interval between GP visits was homogeneous and used information criteria Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to select the optimal model. In addition to the covariates previously specified above, the models incorporated Mundlak variables, (group means of time-varying variables, including frequency of GP contact, regularity of GP contact and comorbidities) to allow for arbitrary correlation between observed and unobserved heterogeneity terms in the model (147, 148). The initial condition—history of diabetes-related hospitalisations at the baseline year—was also included to allow for any endogeneity arising from the dynamic set-up of the approach (149). The optimal maximum time intervals, identified from the threshold effect models in

each cohort, were used to calculate the Cover Index, which is defined as the proportion of time in a financial year people with diabetes were under the cover of primary care (via their GP) as previously described above.

Examining the association between the Cover Index and diabetes-related PPHs and LOS

The association of cover of primary care with diabetes-related PPH, unplanned diabetes-related PPH and LOS was examined using the data structured into two distinct three-year periods (2009/10 to 2011/12 and 2012/13 to 2014/15). A total of 21,965 individuals with full follow up in the two periods were included in the analyses. The average of the Cover Index over the three-year period was the main predictor. As a high proportion of the hospital count outcomes contained zero value, in addition to standard multivariable negative binomial models (NB) we also used zero-inflated negative binomial models (ZINB) with an inflated constant to examine the association between the Cover Index and hospital outcomes. Vuong non-nested tests and information criteria (AIC and BIC) were used to indicate the appropriate model.

Dose-response functions were used to evaluate the effects of cover of primary health care on diabetes-related PPHs, unplanned diabetes-related PPHs and LOS, adjusting for the generalised propensity score (GPS). The GPS of the Cover Index was predicted using a generalised linear regression model with family binomial and link logit for a fractional treatment variable (156). The GPS model included individual demographic, socioeconomic characteristics at the baseline year, comorbidities, and complication status at the start of the three-year period, the frequency of GP contact, regularity,

usual provider index of the current and previous three period and history of diabetes-related PPHs. Model fit for predicting the propensity score was assessed by plotting the propensity score distribution against the actual Cover Index distribution. Then, the balance of the propensity score across four treatment intervals, with cut-off points at 0.75, 0.85 and 0.95, was examined by plotting the overlap of the GPS between the treatment levels against the rest of the study population in term of frequency distribution (228). The covariate balance was assessed by comparing an improvement in t-test statistics and the standardised mean difference between the treatment intervals and the rest of the study population, with a threshold of 1.96 and 0.20, respectively, to indicate if covariate balance was achieved (156, 159). Individuals whose GPS was not within the common support region for all treatment groups were excluded (228). Finally, the dose-response function was performed to evaluate the treatment effect function of the Cover Index on PPHs and LOS (156). All analyses were conducted using STATA for Windows version MP14.

7.3 Results

A total of 24 874 individuals aged 45 years and older were identified as having diabetes in the 45 and Up Study population. The characteristics of the individuals at the baseline year are presented in Table 7.1. Individuals with no complications of diabetes included only a relatively small proportion of people aged 75+ years (17.6 %); less than a quarter were living with severe limitations (22.1 %) or had been diagnosed with diabetes 10+ years previously (24.4%). In contrast, individuals in the cohorts with 1 to 2 or 3+ complications included a higher proportion of people aged 75+ years (28.5%

and 44.5%, respectively), and more than a quarter living with severe level of limitations (29.3% and 42.3%, respectively) or had been diagnosed with diabetes more than 10 years previously (31.7% and 44.9%, respectively).

The optimal maximum time interval estimated from the threshold effect models was 13 months for diabetes with no complications, 8 months for diabetes with 1–2 complications and 6 months for 3+ complications (Table 7.2). Those time intervals were considered as the optimal time intervals under GP cover (according to individuals' complication levels) and were used to calculate the Cover Index. On average, the proportion of time in each year that people with diabetes were under cover of primary care was approximately 90% for the first three-year period, increasing to 93.6% for the second three-year period. The distribution of the time covered varied across subpopulations and remained significantly lower among people aged 85+ years and older (79.5%, 95% CI 77.0%- 82.1%), being male (92.8%, 95%CI 92.5%- 93.2%) or living in very remote areas (77.5%, 95%CI 65.1%- 90.0%) across both the first and second three-year periods (Table 7.3)

Table 7.1. Characteristics of study population by complication cohort at the baseline study

Characteristics	No complication		1-2 complications		3+ complications	
Total	N=11,853		N=6,371		N=6,650	
Gender						
Male	6211	(52.4%)	3482	(54.7%)	3979	(59.8%)
Female	5642	(47.6%)	2889	(45.3%)	2671	(40.2%)
Age groups						
45–54 years	2304	(19.4%)	718	(11.3%)	360	(5.4%)
55–64 years	3716	(31.4%)	1643	(25.8%)	1158	(17.4%)
65–74 years	3746	(31.6%)	2189	(34.4%)	2174	(32.7%)
75-84 years	1765	(14.9%)	1506	(23.6%)	2326	(35.0%)
85+ years	322	(2.7%)	315	(4.9%)	632	(9.5%)
ARIA						
Very remote	12	(0.1%)	11	(0.2%)	8	(0.1%)
Remote	107	(0.9%)	52	(0.8%)	54	(0.8%)
Moderate	1358	(11.5%)	649	(10.2%)	635	(9.5%)
Accessible	4029	(34.0%)	2218	(34.8%)	2297	(34.5%)
Highly Accessible	6347	(53.5%)	3441	(54.0%)	3656	(55.0%)
SEIFA						
Highest disadvantage	3202	(27.0%)	1860	(29.2%)	2013	(30.3%)
High disadvantage	2829	(23.9%)	1449	(22.7%)	1620	(24.4%)
Moderate	2215	(18.7%)	1220	(19.1%)	1164	(17.5%)
Less disadvantage	1850	(15.6%)	939	(14.7%)	922	(13.9%)
Least disadvantage	1757	(14.8%)	903	(14.2%)	931	(14.0%)
Indigenous status						
No	11691	(98.6%)	6294	(98.8%)	6547	(98.5%)
Yes	162	(1.4%)	77	(1.2%)	103	(1.5%)
Education status						
Below secondary school	1970	(16.6%)	1231	(19.3%)	1496	(22.5%)
Secondary school	2830	(23.9%)	1651	(25.9%)	1693	(25.5%)
Higher school/ University/ Tafe	7053	(59.5%)	3489	(54.8%)	3461	(52.0%)
Level of limitations						
None	2440	(20.6%)	757	(11.9%)	389	(5.8%)
Minor	3621	(30.5%)	1645	(25.8%)	1228	(18.5%)
Moderate	3177	(26.8%)	2105	(33.0%)	2219	(33.4%)
Severe	2615	(22.1%)	1864	(29.3%)	2814	(42.3%)
Duration of diabetes						
1–5 years	6247	(52.7%)	2518	(39.5%)	1630	(24.5%)
6–10 years	2713	(22.9%)	1835	(28.8%)	2034	(30.6%)
11+ years	2893	(24.4%)	2018	(31.7%)	2986	(44.9%)
Number of self-reported multimorbidities (Median, IQR)	1	(1-2)	2	(1-3)	2	(1-3)
Quintiles of regularity						
0	548	(4.6%)	186	(2.9%)	183	(2.8%)

Characteristics	No complication		1-2 complications		3+ complications	
1	3386	(28.6%)	1226	(19.2%)	858	(12.9%)
2	3360	(28.3%)	1639	(25.7%)	1330	(20.0%)
3	2769	(23.4%)	1805	(28.3%)	1903	(28.6%)
4	1790	(15.1%)	1515	(23.8%)	2376	(35.7%)
Usual Provider of Care index (Mean, 95%CI)	0.777	(0.772-0.781)	0.778	(0.773-0.784)	0.775	(0.770-0.782)
Specialist visits within FY (Mean, 95%CI)	2.5	(2.45-2.61)	3.92	(3.78-4.06)	6.03	(5.84-6.21)
Frequency of GP visits (Mean, 95%CI)	5.48	(5.44-5.53)	6.15	(6.09-6.22)	6.39	(6.33-6.46)
Comorbidities (MACSS) (Mean, 95%CI)	1.98	(1.93-2.02)	4.70	(4.64-4.77)	6.78	(6.71-6.85)
Any hospitalisations (Mean, 95%CI)	0.38	(0.35-0.42)	0.85	(0.74-0.95)	2.01	(1.74-2.25)
Diabetes-related hospitalisations (Mean, 95%CI)	0.024	(0.021-0.28)	0.13	(0.11-0.14)	0.38	(0.36-0.40)

Table 7.2. Threshold search for the optimal maximum time interval to GP visits by complication cohorts for people aged 45 years and older

Complication cohorts	No complication					1–2 complications					3+ complications					
Number of subpopulations	1	2	3	4	36	1	2	3	4	36	1	2	3	4	5	36
AIC	35681.7	35627.9	35603.5	35596.9	35618.1	34824.4	34759.4	34746.5	34742.5	34779.9	70216.6	69935.6	69867.8	69837.5	69832.7	69853.7
BIC	35951.6	35915.7	35900.3	35902.7	36211.7	35084.9	35037.4	35033.1	35037.8	35335.7	70483.6	70220.4	70161.5	70140.1	70144.2	70423.4
Threshold parameters (months)																
τ_1		13	1	1	-		1	1	1	-		1	1	1	1	-
τ_2			**13**	6	-			**8**	2	-			2	2	2	-
τ_3				16	-				8	-				20	**6**	-
τ_4															20	-
τ_5																
Coefficients																
γ_1		-0.046**	0.387***	0.288**	-		0.445***	0.347***	0.470***	-		0.394***	0.690***	0.595***	0.489***	-
γ_2		0.068***	-0.027	-0.071**	-		-0.003	-0.050*	0.028	-		-0.030*	0.146***	0.097***	0.043	-
γ_3			0.073***	-0.030	-			0.021	-0.031	-			0.013	-0.021	-0.055**	-
γ_4				0.073***	-				0.028	-				0.088***	-0.022	-
γ_5					-					-					0.084***	-

*Notes: * if p-values<0.05; ** if p-value<0.01; *** if p-value<0.001*

Table 7.3. Distribution of the Cover Index and specialist visits across the two study periods

Characteristics	Cover Index				Specialist visit			
	The first three-year period		The second three-year period		The first three-year period		The second three-year period	
	Mean	95% CI	Mean	95% CI	Mean	95% CI	Mean	95% CI
Total	0.907	(0.905-0.909)	0.936	(0.934-0.938)	11.2	(11.0-11.4)	13.0	(12.7-13.2)
Gender								
Male	0.898	(0.895-0.901)	0.928	(0.925-0.932)	11.2	(10.9-11.4)	13.1	(12.8-13.4)
Female	0.918	(0.915-0.920)	0.946	(0.943-0.949)	10.8	(10.5-11.1)	12.1	(11.8-12.4)
Age groups								
45–54 years	0.896	(0.891-0.901)	0.938	(0.933-0.943)	7.2	(6.8-7.5)	8.5	(8.1-9.0)
55–64 years	0.905	(0.901-0.908)	0.943	(0.939-0.947)	9.3	(8.9-9.6)	10.7	(10.4-11.1)
65–74 years	0.921	(0.918-0.924)	0.951	(0.948-0.954)	12.0	(11.7-12.3)	13.9	(13.6-14.3)
75–84 years	0.910	(0.905-0.915)	0.926	(0.920-0.932)	14.6	(14.1-15.1)	16.2	(15.6-16.7)
85+ years	0.816	(0.794-0.839)	0.795	(0.770-0.821)	12.4	(11.2-13.6)	12.5	(11.0-14.0)
ARIA								
Very remote	0.769	(0.647-0.892)	0.775	(0.651-0.900)	7.6	(3.7-11.6)	7.7	(4.7-10.7)
Remote	0.905	(0.883-0.927)	0.938	(0.912-0.965)	7.6	(6.1-9.1)	10.4	(8.3-12.5)
Moderate	0.902	(0.896-0.908)	0.939	(0.932-0.946)	7.3	(7.0-7.7)	8.8	(8.3-9.2)
Accessible	0.904	(0.901-0.908)	0.938	(0.935-0.942)	9.5	(9.2-9.7)	10.9	(10.6-11.2)
Highly Accessible	0.910	(0.908-0.914)	0.935	(0.932-0.939)	12.8	(12.5-13.1)	14.5	(14.2-14.8)
SEIFA								
Highest disadvantage	0.912	(0.909-0.916)	0.936	(0.931-.940)	10.3	(10.0-10.6)	11.3	(10.9-11.6)
High disadvantage	0.909	(0.905-0.914)	0.939	(0.934-0.943)	10.3	(10.0-10.7)	12.0	(11.6-12.4)
Moderate	0.913	(0.909-0.918)	0.943	(0.938-0.948)	11.0	(10.6-11.4)	12.6	(12.2-13.1)
Less disadvantage	0.899	(0.894-0.905)	0.937	(0.932-0.943)	11.4	(10.9-11.9)	13.2	(12.7-13.8)
Least disadvantage	0.894	(0.889-0.900)	0.926	(0.920-0.932)	13.0	(12.5-13.5)	15.5	(14.8-16.1)
Indigenous status								
No	0.907	(0.905-0.909)	0.937	(0.934-0.939)	11.0	(10.9-11.2)	12.7	(12.4-12.9)
Yes	0.899	(0.880-0.918)	0.925	(0.906-0.945)	8.4	(6.6-10.2)	9.6	(7.7-11.5)

Characteristics	Cover Index				Specialist visit			
	The first three-year period		The second three-year period		The first three-year period		The second three-year period	
	Mean	95% CI	Mean	95% CI	Mean	95% CI	Mean	95% CI
Education status								
Below secondary school	0.921	(0.917-0.926)	0.947	(0.941-0.951)	10.9	(10.5-11.3)	11.7	(11.3-12.1)
Secondary school	0.911	(0.907-0.915)	0.936	(0.932-0.941)	10.5	(10.2-10.9)	12.2	(11.8-12.6)
Higher school/Uni/Tafe	0.901	(0.898-0.904)	0.934	(0.931-0.937)	11.2	(11.0-11.5)	13.1	(12.8-13.4)
Level of limitations								
None	0.895	(0.890-0.900)	0.943	(0.938-0.948)	7.3	(7.0-7.7)	8.8	(8.4-9.2)
Minor	0.906	(0.902-0.910)	0.943	(0.940-0.947)	9.3	(9.0-9.6)	11.4	(11.1-11.8)
Moderate	0.911	(0.907-0.915)	0.935	(0.931-0.939)	12.5	(12.2-12.9)	14.3	(13.8-14.7)
Severe	0.911	(0.907-0.916)	0.928	(0.923-0.933)	13.2	(12.8-13.6)	14.2	(13.8-14.7)
Duration of diabetes								
1–5 years	0.906	(0.903-0.909)	0.938	(0.935-0.942)	9.6	(9.3-9.8)	10.9	(10.6-11.2)
6–10 years	0.909	(0.905-0.913)	0.938	(0.934-0.942)	11.0	(10.6-11.3)	12.8	(12.4-13.2)
10+ years	0.907	(0.903-0.911)	0.933	(0.929-0.937)	13.0	(12.7-13.4)	14.9	(14.4-15.3)

The association between the Cover Index and the study outcomes were examined using both NB and ZINB models. The results were similar for both models, although AIC and BIC suggested the NB model was more appropriate for both hospitalisations and LOS, while the Vuong test suggested ZINB for LOS. Thus, we focused on the results of the standard NB model. After adjusting for demographic and socioeconomic characteristics at the baseline year, duration of diabetes, disease severity, including comorbidities and complication level at beginning of the study period, current and history of specialist visits, frequency of GP visits, usual provider index, regularity of GP visits, and history of diabetes-related PPH, a higher Cover Index score was significantly associated with fewer diabetes-related PPHs (Coef. -2.3, 95%CI -2.6;-2.0) and shorter LOS (Coef. -5.5, 95%CI -5.9; -5.1) (Table 7.4, showing all covariates is presented as Appendix I). Similar results were found when unplanned diabetes-related PPH (Coef. -1.8, 95%CI -2.3; -1.4) and their LOS were considered (Coef. -3.9, 95%CI -4.7; -3.2) (Table 7.5, showing all covariates is presented as Appendix J).

Table 7.4. Association between the Cover Index and number of diabetes-related PPHs and length of stay over the three-year period

Characteristics	Diabetes-related PPH				LOS diabetes-related PPH			
	NB		Zero-inflated NB		NB		Zero-inflated NB	
	Coef.	95%CI	Coef.	95%CI	Coef.	95%CI	Coef.	95%CI
Cover Index	-2.3***	(-2.6 ; -2.0)	-2.3***	(-2.6 ; -2.0)	-5.5***	(-5.9 ; -5.1)	-5.5***	(-5.9 ; -5.1)
Cover index in the last period	1.0***	(0.7 ; 1.3)	1.0***	(0.7 ; 1.3)	2.0***	(1.5 ; 2.4)	2.0***	(1.5 ; 2.4)
AIC	35350.9		35352.9		56357.6		56359.6	
BIC	35662.8		35672.7		56669.5		56679.5	
Vuong test	z= -0.01	p-values = 0.502			z=8.86	p-values <0.001		

*Note: * indicate p-values with * if p-value <0.05; ** if p-value <0.01; *** if p-value <0.001*

The models were controlled for age, gender, accessibility, SEIFA, Indigenous status, education, level of limitations, duration of diabetes, self-report multimorbidities, complications (DSCI), comorbidity (MACC index), number of specialist visits, regularity, usual provider index, number of diabetes-related PPHs

Table 7.5. Association between the Cover Index and number of unplanned diabetes-related PPHs and length of stay over the three-year period

Characteristics	Unplanned diabetes-related PPH				LOS unplanned diabetes-related PPH			
	NB		Zero-inflated NB		NB		Zero-inflated NB	
	Coef.	95%CI	Coef.	95%CI	Coef.	95%CI	Coef.	95%CI
Cover Index	-1.8***	(-2.3 ; -1.4)	-1.8***	(-2.3 ; -1.4)	-3.9***	(-4.7 ; -3.2)	-3.9***	(-4.7 ; -3.2)
Cover Index in the last period	0.4	(-0.06 ; 0.9)	0.4	(-0.06 ; 0.9)	1.1**	(0.3 ; 1.9)	1.1**	(0.3 ; 1.9)
AIC	16711.1		16713.1		30861.4		30863.4	
BIC	17022.9		17032.9		31173.3		31183.3	
Vuong test	z=-0.00	p-values=0.5			z= -0.17	p-values=0.56		

*Notes: * indicate p-values with * if p-value <0.05; ** if p-value <0.01; *** if p-value <0.001*

The models were controlled for age, gender, accessibility, SEIFA, Indigenous status, education, level of limitations, duration of diabetes, self-report multimorbidities, complications (DSCI), comorbidity (MACC index), number of specialist visits, regularity, usual provider index, number of unplanned diabetes-related PPHs

All of the above covariates were used to predict the GPS of the Cover Index. Figure 7.2 shows good overlap between the GPS of the Cover Index and the actual distribution of the Cover Index, suggesting a good fit of the GPS model.

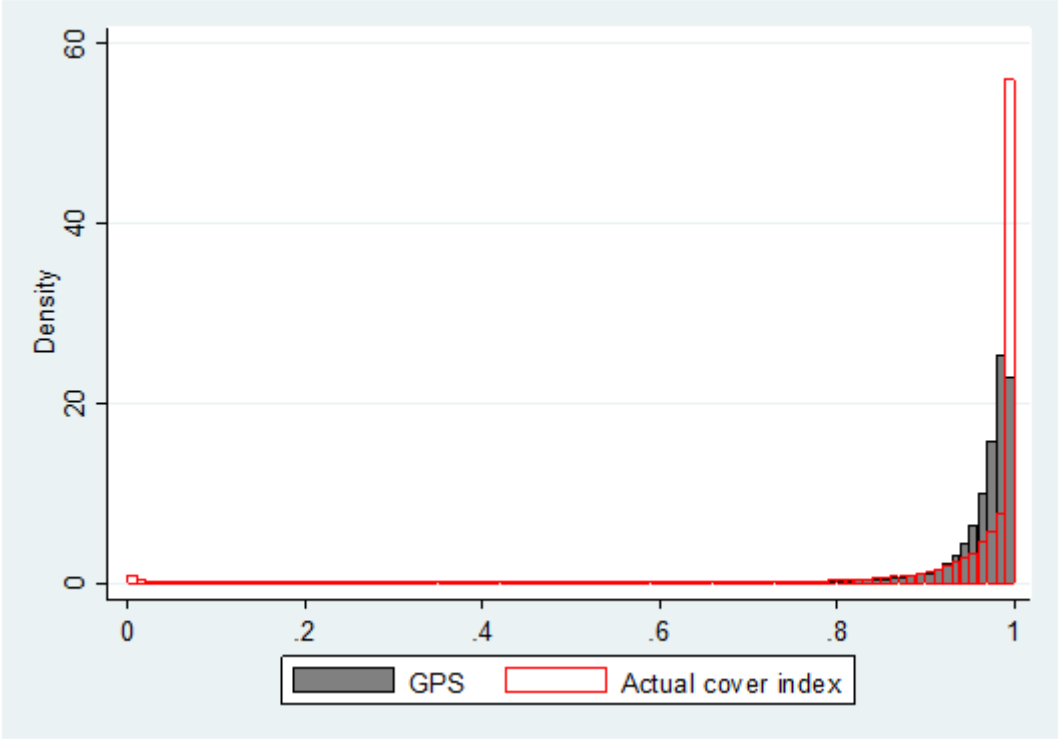


Figure 7.2. Overlapping in distribution of the Cover Index and generalised propensity score of the Cover Index

The common support, in terms of frequency distribution between each cover interval and the rest of the study population, is presented as Figure 7.3. About 5% of the study population were excluded as lacking supporting distribution or overlapping of GPS distribution with other treatment intervals.

The covariate balance, adjusted for propensity score using blocking on quintiles of the GPS, is presented in **Error! Reference source not found.** and **Error! Reference source not found.**. The covariate balance was achieved for most of the demographic characteristics and diabetes severity levels when using the standardised mean difference threshold at 0.2 and t-

test critical values at 1.96. Few subgroups of covariates did not achieve the expected balance, although the balance was better when not adjusting for GPS.

Using t-test critical values, the appropriate covariate balance increased from 15 to 29/43 sub-covariates after adjusting for GPS. A similar balance was obtained after adjusting for GPS when using standardised mean difference threshold values (from 33 to 38/43). A total of 1,951 records (8.8%) with GPS score not in a common support region of GPS distribution across different treatment levels were excluded from estimating dose-response function.

The results of the dose-response function of the Cover Index, adjusting for the GPS, are presented in Appendix K. The results show that the average number of predicted diabetes-related PPH and LOS significantly reduced as the value of the Cover Index increased. The treatment effect function showed a higher effect on diabetes-related PPH and LOS among those with a higher Cover Index score. Similar results were observed for unplanned diabetes-related PPH and associated LOS.

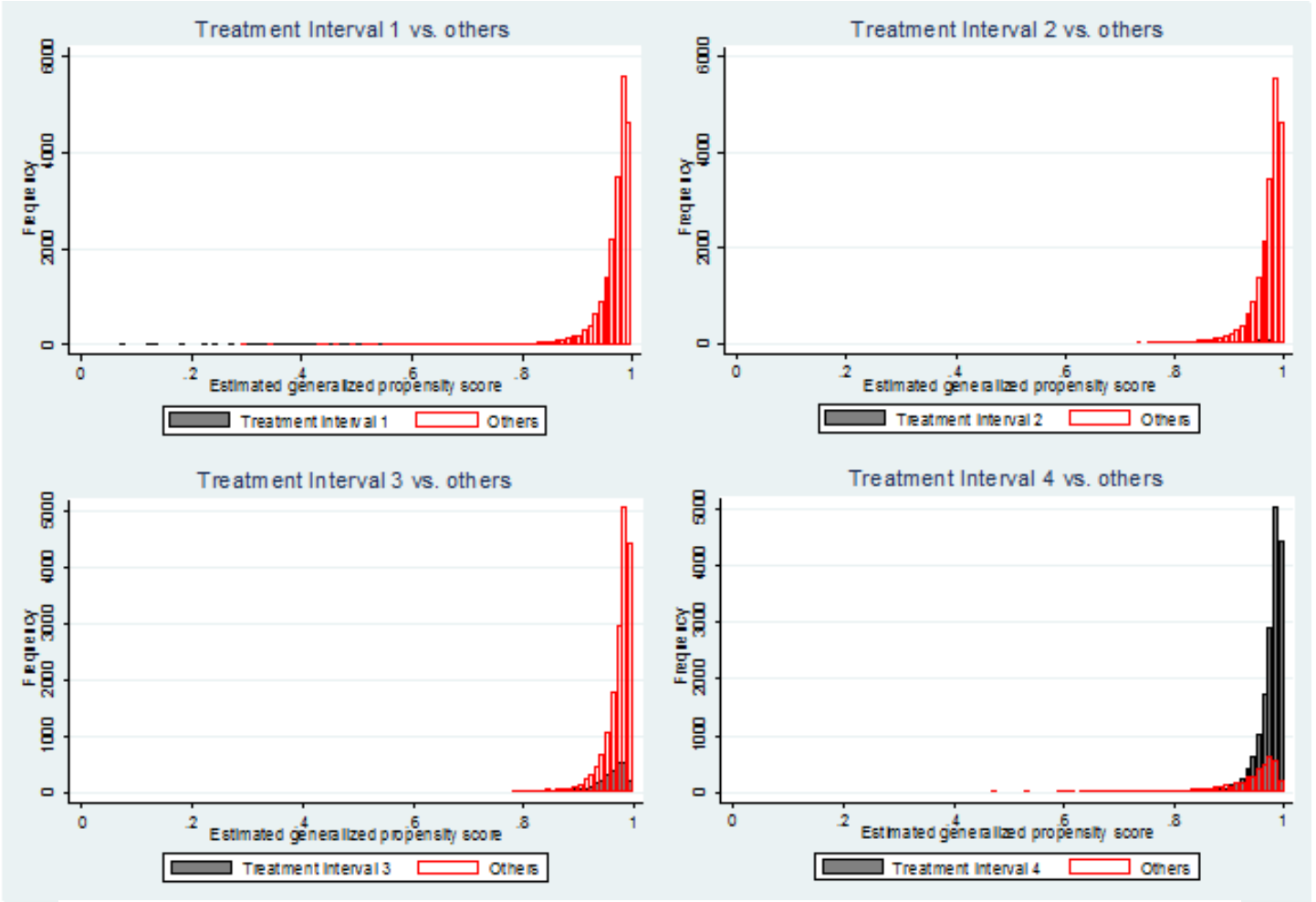


Figure 7.3. Overlapping GPS between treatment intervals

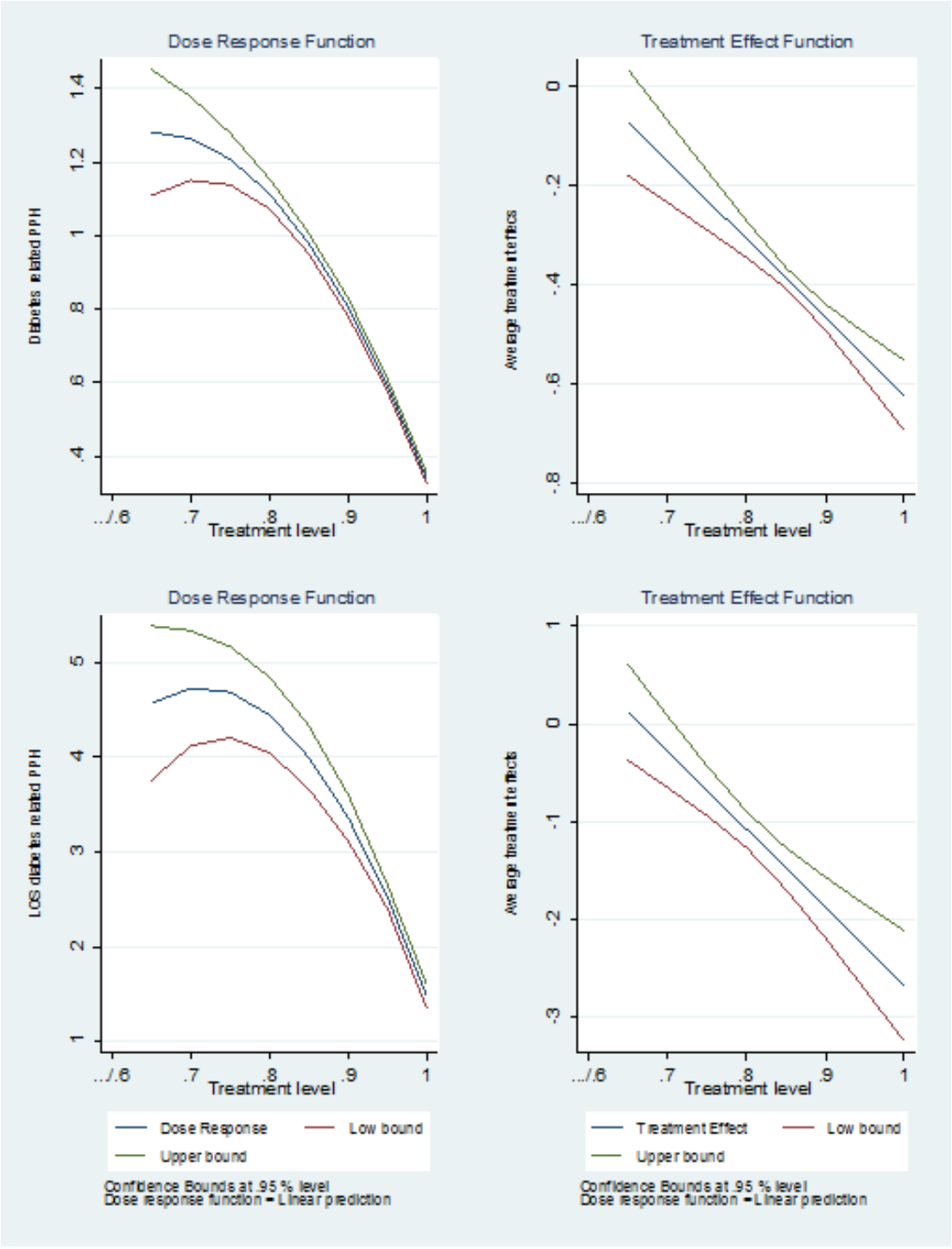


Figure 7.4. Dose-response function of the Cover Index on diabetes-related PPH and LOS

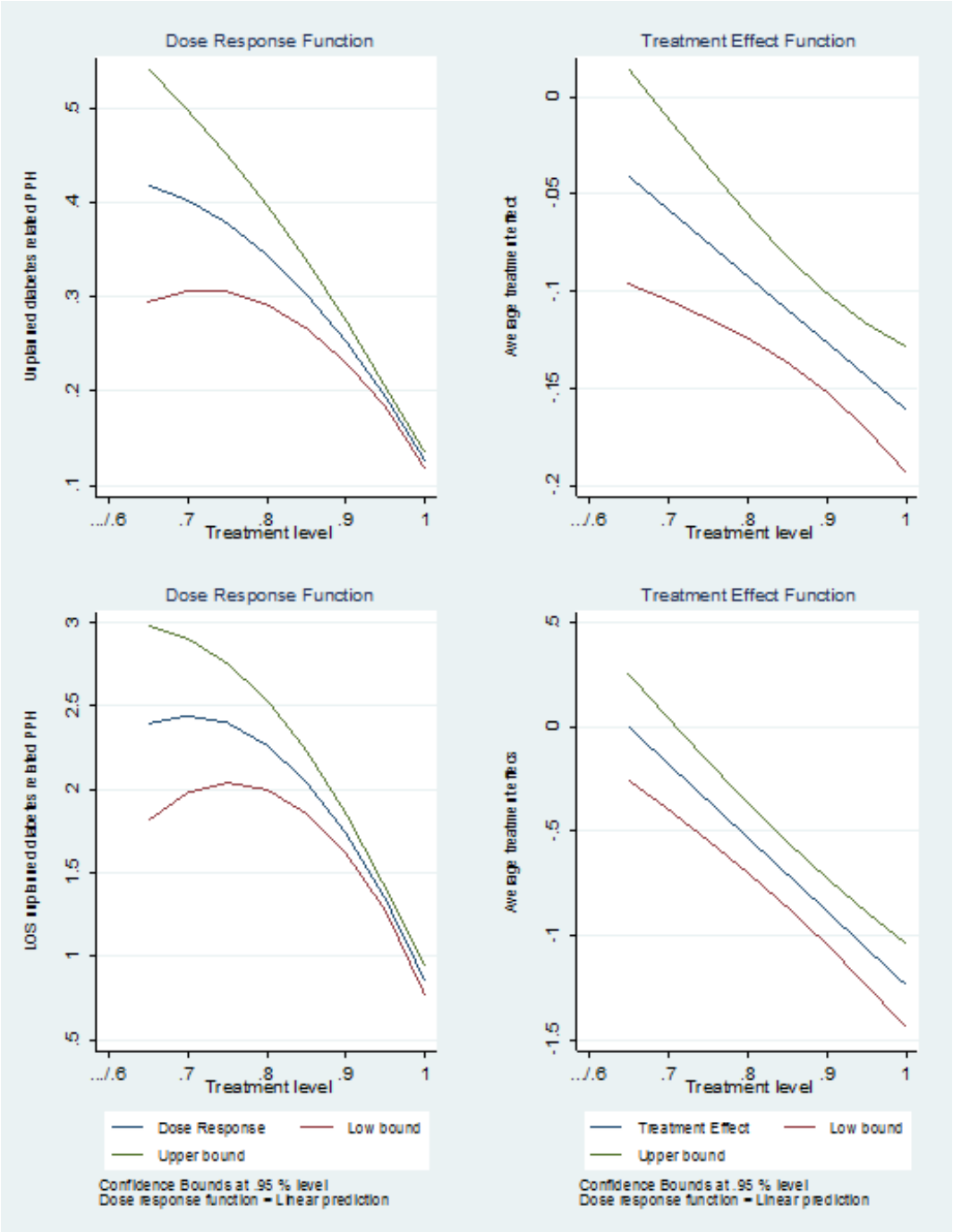


Figure 7.5. Dose-response function of the Cover Index on unplanned diabetes-related PPH and LOS

7.4 Discussion

Although timely and early treatment and prevention is important for people with chronic conditions to prevent adverse health events such as complications and PPH, no previous study has examined the temporal

aspect of continuity of GP care for people with chronic conditions, especially diabetes. This study provides a comprehensive view of how well people with diabetes living in community settings are covered by care provided by a GP across different subpopulations. The impact of continuity of GP care in terms of its time duration protective effect, as distinct from other facets of longitudinal continuity, such as provider and regularity, on diabetes-related PPH was also evaluated. Overall, this study found that most people with diabetes spent an average of 93.6% of time living in the community under cover of a GP over the three-year study period between 2012/13 and 2014/15. However, the proportion of time under cover of a GP care was significantly lower among males, individuals aged 85 years or older, those living in very remote areas, and those with a severe level of limitations. The study also found that individuals with a higher Cover Index score had a significantly lower number of diabetes-related PPHs and shorter lengths of stay. Similar findings were observed when hospitalisation was limited to unplanned diabetes-related PPHs and LOS. Analysis of the dose-response function suggested that the effect of GP cover on hospitalisation and length of stay was negative and linear, which means that incrementally increasing GP cover offers a greater reduction in the number of admissions and LOS for both diabetes-related PPHs and unplanned diabetes-related PPHs.

Strengths and limitations of this study

This study used a large population-based cohort linked with individuals' healthcare service records that allowed for differences across a wide range of demographic, socioeconomic and clinical characteristics. The self-report data provided an opportunity to include individuals at the early stage of

diabetes prior to any hospitalisation for the condition, which makes this study population more likely to be representative of the general population living with diabetes. The data were linked with historical administrative data from 2005, which allowed us to capture the history of complications and comorbidities to better identify health-related factors that may have a strong effect on health service utilisation. By using advanced analytic approaches, the study was able to explore latent patterns of primary care utilisation and unpack further dimensions of longitudinal continuity of primary care.

In this study, days spent in hospital were excluded from the calculation of GP cover so as to accurately capture each person's time spent in the community and hence eligible for GP contact. A maximum of 14 days post-separation from hospital was allowed to observe the first post-discharge GP contact, to more accurately capture the person time eligible for cover by a GP without unduly penalising initial days post-hospitalisation. A 14-day window was used, based on advice from GP clinical experts, who determined that 14 days was the maximum time following discharge from hospital that a person with diabetes should go without seeing their GP. Thus, if a GP contact was not observed by day 15, that day and subsequent days until a GP contact was observed were classed as not under cover of GP care. The total number of specialist visits in the study period and also the previous three-year period were included to control for the impact of specialist care acting as either a substitute or complement to GP care. GPs are considered as cornerstone for coordinating and integrating disease management for people with chronic and/complex conditions such as diabetes (229, 230), thus long gaps between GP contact, even with or without specialist visits, may suggest insufficiency

of comprehensive disease management for patients.

As this is a cross-sectional observational study, caution is required when interpreting any causal relationship between cover of GP care and diabetes-related PPHs, since both were measured over the same time period. To partially counteract this the study controlled for history of clinical characteristics and prior health service utilisation. It could be argued that the outcome of diabetes-related PPH may not be totally avoidable even with effective GP care, and this may lead to difficulty interpreting the association between the Cover Index and the number of diabetes-related PPHs. To explore this, a second outcome was evaluated—unplanned diabetes-related PPHs—which, because of their emergency admission status, are more likely to represent hospitalisations that are unexpected and result from uncontrolled clinical events. The association remained significant when the outcome was limited to unplanned diabetes-related PPHs, confirming that increasing GP cover reduces unplanned hospitalisation, probably via better management of the condition.

The Cover Index was lower across certain subpopulations, including males, people aged 85 years or older, and severe level of the disease or limitation. Except for people living in the remote areas, the other subgroups had a significantly higher number of specialist visits and it may be that specialist care substituting for GP care partially explains this finding. However, these results are consistent with the literature on the prominence of primary care in planning and coordinating care, a role that is often less prominent among people in older age groups and with complex conditions (230). Despite

financial incentives subsidising multidisciplinary care via GP referrals to encourage patient involvement in chronic disease management, less improvement in access to multidisciplinary care has been reported among males and people living in the remote areas (57).

Best practice care for people with chronic complex conditions, including diabetes, recognises the critical role of GPs in providing effective health management and high quality of care (229, 230). GPs are in the best position to manage care, coordinate with appropriate specialists and continuously review and update care plans because of their deep knowledge and close relationship with the individual patient (229). In addition GPs, rather than other specialists, can offer superior care by not primarily focusing on the condition itself but on the condition in the context of the patients' other health problems (19). Appropriate management of disease in the primary care setting can better connect care options, reduce the risk of adverse drug effect and duplicative interactions with the healthcare system, in turn reducing PPHs (57). These statements are consistent with findings of this study that better cover of primary care (*i.e*. increased time covered by a GP) was associated with a reduction of diabetes-related PPHs and LOS after controlling for frequency of GP visits, regularity, usual provider index and specialist visits.

The findings of this study are also in line with previous studies evaluating primary care MBS re-imbursement items that contain time components, such as the annual cycle of care item, review of GP management plan item, and team care arrangement item (4, 231). These studies found that use of these

items were associated with reduced risk of hospitalisation among people with diabetes (4, 231). The findings of this study are also consistent with the previous study that the time interval between GP services is inversely associated with the risk of hospitalisation (212). This suggests that time under cover of a GP is more likely to directly relate to the reduction of hospitalisations among people with diabetes than other measures of longitudinal continuity of care. The Cover Index also has several advantages over other indices. For example, it is easier to interpret than indexes such as regularity, which has no natural units, as it expresses the proportion of time under cover of GP care and therefore can indicate absolute levels of insufficiency of primary care utilisation. The metric can be applied at the individual, subpopulation or whole-of-population level and therefore is suitable for both development of financial levers via payment incentives (e.g. an MBS item) or monitoring the utilisation of primary care. The index can also be calculated for individuals with single or no GP visits, which is better than other continuity care metrics, such as regularity and usual provider index which can only be calculated when at least two GP visits are observed within the ascertainment time (24, 33). Thus, unlike these two metrics the Cover Index can comprehensively capture the whole population.

While the cover period in this study was calculated using a data-driven approach to determine the optimal maximum time interval used in its calculation, this could be derived *a priori* from expert opinion, existing clinical guidelines or funding arrangements. In this context the Cover Index has the potential to explore the impact of pre-specified temporal utilisation arrangements on health outcomes.

7.5 Conclusions

This study reconfirmed the estimation of the optimal maximum time interval between GP visits which offered the minimal number of hospitalisations for people with diabetes in the contemporary data. This study found that longitudinal continuity of care in the shape of a time duration protective effect of GP contact is associated with number of admissions and LOS of all diabetes-related PPHs and unplanned diabetes-related PPHs. Importantly, the proportion of time under cover of GP care acts independently of other facets of longitudinal continuity, such as continuity of provider, regularity or frequency of GP contact. The Cover Index provides an important advance in capturing longitudinal continuity that has superior properties to existing metrics and can be ascertained using either data-driven or *a priori* approaches. These results provide a more comprehensive view of continuity of primary care and provide information valuable for the design interventions and policy levers aimed at optimising disease management for people with diabetes, allocating health resources and improving the quality and effectiveness of health care.

Chapter 8 Discussion and implications

Continuity of primary health care is regarded as a cornerstone by which to judge quality of care for people with chronic conditions, especially diabetes. Although conceptual frameworks for continuity of care have been well developed, finding ways to measure it, especially in terms of management, has been a challenge for researchers. To the best of my knowledge, this thesis is the first study to describe the comprehensive development process of a new measure of continuity of care, the Cover Index, which can evaluate those management aspects. The Cover Index integrates a time duration component into regular interaction with a GP to capture the proportion of the ascertainment period that an individual is subject to the optimal protective effect of GP care. The development process of the Cover Index has also suggested many useful data-driven approaches for assessing the clinical severity of diabetes and exploring features of GP service utilisation. Finally, the application of the Cover Index using contemporary data has successfully evaluated the relationship between the time duration component of management continuity and diabetes-related PPHs disentangled from other domains of longitudinal continuity, such consistency of provider, frequency and regularity of contact.

The following sections of this discussion chapter will begin by highlighting key findings in each separate study of the thesis and discussing how the findings have contributed to the development of the Cover Index and the body of literature. Following is a discussion on the strengths and limitations of this research, its significance to the body of research and future implications.

8.1 Contributions of this thesis

Stratification strategy for diabetes severity classification using linked administrative data

Healthcare services provided for people with chronic and complex conditions like diabetes have been oriented towards proactive, anticipatory and integrated care and ensuring services are adequately resourced (4, 232, 233). To assist in predicting healthcare resource use, a stratification strategy that accounts for disease severity level is considered as an important step to account for disparity in resource requirements (232, 234). Thus, the first study in this thesis developed a stratification strategy for classification of severity levels for the population with diabetes by examining the non-linear relationship between the diabetes complication severity index (DCSI) and the risk of diabetes-related hospitalisations.

This study found that diabetes populations with varying complication severity could be stratified into one, two, and three or higher levels of DCSI. This result added to the literature a better understanding of diabetes risk stratification to improve risk analysis in future evaluation of service and resource provision. While previous studies often used the DCSI classification of six subgroups, which was based on artificial cut-off points (171, 181, 182), the stratification strategy developed in this study was based on a data-driven approach, using whole-of-population real-life data, and recommended a lower number of subgroups. This new stratification approach can reduce over-parameterisation of models and provide more accuracy in reflecting the homogeneous effects of diabetes severity on healthcare service utilisation. The result of this study also provided a mechanism for classifying diabetes

cohorts according to diabetes severity level that could be used in the development of the Cover Index.

Exploration patterns of GP utilisation among people with diabetes

The second study was a preliminary exploration of the latent patterns of GP utilisation by simultaneously examining multiple attributes of GP utilisation using K-mean cluster analysis. The attributes considered in this study were modified from the conceptual framework of customer relationship management theory, where values of customers are evaluated not only based on frequency of services used but also integrated with the time intervals between service utilisation (151, 235). The incorporation of multiple attributes, including frequency and time interval measures of GP contacts (average time intervals, maximum time interval and standard deviation of the time intervals), revealed three meaningful and homogeneous clusters of GP utilisation among people with diabetes.

To the best of my knowledge, this is the first study that has successfully integrated multiple attributes in assessing the patterns of GP utilisation. This integration of multiple dimensions, especially regarding the intervals between GP services, is an improvement on simplistic approaches based on a single indicator, such as counting the number of visits or regularity of visits, as it captures important information about the distribution of GP utilisations. The distribution of time intervals between GP services has implications for both customer relationship management and for our understanding of proactive primary health care. For example, as we know from customer relationship studies, shorter time intervals between customer contacts may imply the

existence of stronger interpersonal relationships (46, 140). In terms of proactive primary health care, a shorter time interval between GP services, in combination with regular provision of GP services, may imply continuous disease management, promoting patient self-management, skills and knowledge and allowing prevention and early treatment of complications in primary health care settings (4, 195).

While previous literature reports inconsistency in the relationship between primary health care and the risk of hospitalisation (188, 190), this study found that GP contacts had a negative association with the risk of hospitalisation. However, the relationship was non-linear, with the lowest number of diabetes-related PPH observed among those with moderate GP usage rather than those with high or very high usage. The result is in line with a previous study which used non-linear models to capture the effect of GP utilisation on hospitalisations (213).

Overall, the second study has added to the literature an application of cluster analysis to identify latent patterns of GP service utilisation, especially the integration of temporal factors that helps to better capture the complexity of the relationship between primary health care and hospitalisations. This study also formed a foundation for the next study by highlighting the importance of the temporal effects of GP contacts in the relationship between primary health care and diabetes-related PPH.

A development of the Cover Index as a measure of the management aspect of continuity of care

The third study developed the Cover Index with an operationalisation among

a cohort of people with diabetes, using a threshold effects model. With use of this model, results suggested three different optimal maximum time intervals under GP cover, corresponding to three levels of diabetes severity. The time intervals providing the best reduction in PPHs were up to 13 months, 11 months and 9 months, in diabetes cohort with 0, 1-2 and 3+ DCSI scores, respectively. This finding is in line with recommendations in primary health care guidelines for diabetes (210, 211), which suggest people with diabetes should receive primary care at regular intervals of 3 to12 months, depending on the complexity of individual needs. In addition, the result is consistent with the finding in the second study of this thesis, which indicated that a moderate level of GP usage offered the lowest risk of diabetes-related PPH (212) and is also consistent with other evidence in the literature (213). The results of this study provide a practical and novel use for threshold modelling in health services research using administrative data. In this study the time interval between GP visits was categorised into groupings as revealed by the relationship between the explanatory variable (time between GP visits) and the outcome (health care utilisation), corresponding to diabetes severity level. Development of data-driven approaches is particularly important for research using linked administrative datasets, since limited clinical information often makes subgroup definition problematic. Threshold modelling in this case allowed the subdivision of the continuous explanatory variable to be suggested by the data and therefore to be meaningful to the relationship of interest, rather than being imposed due to *a priori* rules that may be irrelevant or difficult or impossible to apply due to limitations in the data content (145). Although this study took a data-driven approach, the operationalisation of the

Cover Index could be easily replicated using other inputs, such as expert opinion or clinical guidelines, to indicate the optimal maximum time interval of GP cover. However, given the tremendous growth of large linked health administrative datasets, the data-driven approach suggested in this study may provide a more objective estimation of the optimal maximum time interval of GP cover and offers a promising approach for future applications in health services research.

The third study added to the literature a meaningful measure of managerial continuity of care. The Cover Index appears to be a good indicator to assess underuse of primary health care, as it is consistent with other studies in identifying relevant subpopulations, such as males, Indigenous, lowest socioeconomic status and living in remote areas (196, 236). Underuse of effective and affordable primary health care services has been of concern in many healthcare systems as it is associated with lower quality of care and increased number of PPHs, which are costly and undesirable to patients (236-238). However, capturing the extent of underuse of primary health care has been problematic in many measures of continuity of care (*e.g.* usual provider index or regularity). Thus, this development of the Cover Index may provide a useful instrument to quantify utilisation of primary health care and help to better understand and identify appropriate subpopulations for allocating resources. While not explored in this study, in addition to capturing periods that are not covered (*i.e*. underuse), the metric could also be adapted to capture periods of 'over cover' (overuse) and thus be used to measure over- as well as under-servicing.

The Cover Index, as developed in this study, has advantages in both measurement and interpretation. In terms of measurement, the Cover Index can be calculated for individuals with single or no GP visits, which is better than other continuity-of-care metrics, such as regularity and usual provider index, which can only be calculated when at least two GP visits are observed within a particular time frame (24, 33). Thus, unlike the latter two metrics the Cover Index can comprehensively capture the whole pattern of GP utilisation.

In terms of interpretation, the Cover Index is easier to interpret than the regularity index, which has no natural units and therefore is not easily amenable to practice or policy monitoring or intervention. The Cover Index is also superior to the usual provider index, which only measures distribution of healthcare providers and thus does not reflect the extent of service utilisation. The Cover Index expresses the proportion of a previously defined period of time under cover of GP care; this can be converted into absolute levels (*e.g.* numbers of days over a 12 month period) of primary care utilisation that may be useful for planning resource use. As shown in this thesis, the Cover Index is calculated using inputs based on the individual's specific attributes, such as complication severity. Therefore, time under cover can be calculated using the optimal maximum time intervals that are appropriate for particular sub-populations. This is important, since rather than changing the Cover Index value judged appropriate for adequate utilisation based on clinical characteristics, the calculation of cover is itself linked to these characteristics. This allows direct comparison of cover across populations and time without the need for further adjustment.

The Cover Index measured at the individual level can also support monitoring of care plans and managing continuity of care for people with diabetes. Measured at population level, the Cover Index can provide useful information to support policy makers in allocation of healthcare resources, especially determining and monitoring subpopulations. Given growth of the large administrative data linked and computing capabilities, calculation of the Cover Index using data-driven methods has now become feasible and may provide more accurate estimations of how to manage continuity of care at the population level. The principle of operationalisation of the Cover Index can be potentially applied to other chronic ambulatory care conditions, such cardiovascular diseases and asthma, although further research is needed to understand patterns of service use in each particular chronic condition.

Continuity of care using the Cover Index and its association with diabetes-related PPH

This study applied the Cover Index to evaluate the continuity of care for people with diabetes in the contemporary 45 and Up Study population in NSW between the period 2009/2010 to 2014/15. This study provided a comprehensive view of how well people with diabetes living in community settings were covered by primary health care and the relationship between the Cover Index and diabetes-related PPHs, controlling for other facets of continuity of care.

In this study, the optimal maximum time interval under GP cover was first re-evaluated in the 45 and Up Study using the threshold effect model. Compared with the study of diabetes cohorts conducted in WA, this study found a similar estimation in the optimal maximum time interval under GP

cover, despite its recommendation of slightly shorter time intervals. The results represent an external evaluation of the estimation of the optimal maximum time interval under GP cover for people with diabetes.

Using the Cover Index to evaluate management continuity of care in the 45 and Up Study population, this study found that on average people with diabetes spent 93.6% of their time each year living in the community under sufficient cover of GP during the period 2011/12 to 2013/14. This was higher than the figure (85%) for the diabetes cohorts studied in WA over the period 1998/99 to 2003/04. This result is in line with the literature, which found an increase in regularity of GP visits among people aged 65 years and older after the introduction of chronic disease management incentive items in the MBS (40). The result illustrates the success of primary health care reforms in Australia, which were targeted at strengthening capabilities and involvement of primary health care in chronic disease management (239). Over the past decade, the Australian Government has provided many incentives to reduce barriers in access to health care, such as the introduction of bulk billing that gives practitioners direct reimbursement from MBS (57) and imbursements for a wide ranges of allied health services (102). The Medicare annual report in 2008/09 shows that the government invested about A$298.2 million for primary health care items related to chronic disease management in that year (105). To the best of my knowledge, this is the first study that has evaluated how well the chronic disease management program has performed over the decade in term of sufficient provision of GP care for people with diabetes, arguably the most challenging chronic disease in Australia. However, since the two studies were undertaken in different Australian states, some of the

changes could have been due to inter-state differences and slightly different algorithm used to identify diabetes rather than improvements in cover of GP over time, and so direct comparison of the results from the WA historical data and the NSW contemporaneous data needs to be undertaken with caution.

This study indicated that although there was an improvement in primary health care cover, primary health care in terms of GP cover remains underutilised among populations living in rural/remote areas, those aged 85+ years or those with severe limitations. Although higher specialist utilisation was observed among the older age groups and those with severe level of limitations, this utilisation was not observed in populations living in remote areas. The result is consistent with literature on the role of primary health services in planning and coordinating care, which shows a relative absence among people in older age groups or with complex health conditions (230). This finding is also consistent with literature which indicates limited effects of GP-initiated chronic disease management programs among people living in remote areas (57). Given that sufficient utilisation and continuity to affordable primary health care is a key attribute to effectiveness and equity of healthcare systems (19, 240), this study further confirmed the need to focus on primary health care among these subpopulations and provided information about the magnitude of the healthcare gap to assist the setting of specific targets for improving continuity of care in these groups.

This study found that higher Cover Index scores were associated with a significantly lower number of diabetes-related PPHs and shorter LOS, even when the analysis was limited to unplanned diabetes-related PPHs. This

finding fits well with the existing philosophy of ambulatory care sensitive conditions that hospitalisations for these conditions can potentially be prevented with timely and effective treatment and management provided in primary health care settings (13, 220). This result is in line with previous studies, which found an association between primary care MBS reimbursement items which contain time components, such as the annual cycle of care item or review of GP management plan item, and a reduction in the number of hospitalisations among people with diabetes (4, 231).

However, this study is inconsistent with the findings of a few recent studies which do not support the theory that ambulatory care can prevent hospitalisations (214, 215). The disparity could be because the studies simply considered the count of GP interactions or the frequency of GP interactions immediately before hospitalisation. Given the role of GPs as gatekeepers in the Australian healthcare system, interaction with a GP before hospital admission is likely and may not reflect a long-term variation in GP interactions of people with chronic condition or how care is connected between past, present and future in terms of time duration between services. Time duration between services is likely to be important for people with ambulatory care sensitive conditions like diabetes, as we know regular monitoring can support self-management and adherence to treatment (4, 237). Interrupted care or sub-optimal follow up over time may increase the risk of PPH due to missing early detection of disease deterioration and the opportunity to provide effective primary care (237). Promoting continuity of care, especially being proactive in monitoring conditions, may significantly contribute to high quality of health care and efficiency in resource utilisation

(237). This study suggests that the Cover Index is more likely to directly relate to the reduction of hospitalisations among people with diabetes than simple measures of frequency and could be targeted to improve health outcomes for people with diabetes.

8.2 Strengths and limitations

This thesis has a number of strengths and limitations, earlier described within each study, that need to be considered when interpreting results. Below is a discussion of the overall strengths and limitations of the thesis.

Strengths

This thesis has a number of strengths, including its data capabilities and analysis methodologies. In particular, it uses a whole-of-population dataset, linked at the individual level in WA that is likely to provide good generalisation to the entire population of Australia. Given the well-developed infrastructure and linkage techniques available in Australia, the linked data used in this study provides high accuracy in the ascertainment of health service use, while maintaining privacy protection for the population. The data contains various sources of information that support the measurement of predictors and outcomes and uses a wide range of covariates. In addition, the linked datasets in the NSW 45 and Up Study also include population-based survey information that included useful information related to sociodemographic and lifestyle characteristics. Linkage with the self-reported survey data, including questions about past diagnoses, provided increased ability to include people with diabetes living in the community but not previously recorded in hospital administrative datasets, thus potentially including those with lower severity

levels in the analysis. The linked administrative datasets have been systematically collected over a long time, allowing maximal capture of diagnosis history, use of health services, severity of disease and duration of condition. The longitudinal data also allows us to observe any change in severity of disease together with changes in service utilisation tendency/behaviours.

This research utilised data-driven analysis approaches, including cluster analysis and a threshold effects model, that enabled us to capture the flexible relationship between predictors and hospital outcomes and then to suggest appropriate strategies to identify latent patterns of health care service utilisation. The use of dynamic models, which included the initial value of the outcome variable, overcame issues with endogeneity arising from the dynamic set-up of the approach (149). In addition to the covariates previously specified above, the models incorporated Mundlak variables, (group means of time-varying variables including frequency of GP contact, regularity of GP contact and comorbidities) to allow for any arbitrary correlation between observed and unobserved heterogeneity terms in the model using a random effects estimator (147, 148).

The Cover Index was developed with a comprehensive, rigorous process, commencing with devising a strategy to account for disease severity, then exploring underlying patterns of service utilisation, then developing, re-evaluating and applying it in an external population. To better support care plans and management of chronic complex conditions like diabetes, it is important to account for inter-individual variability and move towards person-

oriented health care (1, 241). Since the Cover Index can take disease severity into account, it can potentially support that sort of personal-oriented and proactive care for people with diabetes.

Limitations

This thesis, like all research, has limitations. Firstly, complications and comorbidity were only measured at the time people were admitted to hospital and may have existed before being recorded in our data. However, this limitation could be mitigated by using a couplet design in which comorbidity and complications were captured in the previous year to control for their effects on healthcare utilisations in the following year.

Secondly, individuals who had not entered healthcare systems, especially those without any history of hospital admissions, may not have been included in the study population. This limitation may have minimal impact in this study, however, as the data had a long look-back period of almost 20 years for WA data and 10 years for NSW data, thus increasing the likelihood of identifying people with diabetes in healthcare records. The inclusion of self-report information in the 45 and Up Study regarding a previous diagnosis of diabetes allowed the identification of more cases that lacked healthcare records relating specifically to diabetes. This thesis used algorithms to capture diabetes based on recommendation of the project clinical steering panel, as well as evidence in the literature, to maximise successful identification of people with diabetes (127, 128). Another limitation related to data source is that the available data is not sufficient to distinguish between type 1 and type 2 diabetes. Thus, any effect due to nature of the type of

diabetes may not be captured. However, this limitation may have minimal effect on achieving the aim of this study which mainly focuses on developing and evaluating management aspect of continuity of care for people with diabetes. A standard care and management framework to reduce the occurrence of diabetes related complications and burden of healthcare resources used are applied for both types of diabetes (242, 243). In Australia, many Medicare Benefits Schedule items for diabetes management such as diabetes cycle of care (Item nos. 2517–2526, 2620–2635) (244), GP management plan (Item nos. 721), and team care management (Item nos. 723) (245) are for both diabetes types.

A third limitation is that the Cover Index has not been evaluated for the purpose of this thesis using qualitative approaches, such as exploring expert perspectives on the estimation of time interval under GP cover. However, we utilised several data-driven analysis approaches to add flexibility in examining the relationship between primary health care utilisation and hospitalisations. In addition, the optimal maximum time interval under GP cover was also re-evaluated using the external NSW dataset, which showed similar results.

This study was only concerned with measuring continuity of GP contact, not the quality of care provided during the contact. Therefore, a limitation of this work is that although better management continuity of care was achieved with increasing levels of cover this does not guarantee better quality of care per se. However it does increase the opportunity for more timely care to be delivered.

Another limitation is that the Cover Index developed in this research is not able to identify overuse of primary health care services. However, the present results have provided a foundation for further development of the Cover Index that could better capture information about the appropriate level of continuity of care for people with diabetes, as well as for other chronic conditions.

Lastly, the Cover Index was only developed to assess diabetes cohorts, not for the wider population; however, the development process itself, using linked data, is an important achievement and could be more widely applied. The application of the Cover Index to suit other ambulatory care sensitive conditions would respond to the same incremental process as has been undertaken in this thesis as long as the inputs (*i.e.* severity groups and optimal maximum time intervals) are ascertained appropriately for each condition. Since diabetes represents a large proportion of PPHs, the results of this study will significantly contribute to reducing the burden of diabetes on the healthcare system in Australia. In addition, this study may also help to better understand management continuity of care and provide a useful approach to develop the Cover Index for other chronic conditions.

8.3 Significance of the thesis

The research presented in this thesis significantly contributes to literature in four important areas:

1. Addressing challenges in measuring complexity of continuity of care

The literature indicates that continuity of care is a crucial element of primary

health care, contributing to patient satisfaction, improving health outcomes and containing resources used for chronic disease management (23-27). A well-known conceptual framework proposed by Haggerty, Reid (26) suggests continuity of care consists of interpersonal continuity, information continuity and management continuity (26). Although continuity of care is a multidimensional concept, most current measures only examine interpersonal continuity of care (24, 27, 31, 32). However, in the context of today's high burden of chronic conditions, management continuity is vital, as it supports comprehensive service delivery and efficient use of resources (26). Management continuity of care is also a key factor associated with patient satisfaction (30). A metric capturing the management continuity of care is needed to improve our understanding of continuity of care and support policy development that promotes continuity.

This research presented in this thesis developed and tested a new measure of continuity of care in terms of the management dimension, the Cover Index. The Cover Index integrates a time duration component into a previously conceptualised proxy measure of proactive engagement with a GP 'regularity of GP contact' to capture the proportion of time people with a chronic condition (in this research the setting used was diabetes) are under sufficient cover of primary health care. The Cover Index can identify and quantify the extent that continuity of care by GPs is persistent over time. This is important, as GPs with their deep-knowledge and close relationship with the patient are the best physicians to manage care, coordinate with appropriate specialists and update care plans to meet the complex needs of patients (229). Regular interaction with their GP may offer patients early capture of complications

and regular updating of care plans, as well as supporting patient self-management (26). By providing a useful tool for capturing the management aspect of continuity of care, this research contributes to improving the effectiveness and efficiency of service delivery to meet complex needs of people with chronic conditions.

2. Identifying the link between primary health care and hospitalisations

Previous literature found inconsistent relationships between primary health care and hospitalisations (4, 188, 190, 200). Some studies found that increased GP contact is associated with higher rate of hospitalisations (4), while others found primary health care contact is associated with fewer hospitalisations (200, 246). This could be explained by the complexity of the relationship which may not be captured by simply using the number of primary care contacts (4).

The research presented in this thesis has identified key drivers influencing the effects of primary care contact on PPH. It indicated that continuity of care, achieved through regular contact with GP within an optimal maximum time interval, is associated with a reduction in diabetes-related PPHs. The time duration effects of GP contact may better explain the relationship between primary health care and hospitalisations compared with other measures of primary health care utilisation. Thus, interventions focused on optimising the follow-up time interval might significantly contribute to containing healthcare costs for people with chronic conditions. This finding also provides a foundation for future research in optimising continuity of care for people with a range of chronic and complex conditions.

3. Evaluating continuity of care among people with diabetes

This research provides a comprehensive evaluation of continuity of primary care in Australia over the past decade using the Cover Index. While the government has made a significant investment in the chronic disease management program through strengthening the roles of GPs in coordinating and managing care for people with chronic conditions (102, 105), limited evidence is available regarding its impact on the element of continuity. This research shows there has been an improvement in the management of continuity of care for people with diabetes over the last decade, as indicated by higher Cover Index scores over time. This may also imply success of the chronic disease management program in Australia.

4. Advancing data analysis approaches for studies using linked administrative data

This research presents many useful applications of data-driven analytical approaches. The approaches used, including threshold effects models and cluster analysis, allow researchers to explore and retain the nuances of the underlying patterns of service utilisation in the analysis and therefore maximise the utilisation of longitudinal data. This can provide powerful information to support the evaluation of primary health care performance and significantly aid in optimising health service utilisation.

8.4 Implications for future research and health policy

This thesis conceptualised and developed a new measure of continuity of care, the Cover Index, to better capture the management aspects of continuity of care, with specific reference to people with diabetes. The

adoption of methodologies developed in this research to other ambulatory care sensitive conditions is recommended, to ultimately provide a comprehensive set of cover indexes incorporating multiple condition-specific attributes.

Although this research has provided the fundamental first step in development of the Cover Index, and provided evidence for successfully employing this tool in practice, further research on the following aspects should be considered.

- Hospitalisations among people with diabetes can be influenced by many attributes, such as individual characteristics, comorbidity status, quality and content of primary health care services, and structures of practices (190). Thus, further research that combines these factors in relation to hospital use would provide further evidence to support the application of the Cover Index in evaluating continuity of care for people with diabetes.
- Evaluation of the Cover Index in other research jurisdictions as well as with different analytic designs (for example, exploring expert opinion as a method of determining the optimal time interval between GP visits) rather than the empirical method used in this research, would help to provide meaningful recommendations and evidence to support its efficacy and usefulness.
- Appropriate use of healthcare services is increasingly emphasised in many healthcare systems, including Australia, with the phrase ‘Choosing Wisely’ (247, 248). The campaign calls for evidence and

transparency in clinical practice, to reduce overuse as well as underuse of medical services and remove ineffective, wasteful or harmful services (247). A further study aiming to improve performance of the Cover Index in capturing both underuse and overuse of primary health care simultaneously would support development of efficient chronic disease management strategies and provide evidence for improved clinical guidelines.

- Furthermore, continuity of care is a complex and multi-dimensional concept which comprises information, interpersonal relationship and management continuity of care. A further study aiming at incorporating information and interpersonal relationship in evaluating the cover index would help to better design service delivery and make cost-effective use of finite healthcare resources.

Based on the evidence found in the research presented in this thesis, the following recommendations would be a reasonable starting point for directing primary health care policy and practice interventions.

- Provide incentives for making appropriate GP–patient care plans, incorporating proactive follow up, within the time duration predicted by the data for that population group, to better document history of disease, ensure the needs of patients are addressed and support efficient self-management for people with chronic conditions.
- Although other healthcare professionals play essential roles, the GP-led team model of primary health care should be maintained and strengthened to promote efficient use of services and to contain

healthcare costs.

- Establishing a benchmark of recommended GP cover should be considered among other interventions aimed at enhancing primary health care in chronic disease management.
- Management systems that can support GPs within or between practices to provide comprehensive care for people with chronic conditions should be supported.
- Those living in rural and remote areas or with Indigenous status have relatively lower GP cover, although this has slightly improved in recent years. Properly funded activities, appropriate GP arrangements and strengthening primary health care services should be targeted to this population to address this inequity and help close the gaps in health service utilisation and health outcomes in Australia.
- More research funding for optimising primary health care utilisation, especially focused on GP services, would help to improve clinical practice and health outcomes for the population and contain healthcare expenditure.
- Finally, given the well-developed data linkage systems now available, funding bodies should direct research towards maximising the utilisation of the data (via a focus on methodological development) and use research to support health policy development, especially in the area of primary health care.

Appendix A ICD Codes for Diabetes Complication Severity Index

Appendix A. Adapted Diabetes Complication Severity Index and list of complications

Complications	**ICD-9-CM**	**ICD-10-AM**	**DCSI Score**	
			1	**2**
1) Retinopathy				
Diabetic ophthalmologic disease	250.5x	E10.3, E11.3, E13.3, E14.3	‘’	
Background retinopathy	362.01	E11.319	‘’	
Other retinopathy	362.1	H35.0	‘’	
Retinal oedema	362.83	H35.8	‘’	
CSME	362.53	H35.3	‘’	
Other retinal disorders	362.81, 362.82	H35.60	‘’	
Proliferative retinopathy	362.02	E11.359		‘’
Retinal detachment	361.xx	H33		‘’
Blindness	369.xx	H54		‘’
Vitreous haemorrhage	379.23	H43		‘’
2) Nephropathy				
Diabetic nephropathy	250.4	E10.2, E11.2, E13.2, E14.2		
Acute glomerulonephritis	580	N00, N01, N03-N05, N07, N08, N16-N19	‘’	
Nephrotic syndrome	581		‘’	
Hypertension, nephrosis	581.81		‘’	
Chronic glomerulonephritis	582		‘’	
Nephritis/nephropathy	583		‘’	
Chronic renal failure	585	N18		‘’
Renal failure NOS	586	N19		‘’
Renal insufficiency	593.9	N28		‘’
3) Neuropathy				
Diabetic neuropathy	356.9, 250.6	E10.4, E10.61, E11.4, E11.61, E13.4, E13.61, E14.4, E14.61	‘’	
Amyotrophy	358.1	G73.3	‘’	
Cranial nerve palsy	951.0, 951.1, 951.3	S04.1; S04.2; S04.4	‘’	
Mononeuropathy	354.0-355.9	G56, G58.7; G57	‘’	
Charcot’s arthropathy	713.5	M14.6	‘’	
Polyneuropathy	357.2	E10.42, E11.42, E13.42	‘’	
4) Cerebrovascular				
TIA	435	G45.xx	‘’	
Stroke	431, 433, 434, 436	H34.1-I63.x- I64		‘’
5) Cardiovascular				
Atherosclerosis	440.xx	I70.xx		
Other IHD	411	I24		
Angina pectoris	413	I20		
Other chronic IHD	414	I25		
Myocardial infarction	410	I.21		‘’
Ventricular fibrillation, arrest	427.1, 427.3	I47.2; I48.91; I48.92		‘’
Atrial fibrillation, arrest	427.4, 427.5	I46.9;I49.0		‘’

Complications	ICD-9-CM	ICD-10-AM	DCSI Score	
			1	2
Other ASCVD	429.2	I25.10		‘’
Old myocardial infarction	412	I25.2		‘’
Heart failure	428	I50		‘’
Atherosclerosis, severe	440.23, 440.24	I70.23; I70.24		‘’
Aortic aneurysm/dissection	441	I71		‘’
6) Peripheral vascular disease				
Diabetic PVD	250.7	E10.5; E10.62; E10.63; E10.69; E10.73; E11.5; E11.62; E11.63; E11.69; E11.73; E13.5; E13.62; E13.63; E13.69; E13.73; E14.5; E14.62; E14.63; E14.69; E14.73	‘’	
Other aneurysm, LE	442.3	I72	‘’	
PVD	443.81, 443.9	I79.8, I73	‘’	
Foot wound + complication	892.1	S91.3	‘’	
Claudication, intermittent	443.9	I73.9	‘’	
Embolism/thrombosis (LE)	444.22	I74.3		‘’
Gangrene	785.4	I96		‘’
Gas gangrene	040	A48.0		‘’
Ulcer of lower limbs	707	L89; L97; L98.4		‘’
7) Metabolic				‘’
Ketoacidosis	250.1	E10.0; E10.1; E10.64; E10.65; E10.72; E11.0; E11.1; E11.64; E11.65; E11.72; E13.0; E13.1; E13.64; E13.65; E13.72; E14.0; E14.1; E14.64; E14.65; E14.72		‘’
Hyperosmolar	250.2			‘’
Other coma	250.3			‘’

Appendix B Paper 1

Journal of Diabetes and Its Complications 31 (2017) 1175–1180

Contents lists available at ScienceDirect

Journal of Diabetes and Its Complications

journal homepage: WWW.JDCJOURNAL.COM

Stratification strategy for evaluating the influence of diabetes complication severity index on the risk of hospitalization: a record linkage data in Western Australia

Ninh Thi Ha [a,*], Mark Harris [b], Suzanne Robinson [a], David Preen [c], Rachael Moorin [a,c]

[a] School of Public Health, Curtin University, Perth, Western Australia 6845, Australia
[b] School of Economics and Finance, Curtin University, Perth, Western Australia 6845, Australia
[c] Centre for Health Services Research, School of Population Health, The University of Western Australia, 35 Stirling Highway, Crawley, WA 6009, Australia

ARTICLE INFO

Article history:
Received 27 January 2017
Received in revised form 27 March 2017
Accepted 29 March 2017
Available online 5 April 2017

Keywords:
Diabetes complication severity index
Diabetes mellitus
Hospitalizations
Diabetes severity stratification
Threshold effect model
Western Australian (WA) Data Linkage System

ABSTRACT

Objective: This study aimed to develop a risk stratification strategy for evaluating the relationship between complications of diabetes and the risk of diabetic-related hospitalization to accurately classify diabetes severity.
Methods: The study used administrative health records for 40,624 individuals with diabetes aged ≥18 years in Western Australian. The adapted Diabetes Complication Severity Index (DCSI), socio-demographic and clinical characteristics were used in random effects negative binomial and threshold effect models to determine the optimal stratification strategy for diabetes severity based on the homogeneity of the risk of hospitalization in response to variation of the DCSI.
Results: The optimal stratification of people with diabetes was specified by four sub-populations. The first sub-population was no complications with an inverse association with the risk of hospitalizations (coefficient − 0.247, SE 0.03). Further three sub-populations with DCSI at one (coefficient 0.289, SE 0.01), two (coefficient 0.339, SE 0.01) and three or more (coefficient 0.381, SE 0.01) were used to accurately describe the impact of DCSI on the risk of hospitalization.
Conclusion: A stratification into four subpopulations based on the homogeneous impact of diabetes DCSI on the risk of hospitalization may be more suitable for evaluating health care interventions and planning health care provision.

1. Introduction

Diabetes is a serious chronic condition leading to complications in multiple body systems and high risk of premature mortality.[31] It affects 422 million adults, equal to 8.5% of the global adult population in 2014.[31] The prevalence of diabetes in Australia was around one million in 2012, and is estimated to increase to three million Australians by the year 2025.[1,30] Diabetes imposes a considerable economic burden both at the individual level and for health care systems.[7,31] It has been predicted that the burden will substantially increase in the next several decades as a result of an increase in prevalence, cost of health care and population aging.[31]

It has been estimated that only half of those with diabetes in both Australia and the United States achieve adequately managed blood glucose control in the long-term.[29,30] It is, therefore, unsurprising that rates of complications from diabetes have been found to be high with one study finding that approximately 27% of people with diabetes have some form of macrovascular related complications and 50% have microvascular related complications.[26] In addition to affecting an individual's health, complications from diabetes also have a large impact on hospitalization rates and costs. People with diabetes who have multiple chronic complications tend to be hospitalized at a higher rate and stay in hospital longer than those with no complications.[13,25,33] Costs of health care for people with diabetes with complications have been found to be substantially higher than in those without complications.[11,13,14]

Recent studies have examined the effect of diabetic complications on health care utilization using the number of complications or DCSI as a continuous variable or a categorical (ordinal) factor in linear regression.[13,14,32,33] Although the linear approach is flexible enough to examine the overall pattern of the relationship between the number of complications or DCSI and health care utilization, it may not reflect the underlying probability of the relationship given the conditional nature of subsequent events on prior complication.[20] Our assumption is that if diabetic complications are treated as a continuous variable, the impact of subsequent complications may

Conflict of interest: None.

* Corresponding author.
E-mail addresses: thininh.ha@student.curtin.edu.au (N.T. Ha), mark.harris@curtin.edu.au (M. Harris), Suzanne.robinson@curtin.edu.au (S. Robinson), david.preen@uwa.edu.au (D. Preen), r.moorin@curtin.edu.au (R. Moorin).

http://dx.doi.org/10.1016/j.jdiacomp.2017.03.015
1056-8727/

not be accurately characterized since by definition the linear nature of the model treats each subsequent increment of one complication as having the same impact across the full range of number of complications. Alternatively, if the number of complications are categorized into subgroups, using appropriate cut-off points for stratification, then non-linear relationships between the cumulative number of complications and health care use could be included in models. This approach could provide a greater understanding of the impact of diabetic complications on health care utilization and such a classification of the diabetic population would be more suitable for evaluating health care interventions and planning health care provision, than current approaches.

The aim of this study was to examine if the relationship between prior complications from diabetes and the risk of subsequent diabetic-related hospitalization is heterogeneous and how the relationship varies across different levels of complication using individual-level linked whole-of-population administrative data in Western Australia (WA).

2. Material and methods

2.1. Data sources

The guidelines from the Reporting of Studies Conducted using Observational Routinely-collected Health Data Statement[8] were applied to present this study. The study used whole-of-population administrative health data that were linked at the individual level using the WA Data Linkage System.[23] The linked data were limited to individuals aged ≥18 years who were enrolled to vote in WA at any time between 1 January 1988 and 31 December 2004. For each individual, the following person-level linked data were extracted:

- WA Hospital Morbidity Data System (HMDS) records (1980–2004) comprise diagnoses, date of admission and discharge for all hospital separations in WA. Diagnoses are coded using International Classification of Disease (ICD) codes, including principal and up to 21 additional diagnoses.
- Medicare Benefit Scheme (MBS) claim records originating in WA (1984 to 2004) includes all claims for medical (general practitioners), specialist, nursing and allied health care and diagnostic services provided to all Australian citizens. The data provide the date of service and item number of the claim.
- WA Electoral Roll records (1988–2004) include information indicating the dates individuals migrated in and out of WA and therefore time periods individuals were eligible for the study. As voting is compulsory for all Australian adults the Electoral Roll provides almost comprehensive population data[5] incorporating gender, date of birth, and residential location; furthermore changes to address are actively captured (including emigration).[4,27]
- WA mortality records (1988–2004) include all deaths in WA registered in the WA Registry of Births, Deaths and Marriages. These data provided information to identify any individuals in the cohort died during the study period.

2.2. Study population

Eligibility for the study was based on (i) at least one previous record indicating diabetes in the HMDS or MBS data prior to the start of, or in the baseline financial year (1998/99); and (ii) at least two continuous years alive and resident in WA. Diabetes mellitus was determined using the International Classification of Disease, 9th edition-clinical modification (ICD-9-CM) codes in HMDS records (Table 1-Appendix A). MBS claims indicative of presence of diabetes (Table 1-Appendix A) were identified for each individual. The study examined the relationship between complications of diabetes in one year (the exposure year), and hospitalization in the following year (the outcome year). Thus for each individual in the study population, data pertaining to a series of pairs (or couplets) of eligible financial years, one being the exposure year and one being the outcome year formed the unit of evaluation. The couplet design has been applied in the recent publication.[16] Periods of temporary exit and re-entry to the study cohort were captured via Electoral Roll records that indicated outward or inward state-migration. These data were used to ascertain residence within WA. The individuals were observed from the baseline year to 30 June 2004 for any change in complications, hospitalizations or related characteristics.

Ethical approval was provided by The University of Western Australia and Curtin University Human Research Ethics Committees who exempted the study from obtaining individual patient consent.

2.3. Study outcome and predictors

2.3.1. Diabetes-Related Hospitalizations

Hospital separations classified as potentially preventable for diabetes by the National Health Performance Framework[6] and those where diabetes was identified as a significant risk factor by Davis et al.[17] were classified as diabetes-related hospital admissions using the primary or secondary diagnosis codes and all procedure codes on the HMDS separation record. The number of diabetes-related hospitalizations in each follow-up financial year over the study period was captured as a count variable.

2.3.2. Diabetes complication severity index

The 13 point Diabetes Complication Severity Index (DCSI) developed by Young et al.[33] and modified by Chang et al.[12] was used to measure the severity level of diabetic complications. The DCSI has been validated and widely used, and has shown a better performance than a simple count of the number of complications.[12,32,33] The DCSI includes a severity score (0, 1, and 2) for seven categories of diabetic complication: cardiovascular disease, nephropathy, retinopathy, peripheral vascular disease, stroke, neuropathy, and metabolic. Scores range from zero to a maximum of 13, indicating complication severity level. Complications were identified as suggested by Davis et al.[17] and Young et al.[33] and coded using ICD-9-CM mapped to the 10th Revision, Australian Modification ICD codes (ICD-10-AM) where appropriate (Table 2-Appendix A). The DCSI in each financial year was an accumulation of the DCSI from the first ever record of the complication in the data for each individual.

2.3.3. Covariates

This study used the following covariates in the multivariate analysis: general demographic covariates (sex, age, and aboriginal status); quintiles of the census specific Socio-Economic Indexes for Areas (SEIFA) Index for Relative Socio-economic Disadvantage, a relative classification of socio-economic status by geographic area obtained from the Australian Census conducted every five years[3]; accessibility to services using, the Accessibility and Remoteness Index of Australia (ARIA+) derived from census specific ARIA indices[2]; quintile of frequency of general practice visits ascertained from MBS claims data (categorized into 0 to 4); history of diabetic-related hospitalization in the observed year (yes/no) ascertained using all prior HMDS records; duration of diabetes in years between the date of the first identification with diabetes in either MBS or HDMS and the 30 June of each study year. Both socio-economic status using SIEFA and accessibility to services using ARIA+ were ascertained using the postcode of residence on the Electoral Roll data for each year of residency in WA.

2.4. Statistical analyses

The data in this study were constructed as a panel structure where individuals had multiple records indicating changes in exposure,

outcomes and covariates over the study financial years. The panel was unbalanced and complex since individuals moved in and out the study population on multiple occasions or died prior to the end of the studied period. Descriptive and multivariate analyses were conducted for the unbalanced panel data. Threshold effects models were used to examine the non-linear relationship between the DCSI and the risk of hospitalization. Threshold effect models were performed on a restricted panel data-set (restricted sub-population B) which excluded those who moved in and out of the state during the study period or died prior to the end of the study period as an internal validation of the final threshold model. Another internal validation was also conducted on a sub-population (restricted subpopulation B) without those who have diabetes with kidney dialysis to examine if serious complications may cause bias in the models. The STATA for Window version 14.1 were used.

Descriptive analyses were performed to evaluate the distribution of hospitalization and no hospitalization in the baseline financial year 1998/99 across socio-demographic and clinical characteristics. The results were presented in mean, standard deviation (SD) and range for continuous variables and percentage for categorical variables.

Random effects negative binomial regression models for panel data were used to examine the relationship between the DCSI and hospitalizations in bivariate and multivariate analyses. The negative binomial regression model was chosen for use in this study because the outcome variable (the number of hospitalizations) was over-dispersed.[22] Both the Bayes Information criterion (BIC) and Akaike Information Criterion (AIC) statistics and a graph of observed versus predicted counts of hospitalizations indicated that a negative binomial model was preferable to a Poisson model (Fig. 1-Appendix C). A random effects estimator was more efficient than the fixed effects estimator in our study as our study included a large number of observations (n = 180,385 observations).[9] Mundlak variables were defined as group-means of time-varying variables. Mundlak variables were used in our models to relax the assumption in the random-effects estimator that observed variables were uncorrelated with the unobserved variables.[10,28] The Mundlak variables used in this study includes the DCSI, duration of disease, hospitalization status, SEIFA, accessibility to services, and quintile of frequency of general practitioner (GP) visits.

Threshold effect models were used to further examine the homogeneity in the impact of the DCSI on the risk of hospitalizations given the DCSI at each observed financial year. The model searched for sample homogeneity in the response of number of hospitalizations to variations in the complication severity index identified in each financial year. The approach was proposed in previous publications[18,19] to determine both the number of subpopulations and their definition. The "true" regression model was the one with minimum information criteria (AIC and BIC). A similar procedure for the threshold models was also performed on the restricted panel data. Details of the empirical model used are presented in Appendix B.

3. Results

The baseline characteristics of the 40,625 individuals with diabetes included in the study are presented in Table 1. The mean (±SD) age of study population was 61.9 ± 14.4 years, 51% were male, 7.3% were indigenous, about 50% were classified as highest or highly disadvantaged, and 90% lived in moderately-to-highly accessible areas. The mean duration of diabetes was 5.2 years, ranging from 0 to 18.5 years. The mean of DCSI was 1.1, ranging from 0 to 13 (out of a possible 13). Individuals having at least one hospitalization at the baseline were significantly older (63.1 years vs. 61.2), more likely to be female (51.1% vs. 47.8%), indigenous (9.4% vs. 6.0%), classified as disadvantage or highly disadvantage (51.1% vs. 48.8%), and living in very remote areas (6.7% vs. 3.1%) compared with those having no hospitalizations at the baseline year. The average duration of diabetes was shorter among those with hospitalizations than with no hospitalization. The mean DCSI was higher among those with hospitalizations (1.6, SD 1.9) than those with no hospitalization (0.8, SD 1.4).

Table 1
Baseline characteristics of study cohorts in 1998/99.

Variables	Outcomes		Total
	No hospitalization	≥1 hospitalizations	
N	25,919 (63.8)	14,706 (36.2)	40,625 (100)
Age (mean ± SD)	61.2 ± 14.1)	63.1 ± 14.9)	61.9 ± 14.5)
Sex			
Female	12,388 (47.8)	7512 (51.1)	19,900 (49.0)
Male	13,531 (52.2)	7194 (48.9)	20,725 (51.0)
Indigenous			
Yes	1473 (6.0)	1369 (9.4)	2842 (7.3)
No	23,013 (94.0)	13,157 (90.6)	36,170 (92.7)
SEIFA			
Highest disadvantage	4950 (20.9)	3172 (21.8)	8122 (21.3)
High disadvantage	6604 (27.9)	4267 (29.3)	10,871 (28.5)
Moderate disadvantage	3283 (13.9)	2185 (15.0)	5468 (14.3)
Less disadvantage	3778 (16.0)	2154 (14.8)	5932 (15.5)
Least disadvantage	5032 (21.3)	2760 (18.9)	7792 (20.4)
Accessibility			
Very remote	736 (3.1)	977 (6.7)	1713 (4.5)
Remote	412 (1.8)	342 (2.4)	754 (2.0)
Moderate	1109 (4.9)	888 (6.1)	1997 (5.3)
Accessible	1189 (5.1)	905 (6.2)	2094 (5.5)
Highly accessible	20,203 (84.8)	11,427 (78.6)	31,630 (82.5)
Frequency of GP visits (quintile)			
0	3804 (16.0)	2191 (14.9)	5995 (15.6)
1	5110 (21.5)	2184 (14.8)	7294 (18.9)
2	4706 (19.7)	2405 (16.3)	7111 (18.5)
3	5096 (21.4)	3217 (21.8)	8313 (21.6)
4	5096 (21.4)	4709 (32.0)	9805 (25.5)
Duration of disease (mean ± SD)	5.5 ± 4.2	4.9 ± 4.5	5.2 ± 4.3
DCSI (mean ± SD))	0.8 ± 1.4	1.6 ± 1.9	1.1 ± 1.6

Table 2 shows the relationship between the DCSI and the risk of hospitalizations in the following year, presenting results from bivariate and multivariate analyses. Model performance was better in the third model controlling for all covariates and mean of time-variance variables with a smaller value of BIC and AIC. The model shows that the risk of hospitalizations in the following year increased by 55% for each unit increase in DCSI (coefficient 0.44, 95%CI 0.43–0.45, $p < 0.001$) after controlling other factors. Age (coefficient 0.03, 95%CI 0.01–0.04), gender (coefficient 0.00, 95%CI 0.00–0.00) and indigenous status (coefficient 0.08, 95%CI 0.04–0.13) had a minor impact on the risk of hospitalization. While high number of GP visits (coefficient 0.27, 95%CI 0.26–0.28) increased the risk of hospitalizations, duration of disease (coefficient − 0.10, 95%CI −0.10 to −0.09) and history of hospitalization in the previous year (Coefficient − 0.43, 95%CI −0.44 to −0.41) were negatively associated with the risk of hospitalization. SEIFA and accessibility were not significantly associated with the risk of hospitalization.

Table 3 presents the various information criteria along with the optimal model for each number of subpopulations. Considering the information criteria, the model with the lowest value of BIC and AIC (representing the most parsimonious fit) was chosen with four subpopulations characterized by DCSI at 0, 1, 2 and ≥3 for both the full panel data and the restricted panel data. The results suggested that a DCSI score of zero had a negative effect on the risk of hospitalization (Coef. −0.247, SE 0.03) while a DCSI of 1 and 2 had a significant positive effect on the risk of hospitalization (Coef. 0.289, SE 0.01 and Coef. 0.339, SE 0.01, respectively). From a DCSI of 3 or more, the effect of DCSI on the risk of hospitalization was highest (Coef. 0.381, SE 0.01) and there was no further classification into subpopulations. The results were consistent with the results from both sub-population A and sub-population B. The results of the model are further illustrated in Fig. 1 to visualize the risk of hospitalizations varying by DCSI from 0

Table 2
Association of complication severity index and hospitalizations with and without adjustment for independent variables (result from random effects negative binomial regression).

	Model 1		Model 2		Model 3	
	Coef.	95%CI	Coef.	95%CI	Coef.	95%CI
DCSI	0.29***	(0.28,0.29)	0.27***	(0.26,0.27)	0.44***	(0.43,0.45)
Gender (males)			−0.02*	(−0.05,−0.00)	0.03**	(0.01,0.04)
Age in years			0.00***	(0.00,0.00)	0.00***	(0.00,0.00)
Indigenous (yes)			0.25***	(0.20,0.30)	0.08***	(0.04,0.13)
SEIFA						
Highest disadvantage			REF		REF	
High disadvantage			0.01	(−0.03,0.03)	−0.01	(−0.04,0.02)
Moderate disadvantage			−0.04*	(−0.07,−0.01)	−0.03	(−0.08,0.01)
Less disadvantage			0.01	(−0.02,0.04)	0.01	(−0.05,0.07)
Least disadvantage			−0.01	(−0.04,0.02)	−0.01	(−0.08,0.06)
Accessibility						
Very remote			REF		REF	
Remote			−0.13**	(−0.21,−0.05)	−0.02	(−0.10,0.06)
Moderate			−0.21***	(−0.28,−0.14)	−0.06	(−0.15,0.04)
Accessible			−0.16***	(−0.23,−0.09)	0.01	(−0.10,0.13)
Highly Accessible			−0.40***	(−0.46,−0.34)	−0.03	(−0.18,0.11)
Duration of disease			−0.03***	(−0.04,−0.03)	−0.10***	(−0.10,−0.09)
History of hospitalization (yes)			0.13***	(0.11,0.14)	−0.43***	(−0.44,−0.41)
Quintile of GP visits			0.22***	(0.21,0.23)	0.27***	(0.26,0.28)
Mean severity index					−0.39***	(−0.40,−0.38)
Mean duration of disease					0.10***	(0.09,0.10)
Mean hospitalization status					3.08***	(3.04,3.12)
Mean SEIFA					−0.01	(−0.02,0.02)
Mean accessibility					−0.02	(−0.06,0.02)
Mean quintile of GP visits					−0.19***	(−0.21,−0.18)
AIC	382,557.45		369,081.20		344,032.61	
BIC	382,597.86		369,262.17		344,273.89	

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

to 13, and show a marginal effect of DCSI on predicting number of hospitalizations across subpopulations.

4. Discussion

To our knowledge, this study is the first to examine the non-linear relationship between diabetes complication and the risk of related hospitalizations at the whole-population level. The results show that the risk of hospitalizations among diabetics without complication is different from those with complications. However, our results importantly indicate that diabetics with varying degrees of complication severity should be stratified into three subpopulations with one, two and three or more of the DCSI score based on the homogeneity of the risk of hospitalization in response to variation of the DCSI. These findings may contribute to a better understanding

Table 3
Threshold model estimation results.

	Full population							Restricted sub-population A	Restricted sub-population B
Number of subpopulation	2	3	4	5	6	7	13	4	
BIC	342,866.0	342,827.1	342,794.4	342,804.2	342,813.6	342,824.8	342,887.1	282,988.9	335,741.0
AIC	342,584.5	342,535.5	342,492.4	342,492.5	342,492.9	342,493.03	342,494.9	282,691.5	335,439.5
Threshold parameters									
τ_1	0	0	0	0	0	0	–	0	0
τ_2		4	1	1	1	1	–	1	1
τ_3			2	2	2	2	–	2	2
τ_4				7	4	4	–		
τ_5					7	7	–		
τ_6						10			
Complications coefficients									
γ_1	−0.043*** (0.01)	0.047* (0.02)	−0.247*** (0.03)	−0.222***(0.03)	−0.139*** (0.06)	–	–	−0.289*** (0.03)	−0.253*** (0.03)
γ_2	0.408*** (0.00)	0.442*** (0.01)	0.289*** (0.01)	0.302*** (0.02)	0.344*** (0.03)	–	–	0.270*** (0.01)	0.286*** (0.01)
γ_3		0.418*** (0.01)	0.339*** (0.01)	0.348*** (0.01)	0.376*** (0.02)	–	–	0.332 *** (0.01)	0.339*** (0.01)
γ_4			0.381*** (0.01)	0.387*** (0.01)	0.407*** (0.01)	–	–	0.376*** (0.01)	0.383*** (0.01)
γ_5				0.382*** (0.01)	0.398*** (0.01)	–	–		
γ_6					0.391** (0.01)	–	–		

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

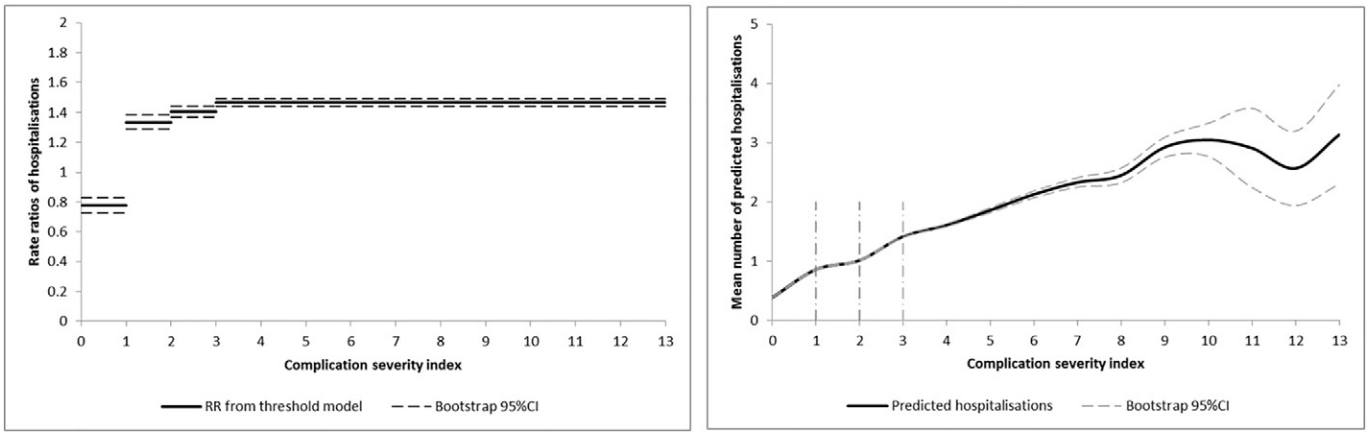


Fig. 1. Estimated rate ratios under threshold model and predicted hospitalization for each sub-population.

of diabetic risk stratification and therefore better risk adjustment for use in planning and evaluating health care provision strategies targeting high-risk populations to improve health outcomes.

The significant increase in hospitalizations in response to the increase in diabetes severity observed in the literature is consistent with our findings when examining the linear association between hospitalizations and the DCSI.[13,21,33] The DCSI was stratified into six subgroups from 0 to ≥5 in studies examining the impact of complications on health care utilization and costs and adjusting for its impact.[15,21,32] Compared with all potential subpopulations derived from the observed DCSI range in this study, the optimal model indicated that from 3 to 13 the DCSI does not seem to be subject to any subpopulation, and hence it may not be necessary to distinguish the complication index when values exceed an index score of 3. While recent studies used the six subgroup stratification suggested by Young et al.,[33] our study suggests that stratification into four subgroups (0,1,2 and 3 or more) may be a better approach to reduce over parameterization of models and more accurately reflect the homogeneous impact of the DCSI on health care utilization.

Our findings have major implications for planning and targeting health care provision. Previous studies suggested that DCSI is an important indicator to predict health care costs and resource uses.[11,13,21] Our study supports those findings and adds further that four sub-populations with particular DCSI had different effects on predicting the risk of hospitalization after controlling for clinical and socio-demographic characteristics. This result highlighted a substantial increase in hospital use among those with DCSI 3 + that would not have been indicated by specifying the association in a linear manner. Our model aides in estimating future resource use and health care provision, by providing a method to more accurately reflect real world settings. In addition, with a considerable gap in the risk of hospitalization between people with diabetes who do and do not have diabetes-related complications observed in our study, proactive provision of primary care and interventions targeted to avoiding existing or newly diagnosed diabetics progressing to their first complication would appear to offer the largest reduction in hospitalizations and save health care resources.

The strength of our study was the use of linked administrative data at the individual level which covered the whole population diagnosed with diabetes for assessing exposure and outcome. Use of whole-of-population data provides strong external validity. The linked data provided an accurate access to both baseline and following-up participant characteristics and trends of the characteristics over the studied period reducing loss to follow up. The data also enabled us to include a range of covariates in the regression models. The study used a panel data structure that contained information on both within and between individual variations allowing us to control for the effect of unobserved covariates.[24] In addition, our study applied the recent advanced analytic approach "the threshold effects model"[18] that enabled us to capture the most flexible relationship between complications and the risk of hospitalization and suggest the most appropriate subpopulations in which the relationship is constant.

However, this study also has limitations which should be considered when interpreting the results. The severity of complications was obtained using DCSI which is an unweighted index that did not independently examine the association between the adverse outcome and each complication.[33] Use of this index may cause some potential bias due to the impact of some serious conditions like kidney failure with dialysis. However, since the analysis of the sub-population without serious complications showed results consistent with the analysis without this exclusion, the presence of serious conditions did not drive the results. Individuals with undiagnosed diabetes or who did not use health care services for diabetes in WA during the study period could not be captured by the data. This limitation was somewhat mitigated by the fact that we had access to data for almost 20 years that enabled us to look back to identify use of health services over an extended period of time. However, the data could not capture people with diabetes in the community unless they had accessed a primary care provider for diabetes related care or been hospitalized previously either for diabetes or been hospitalized for another reason where pre-existing diabetes was recorded on the hospital record as a comorbidity. Using the administrative datasets, the duration of diabetes was less likely to be under-represented as the actual date of the onset would likely have been before the first date of using health care services recorded in datasets. In addition, while we could accurately identify person–time resident in WA and therefore accurately capture health service use in WA, we could not capture health service use or prior diagnosis of diabetes that occurred outside of WA. This limitation was partially offset by the use of a validation "restricted panel" dataset that only included those individuals who had been resident in WA for the entire study period. These limitations are common and well known in administrative data. They do not affect our examination of the homogeneous impact of diabetic complication on the risk of hospitalizations but they do limit the generalizability of our findings to diabetics who have had at least one interaction with the health system.

5. Conclusion

The homogeneous impact of diabetes DCSI on the risk of hospitalization varied significantly across four subpopulations. This

stratification strategy may serve as an efficient tool for classification diabetes severity in management programs and population-based studies and interventions.

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.jdiacomp.2017.03.015.

Acknowledgements

This work was supported by the National Health and Medical Research Council, project grant APP1078345.

The authors wish to thank the staff at the Western Australian Data Linkage Branch and Commonwealth Department of Health and Aging for providing the linked data for this project.

References

1. AIHW. How many Australians have diabetes? Retrieved from http://www.aihw.gov.au/how-common-is-diabetes/ 2014.
2. Australian Bureau of Statistics. *Census of population and housing: Socio-economic Indexes for areas. 1981-2006. [Retrieved from Canberra].*
3. Australian Bureau of Statistics. *Census of population and housing: Socio-economic Indexes for areas. 2001, 2006 & 2011. [Retrieved from Canberra].*
4. Australian Electoral Commission. Enrolment - frequently asked questions. Retrieved from http://www.aec.gov.au/faqs/enrolment.htm 2016.
5. Australian Electoral Commission. Enrolment statistics. Retrieved from http://www.aec.gov.au/Enrolling_to_vote/Enrolment_stats/ 2016.
6. Australian Institute of Health and Welfare. *A set of performance indicators across the health and aged care system. 2008. [Retrieved from Canberra].*
7. Australian Institute of Health and Welfare. *Diabetes expenditure in Australia 2008–09. 2013. [Retrieved from Canberra].*
8. Benchimol EI, Smeeth L, Guttmann A, Harron K, Moher D, Petersen I, et al. The REporting of studies conducted using observational routinely-collected health data (RECORD) statement. *PLoS Med.* 2015;12:e1001885, http://dx.doi.org/10.1371/journal.pmed.1001885.
9. Cameron AC, Trivedi PK. Count panel data. In: B.H.B, ed. The Oxford handbook of panel data econometrics. Oxford University Press; 2014.
10. Chamberlain G. Multivariate regression models for panel data. *J Econ.* 1982;18:5-46, http://dx.doi.org/10.1016/0304-4076(82)90094-X.
11. Chang HY, Weiner JP, Richards TM, Bleich SN, Segal JB. Predicting costs with diabetes complications severity index in claims data. *Am J Manag Care.* 2012;18:213-9. [Retrieved from http://europepmc.org/abstract/MED/22554010] .
12. Chang HY, Weiner JP, Richards TM, Bleich SN, Segal JB. Validating the adapted diabetes complications severity index in claims data. *Am J Manag Care.* 2012;18:721-6.
13. Chen H-L, Hsiao F-Y. Risk of hospitalization and healthcare cost associated with diabetes complication severity index in Taiwan's National Health Insurance Research Database. *J Diabetes Complicat.* 2014;28:612-6, http://dx.doi.org/10.1016/j.jdiacomp. 2014.05.011.
14. Chen H-L, Hsu WW-Y, Hsiao F-Y. Changes in prevalence of diabetic complications and associated healthcare costs during a 10-year follow-up period among a nationwide diabetic cohort. *J Diabetes Complicat.* 2015;29:523-8, http://dx.doi.org/10.1016/j.jdiacomp.2015.02.002.
15. Chen T-T, Chung K-P, Lin IC, Lai M-S. The unintended consequence of diabetes mellitus pay-for-performance (P4P) program in Taiwan: are patients with more comorbidities or more severe conditions likely to be excluded from the P4P program? *Health Serv Res.* 2011;46:47-60, http://dx.doi.org/10.1111/j.1475-6773.2010.01182.x.
16. Comino EJ, Islam MDF, Tran DT, Jorm L, Flack J, Jalaludin B, et al. Association of processes of primary care and hospitalisation for people with diabetes: a record linkage study. *Diabetes Res Clin Pract.* 2015;108:296-305, http://dx.doi.org/10.1016/j.diabres.2015.02.003.
17. Davis WA, Knuiman MW, Hendrie D, Davis TM. Determinants of diabetes-attributable non-blood glucose-lowering medication costs in type 2 diabetes: the Fremantle diabetes study. *Diabetes Care.* 2005;28:329-36.
18. Gannon B, Harris D, Harris M. Threshold effects in nonlinear models with an application to the social capital-retirement-health relationship. *Health Econ.* 2014;23:1072-83, http://dx.doi.org/10.1002/hec.3088.
19. Gonzalo J, Pitarakis J-Y. Estimation and model selection based inference in single and multiple threshold models. *J Econ.* 2002;110:319-52. [Retrieved from http://eprints.soton.ac.uk/33366/] .
20. Greene WH. In: Greene WH, ed. Econometric analysis. 6th (International) ed. Upper Saddle River, N.J.: Pearson/Prentice Hall; 2008
21. Hazel-Fernandez L, Li Y, Nero D, Moretz C, Slabaugh L, Meah Y, et al. Relationship of diabetes complications severity to healthcare utilization and costs among Medicare advantage beneficiaries. *Am J Manag Care.* 2015;21:e62-70.
22. Hilbe J. In: Hilbe JM, ed. Negative binomial regression. Cambridge: Cambridge University Press; 2007.
23. Holman CD, Bass AJ, Rouse IL, Hobbs MS. Population-based linkage of health records in Western Australia: development of a health services research linked database. *Aust N Z J Public Health.* 1999;23:453-9.
24. Hsiao C. Panel data analysis—advantages and challenges. *TEST.* 2007;16:1-22, http://dx.doi.org/10.1007/s11749-007-0046-x.
25. Khalid JM, Raluy-Callado M, Curtis BH, Boye KS, Maguire A, Reaney M. Rates and risk of hospitalisation among patients with type 2 diabetes: retrospective cohort study using the UK general practice research database linked to English hospital episode statistics. *Int J Clin Pract.* 2014;68:40-8, http://dx.doi.org/10.1111/ijcp.12265.
26. Litwak L, Goh S-Y, Hussein Z, Malek R, Prusty V, Khamseh ME. Prevalence of diabetes complications in people with type 2 diabetes mellitus and its association with baseline characteristics in the multinational A1chieve study. *Diabetol Metab Syndr.* 2013;5:1-10, http://dx.doi.org/10.1186/1758-5996-5-57.
27. Moorin RE, Holman CD, Garfield C, Brameld KJ. Health related migration: evidence of reduced "urban-drift". *Health Place.* 2006;12:131-40, http://dx.doi.org/10.1016/j.healthplace.2004.10.013.
28. Mundlak Y. On the pooling of time series and cross section data. *Econometrica.* 1978;46:69-85, http://dx.doi.org/10.2307/1913646.
29. Saydah SH, Fradkin J, Cowie CC. Poor control of risk factors for vascular disease among adults with previously diagnosed diabetes. *JAMA.* 2004;291:335-42, http://dx.doi.org/10.1001/jama.291.3.335.
30. Shaw J, Tanamas S. Diabetes: The silent pandemic and its impact on Australia. Retrieved from Canberra: https://static.diabetesaustralia.com.au/s/fileassets/diabetes-australia/e7282521-472b-4313-b18e-be84c3d5d907.pdf 2012.
31. World Health Organization. *Global report on diabetes. 2016. [Retrieved from Geneva].*
32. Wu CX, Tan WS, Toh MPHS, Heng BH. Stratifying healthcare costs using the diabetes complication severity index. *J Diabetes Complicat.* 2012;26:107-12, http://dx.doi.org/10.1016/j.jdiacomp. 2012.02.004.
33. Young BA, Lin E, Von Korff M, Simon G, Ciechanowski P, Ludman EJ, et al. Diabetes complications severity index and risk of mortality, hospitalization, and healthcare utilization. *Am J Manag Care.* 2008;14:15-23. [Retrieved from http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3810070/].

Appendix C Paper 2

Contents available at ScienceDirect

Diabetes Research and Clinical Practice

journal homepage: www.elsevier.com/locate/diabres

International Diabetes Federation

Identifying patterns of general practitioner service utilisation and their relationship with potentially preventable hospitalisations in people with diabetes: The utility of a cluster analysis approach

Ninh Thi Ha [a,*], *Mark Harris* [b], *David Preen* [c], *Suzanne Robinson* [a], *Rachael Moorin* [a,d]

[a] *School of Public Health, Curtin University, Perth, Western Australia 6845, Australia*
[b] *School of Economics and Finance, Curtin University, Perth, Western Australia 6845, Australia*
[c] *Centre for Health Services Research, School of Population and Global Health, The University of Western Australia, 35 Stirling Highway, Crawley, WA 6009, Australia*
[d] *School of Population and Global Health, The University of Western Australia, 35 Stirling Highway, Crawley, WA 6009, Australia*

ARTICLE INFO

Article history:
Received 18 August 2017
Received in revised form
24 November 2017
Accepted 26 January 2018
Available online 9 February 2018

Keywords:
Cluster analysis
Primary health care
Potentially preventable hospitalisation
Diabetes
Data linkage

ABSTRACT

Aims: We aimed to characterise use of general practitioners (GP) simultaneously across multiple attributes in people with diabetes and examine its impact on diabetes related potentially preventable hospitalisations (PPHs).

Methods: Five-years of panel data from 40,625 adults with diabetes were sourced from Western Australian administrative health records. Cluster analysis (CA) was used to group individuals with similar patterns of GP utilisation characterised by frequency and recency of services. The relationship between GP utilisation cluster and the risk of PPHs was examined using multivariable random-effects negative binomial regression.

Results: CA categorised GP utilisation into three clusters: moderate; high and very high usage, having distinct patient characteristics. After adjusting for potential confounders, the rate of PPHs was significantly lower across all GP usage clusters compared with those with no GP usage; IRR = 0.67 (95%CI: 0.62–0.71) among the moderate, IRR = 0.70 (95%CI 0.66–0.73) high and IRR = 0.76 (95%CI 0.72–0.80) very high GP usage clusters.

Conclusions: Combination of temporal factors with measures of frequency of use of GP services revealed patterns of primary health care utilisation associated with different underlying patient characteristics. Incorporation of multiple attributes, that go beyond frequency-based approaches may better characterise the complex relationship between use of GP services and diabetes-related hospitalisation.

* Corresponding author.
E-mail addresses: thininh.ha@student.curtin.edu.au (N.T. Ha), mark.harris@curtin.edu.au (M. Harris), david.preen@uwa.edu.au (D. Preen), Suzanne.robinson@curtin.edu.au (S. Robinson), r.moorin@curtin.edu.au (R. Moorin).

https://doi.org/10.1016/j.diabres.2018.01.027
0168-8227/

1. Introduction

Diabetes is an increasing public health issue causing a substantial burden on health care systems around the world [1]. In Europe, the number of people with diabetes was nearly 60 million in 2013, and is estimated to increase to 70 million by the early 2030s [2]. Similarly, in the United States the prevalence of diabetes was estimated at 29.1 million in the national report in 2014 [3]. In Australia, a country of approximately 24 million people, the prevalence of diabetes was about 1.2 million in 2014–15 [4] and is estimated to increase to 3.4 million by early 2030s [5].The condition costs the Australian Health system more than $AU6.5 billion each year [5]. Diabetes is considered an ambulatory care sensitive condition [5], and consequently enhancing primary health care to better manage diabetes has been a major approach in the health care system of Australia [5,6].

The literature suggests that better primary health care delivery reduces the risk of hospitalisations for ambulatory care sensitive conditions in general [7–9]. With respect to diabetes, a recent systematic review indicated that regular primary care was associated with reduced risk of hospitalisation [10]. However, other aspects such as frequency of visits or access to primary health care show inconsistent results [10].

In Australia, primary care services, mainly provided by general practitioners (GP), are subsidised through a universal health insurance scheme, Medicare, on a fee-for-service basis [6]. Dedicated financial incentives have been provided under Medicare for GPs to provide comprehensive care for diabetes [6]. However, to our knowledge, limited research has evaluated patterns of utilisation of primary health care services for people with diabetes and their impact on health outcomes. Current studies are limited to examining the utilisation of primary health care based on single indicators such as frequency [6] or regularity of services used [11].

Since patterns of primary health care utilisation are likely to be complex, more advanced approaches that account for multiple factors are required to more accurately classify and discover meaningful patterns of primary health care utilisation by people with diabetes. K-mean cluster analysis, a data-driven approach, is capable of taking into account multiple dimensions simultaneously and is suitable for use with large datasets [12]. The technique can classify individuals with similar characteristics into homogeneous groups which can also maximise heterogeneity between groups [12]. The technique has been applied to a variety of settings, for example, health behaviour [13]; health psychology [14]; health care cost analysis [12] and genetic classification [15].

Thus, our study aims to apply K-mean cluster analysis to identify GP utilisation patterns using multiple attributes of GP usage among people with diabetes. We will also examine the impact of identified GP utilisation patterns on the risk of potentially preventable hospitalisations (PPHs). Understanding patterns of GP utilisation and how they impact on health outcomes is useful for planning health care provision targeted to encouraging particular patterns in utilisation and enhancing the relationship between patients and their primary health care provider.

2. Material and methods

2.1. Data sources

The Western Australian (WA) linked data used for this study comprised whole-of-population administrative health data linked at the individual level, for residents of WA aged 18 years or older who were registered at any time on the WA Electoral Roll [16]. The data included a complete set of WA Hospital Morbidity Data System (HMDS) records; Medicare Benefit Scheme (MBS) claim records; WA Electoral Roll (ER) records; and WA mortality records for each individual subsequent to their first ever WA Electoral Roll record. Details of each dataset have been described previously [17]. In brief, the datasets provide statutory information on all hospitalisations (HMDS), claims for medical services out-of-hospital including GP visits (MBS), dates individuals migrated in and out of WA or changed address while living in WA (Electoral Roll) and date/cause of death.

2.2. Study population

Annual panel data from 1998/1999 to 2003/2004 were constructed consisting of individuals with diabetes identified via HMDS or MBS data prior to the start of or in the baseline financial year (1998/99). Diabetes mellitus was determined using the International Classification of Disease (ICD), 9th edition-clinical modification (ICD-9-CM) codes in HMDS records and MBS claims indicative of the presence of diabetes as described elsewhere [17]. All individuals were observed annually from the baseline year to 30 June 2004, last year living in WA or death (whichever occurred first) for any change in GP utilisation, hospitalisations and clinical and demographic characteristics. GP utilisation and demographic and clinical characteristics were measured in the exposure year, and PPH outcomes measured in the following year. Only individuals who were alive and resident in WA for at least two consecutive years were included in the study. The couplet design (ie. comprising pairs of years, the exposure year followed by an outcome year) has been applied in recent publications [6,17].

Ethical approval was provided by The University of Western Australia and Curtin University Human Research Ethics Committees who exempted the study from obtaining individual patient consent.

2.3. Study outcome and predictors

2.3.1. Diabetes related potentially preventable hospitalisations

The primary outcome measure was diabetes related potentially preventable hospitalisations (PPH) during the following-up year of each couplet. Hospitalisations were deemed PPHs based on either their principal diagnosis being identified by the National Health Performance Framework [18] as a diabetes related PPH or identification by Davis et al. [19] as associated with increased risk for people with diabetes. Principal diagnoses were captured using ICD-9-CM and Aus-

tralian Modification ICD codes 10th revision (ICD-10-AM) codes included in the HMDS records (Appendix 1).

2.3.2. *Variables for GP usage clustering*

The goal of these cluster analyses was to identify patterns of GP service utilisation among people with diabetes. Candidate variables included in the cluster analyses were adapted from the customer relationship management framework proposed by Hughes (2005) [20] that capture both level of usage and strength of the relationship between patients acting as customers and GPs acting as primary care providers. Three main components suggested from the framework were Recency, Frequency and Monetary [20] which have been applied to healthcare data previously [21]. Since healthcare costs for Australia are covered by Medicare, with limited out of pocket payment from patients, the monetary component was not considered in our analyses. Greater recency and frequency are indicators of how well the relationship between patients with diabetes acting in the role of a customer and primary health care provider (GP) acting in the role of the service provider has been maintained [21].

In our study recency of GP usage consisted of three factors including: (i) the average time interval between access of health care service capturing the overall interaction between patients and GPs, (ii) the standard deviation from the average time interval capturing the extent of consistency in service utilisation, and (iii) the longest time interval between services capturing the extent that patients were out of coverage of primary care. Since the mean and standard deviation values may be driven by extreme values, two alternatives to the recency variable group were also considered in the cluster analyses including (A) mean time interval, mean absolute deviation from the mean and the longest time interval and (B) median time interval, median absolute deviation from median, and the longest time interval. The results of cluster analysis of the three groups of variables were compared in Table 1. The time interval was determined between the date of a GP visit and the date of the previous health care service provided either from a GP or hospitalisation.

Frequency of GP usage was defined as the number of GP visits in a financial year. Those GP visits occurring within 14 days of the previous GP visit were counted as one GP usage to minimise over counting GP service utilisation, as those within 14 days of each other are likely to be associated with a single episode of care, for example where people may need to return to a GP to receive laboratory test results, rather than a subsequent discrete GP service as discussion with our GP experts.

All indicators were measured within financial years. However, a three-year look-back period was used, where necessary, to calculate the time interval between the first GP service in that year and the previous service. Three years was found to be the tie period that maximised capturing recency of GP utilisation for the cohort. Individuals having only one GP visit within a financial year were included in the cluster analysis if they had a previous health care service within the look-back period to enable the calculation of recency of GP usage.

2.3.3. *Covariates*

For this study, a number of individual characteristics were included to control for potential confounders in the relationship between GP usage cluster and PPHs. Demographic characteristics included were age group (18–44, 45–59, 60–74 and ≥75 years), gender, Indigenous status, quintile of the Census specific Socio-Economic Indexes for Areas (SEIFA) Index of Relative Socioeconomic Disadvantage [22] and quintile of accessibility to services [23]. Diabetes complications were identified using ICD codes suggested by Young, Lin [24] and classified into four groups (0, 1, 2 and 3 or more complications) according to our previously published methods [17]. The number of comorbidities was summed from a list of comorbidities suggested by Holman et al. [25], excluding conditions classified as complications of diabetes. Regularity of GP visits was calculated as [1/(1 + variance)] [9], where variance is a variance of the time interval between GP visits occurring within the financial year and classified into four quantiles. Number of specialist visits, and non-diabetes

Table 1 – Cluster analysis outputs with different groups of recency variables.

	Group of indicators used in K-mean cluster		
	Candidate group	Alternative A group	Alternative B group
Mean	✓	✓	
Median			✓
Mean absolute deviation from the mean		✓	
Median absolute deviation from median			✓
Standard deviation	✓		
The longest time to GP visit	✓	✓	✓
Frequency of GP visits	✓	✓	✓
Cluster stopping (Caliński rule)	133,805	132,616	129,095
Number of clusters	3	3	3
% of agreement vs. group 1 (Kappa values)	–	99.3%	95.5%

related hospitalisation were calculated within a financial year. Duration of diabetes was calculated in years.

2.4. Statistical analyses

Cluster analyses were conducted using different alternative combinations of recency and frequency of GP usage among those with at least one GP visit in a financial year. First, the values of the mean/median time interval, the standard deviation/absolute deviation of mean/median time intervals, longest time interval and frequency of GP visits were normalised by subtracting the minimum of each value and dividing that difference by the range of all values [12]. K-mean cluster analyses were then conducted on normalised values of recency and frequency of GP visits. The K-mean cluster approach was preferred as it is less susceptible to outliers in the data and is appropriate for use with large datasets [12]. The number of clusters was indicated using Calinski-Harabasz stopping rules for the options of 2 to 6 clusters, the large values of the Calinski-Harabasz pseudo-F index indicated distinct clustering [26]. Characteristics of final GP usage clusters were described using a box plot.

Both descriptive bivariate and multivariate analyses were performed. Descriptive analyses were used to summarise characteristics of participants among no GP usage and each GP usage cluster in the baseline year. The results were presented as the mean and standard deviation (SD) for continuous variables and percentage for categorical variables. Multivariate analyses were conducted using random-effects negative binomial regression model (NB) for panel data and zero-inflated negative binomial regression model (ZINB) with the inflated component contained in the intercept only. The Bayes Information Criterion (BIC) and Akaike Information Criterion (AIC) statistics were used to assess the fit of the model where NB with random effects was the preferred model compared to ZINB. We included Mundlak variables, defined as group-means of time-varying variables, to relax the assumption in the random-effects estimator that observed covariates were uncorrelated with the unobserved covariates [27,28]. The group mean variables used were number of specialist visits and non-diabetes related hospitalisation. All analyses were conducted using STATA for Windows version 14.1.

3. Results

3.1. Clustering results

Table 1 presents summary results of cluster analyses with different groups of recency variables. The candidate group included mean time interval, mean absolute deviation from the mean, longest time to GP visit and frequency of GP visits; alternative A group included mean, standard deviation, the longest time interval and frequency; alternative B group included median, median absolute deviation from median, the longest time interval to GP visit and frequency of GP visits. Using the Calinski cluster stopping rule, all three groups identified three clusters. Compared with the candidate group, the other alternative groups had very high percentage of agreement in term of grouping subjects into a cluster with 99.3% in the alternative A group and 95.5% in the alternative B group. The candidate group also had highest Calinski F index value. Thus, the results of the candidate group were kept to present in this paper (Table 1). Fig. 1 and Table 2 summarise the GP usage clusters from K-mean analyses. Three clusters were identified, including (1) moderate GP usage with mean time interval of approximately 10 months (296 days), standard deviation of about 4 months (115 days), the longest time interval of 14 months (404 days) and frequency of about 2 times a year; (2) high GP usage with mean time interval to a GP visits of 3 months (88 days), standard deviation of 1.5 months (48 days), the longest time interval of 5 months (147 days) and frequency of 3.7 times a year; and (3) very high usage with mean time interval of 1.5 months (40 days), deviation of 0.5 months (20 days), the longest time interval of 2 months (76 days) and frequency of visit approximately 7.8 times a year.

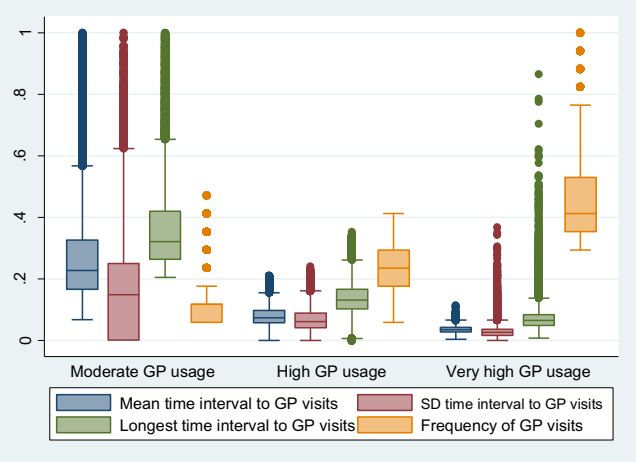


Fig. 1 – GP usage by clusters.

3.2. Characteristics of study population by GP usage cluster at the baseline year

Basic demographic and clinical characteristics of the study population are described in Table 3 by no GP usage and each GP usage cluster. The majority of the study population had high (n = 17 077, 42.0%) and very high (n = 15 858, 39.0%) GP usage, were aged 45 years or older (86.2%), and were more likely to be male (51%), non-indigenous (92.7%), moderate to least disadvantaged (51.6%), and living in areas with moderate to high accessibility to services (93.4%). Those with complications accounted for 43.3% in the study population, higher in very high GP usage cluster (51.5%). The average number of comorbidities was 4.5 (SD3.6), the highest in those with very high GP usage cluster (mean 5.6; SD 3.5), followed by high GP usage cluster (mean 4.1, SD 3.5), no GP usage cluster (mean 3.5; SD 4.4) and moderate GP usage cluster (mean 3.2; SD 2.9). The average duration of diabetes was 6.4 (SD = 4.3) years, similar duration across GP usage clusters and the no GP usage group. None and low regularity of GP visits were observed across GP usage clusters, except the very high GP

Table 2 – GP usage clusters summary.

Clusters	Mean (days)	SD (days)	The longest (days)	Frequency of GP visits
Moderate usage				
Min	75	0	225	1
Mean	296.8412	115.0688	404.0527	1.919529
Max	1093	744.5834	1095	8
High usage				
Min	1	0	1	1
Mean	88.19658	48.81665	147.0608	3.716618
Max	230	178.1975	387	7
Very high usage				
Min	5.2	0	9	5
Mean	39.71341	20.81995	76.12468	7.819856
Max	124.75	273.0432	947	17

usage cluster. High numbers of hospitalisations were observed among those with no GP usage (average of 3.4 admissions), followed by the very high GP usage cluster (0.8 admissions), high GP usage cluster (0.7 admissions) and moderate GP usage cluster (0.2 admissions).

Overall, the moderate GP usage cluster tended to be younger (25.1% aged 18–44 years, and 37.7% aged 45–60 years), male (62.6%), Indigenous (10.1%), live in less accessible areas (25.7%), compared with both the high and very GP usage cluster (Table 3). The moderate GP usage cluster was less likely to have complications (27.2%); had a lower number of comorbidities (3.2 (SD 2.9)); was less likely to have regular GP visits (20.5%) and had a lower number of hospitalisation (0.2; SD 0.8) compared with both high and very GP usage clusters The no GP usage group was quite comparable to other GP usage clusters in term of age, gender, complications and comorbidity distribution. However, the no GP usage group had a higher proportion of individuals who were indigenous (23.7%), in the highest disadvantage SEIFA quintiles (31.1%) and resided in very remote areas (20.1%).

3.3. *Association between GP usage and the risk of hospitalisations*

The preferred model was the panel negative binomial regression model based on information criterion (AIC and BIC). The results show that GP usage across all clusters had a protective effect against the risk of PPH in the following year after adjusting for all covariates. However, the greatest protective effect was observed for individuals in the moderate GP usage cluster (IRR = 0.67 (95%CI: 0.62–0.71) (Table 4). The average adjusted predictions indicate that on average 0.25 PPHs per year (95%CI: 0.24–0.27) can be expected for those in the moderate GP cluster; 0.26 per year (95%CI 0.259–0.27) for those in the high GP usage cluster and 0.29 per year (95%CI: 0.28–0.30) for those in the very high GP usage cluster, while those with no GP usage are estimated to have on average 0.38 hospitalisations per year (95%CI: 0.36–0.40) (Table 5 and Fig. 2).

4. Discussion

This study aimed to reveal the latent pattern of GP contact using K-mean cluster analysis, a novel statistical technique, which overcomes many of the limitations associated with current studies by examining GP service use simultaneously across multiple attributes. Importantly we were able to include time intervals between service utilisations including average time interval, deviation of the time intervals and the longest time interval in assessing the patterns of GP service use which enhance the classification accuracy.

The rationale behind our exploration of incorporating multiple attributes to categorise GP use is our hypothesis that using frequency or regularity of GP contact alone may be too simplistic, since individuals that have the same number of visits or the same regularity in a year may have differences in the temporal distribution of visits. Shorter time intervals between services in combination with more regular provision may reflect “proactive care” and the strengthening of the relationship between patients and their GP. In turn, proactive care may allow the opportunity for continuous improvement in self-management skills and health literacy which may assist in the prevention and early treatment strategies in the primary care setting [6,29]. The characterisation of GP utilisation based on multiple domains of GP use has not to our knowledge been previously reported and, we argue represents an advance on current single domain methods.

In our study, although the no GP usage group was comparable to other GP usage clusters in term of age and gender and disease severity, the group comprised higher proportion of disadvantage population (Indigenous status, highest disadvantage SEIFA and very remote). These findings highlight the existence of inequity in access of primary care for people with diabetes in particular sub-populations which have been previously reported in the literature [30,31]. The majority of individuals with diabetes were categorised in high or very high GP usage clusters. Those in high and very high GP usage clusters had high and very high recency and frequency of GP usage, respectively while those in the moderate GP usage

Table 3 – Characteristics of study population by GP usage cluster.

Characteristics	No GP usage (N, (%))	Moderate GP usage (N, (%))	High GP usage (N, (%))	Very high GP usage (N, (%))
N (%)	4 198 (10.3)	3 492 (8.6)	17 077 (42.0)	15 858 (39.0)
Age group (years)				
18–44	781 (18.6)	877 (25.1)	2668 (15.6)	1178 (7.4)
45–59	1059 (25.2)	1316 (37.7)	5649 (33.1)	3543 (22.3)
60–74	1183 (28.2)	1016 (29.1)	6655 (38.9)	7465 (47.1)
≥75	1175 (28.0)	283 (8.1)	2105 (12.3)	3672 (23.2)
Gender				
Female	1679 (40.0)	1307 (37.4)	7,912(46.3)	9002 (56.8)
Male	2519 (60.0)	2185 (62.6)	9165 (53.7)	6856 (43.2)
Indigenous status				
No	3084 (76.3)	2911 (89.8)	15,197 (93.8)	14,978 (96.5)
Yes	961 (23.7)	329 (10.1)	1003 (6.2)	549 (3.5)
SEIFA				
Highest Disadvantage	1285 (31.4)	631 (18.4)	23,240 (19.2)	3435 (21.8)
High disadvantaged	1037 (25.3)	918 (26.7)	4797 (28.4)	4558 (28.9)
Moderate disadvantage	573 (14.0)	593 (17.3)	2381 (14.1)	2185(13.8)
Less disadvantage	544 (13.5)	561 (16.3)	2754 (16.3)	2416(15.3)
Least disadvantage	645 (15.7)	728 (21.2)	3691 (21.8)	3158 (20.0)
Accessibility				
Very remote	825 (20.1)	251 (7.3)	611 (3.6)	79 (1.2)
Remote	172 (4.0)	90 (2.6)	355 (2.1)	184 (1.1)
Moderate	268 (6.5)	265 (7.7)	946 (5.6)	659 (4.2)
Accessible	210 (5.1)	273 (7.9)	1027 (6.1)	695 (4.4)
Highly accessible	2619 (63.9)	2552 (74.3)	13,926 (82.6)	14,036 (89.1)
Complication severity level				
No complication	1957 (46.6)	2543 (72.8)	10,845 (63.5)	7694 (48.5)
1 complication	746 (17.8)	385 (11.0)	2372 (13.9)	2638 (16.6)
2 complications	577 (13.7)	322 (9.2)	1804 (10.5)	2266 (14.3)
3 + complications	918 (21.9)	242 (6.9)	2056 (12.0)	3260 (20.6)
Number of comorbidity				
Mean (SD)	3.5 (4.4)	3.2 (2.9)	4.1 (3.4)	5.6 (3.5)
Duration of diabetes (years)				
Mean (SD);	6.7 (4.4)	6.3 (4.2)	6.1 (4.2)	6.5 (4.4)
Regularity quantiles				
No regularity	4198 (100.0)	2,776(79.5)	3315 (19.4)	0
Quantile 1		716 (20.5)	6684 (39.1)	287 (1.8)
Quantile 2			4719 (27.6)	2972 (18.7)
Quantile 3			1497 (8.8)	5917 (37.3)
Quantile 4			862 (5.0)	6682 (42.1)
Diabetes related PPH				
Mean (SD)	2.5 (17.5)	0.07 (0.38)	0.25 (2.6)	0.25 (1.02)

cluster had both lower recency and frequency of contact. The clinical characteristics of each cluster differed significantly with those in the high or very high GP usage clusters more likely to have a higher number of complications and comorbidities compared with the moderate GP usage cluster. These results were in line with literature that showed higher health care service utilisation was observed among diabetes with multiple comorbidities and complications [32–34]. Thus, the multidimensional GP usage clusters identified in our study may be an indicator of patients' clinical characteristics which is driving their health care needs. This represents an improvement on other more simplistic measures such as frequency that do not correlate well with health outcomes [6,10].

The literature does not show a consistent relationship between the level of primary health care and the risk of hospitalisation [7,10]. While Comino et al. found that higher number of GP visits increased the risk of hospitalisation [6], other authors found an inverse relationship between the frequency of GP visits and hospitalisation [35]. Discordant results in the literature may be due to the complexity of the mechanism in the relationship between primary health care and hospitalisation, which may not be adequately captured

Table 4 – Association of GP usage pattern and potentially preventable hospitalisation with and without adjustment for other covariates (results from random effects negative binomial regression & zero-inflated negative binomial regression).

	Multivariate NB		Adjusted multivariate NB		ZINB	
	IRR	(95%CI)	IRR	(95%CI)	IRR	(95%CI)
GP cluster usage						
No usage	1	(1; 1)	1	(1; 1)	1	(1; 1)
Moderate usage	0.62***	(0.57; 0.66)	0.67***	(0.62; 0.72)	0.41***	(0.33; 0.50)
High usage	0.67***	(0.64; 0.71)	0.70***	(0.66; 0.73)	0.40***	(0.35; 0.46)
Very high usage	0.76***	(0.72; 0.79)	0.76***	(0.72; 0.80)	0.39***	(0.34; 0.45)
Gender						
Males vs. females	1.06***	(1.03; 1.10)	1.07***	(1.04; 1.11)	1.24***	(1.13; 1.36)
Age (years)						
18/44	1	(1; 1)	1	(1; 1)	1	(1; 1)
45/59	1.20***	(1.12; 1.28)	1.21***	(1.14; 1.29)	1.10	(0.91; 1.32)
60/74	1.74***	(1.64; 1.86)	1.73***	(1.62; 1.84)	1.44***	(1.20; 1.73)
75+	2.30***	(2.15; 2.46)	2.31***	(2.16; 2.47)	1.42***	(1.18; 1.71)
Indigenous status						
Yes vs. No	1.47***	(1.37; 1.59)	1.50***	(1.39; 1.61)	2.18***	(1.79; 2.67)
SEIFA						
Highest Disadvantage	1	(1; 1)	1	(1; 1)	1	(1; 1)
High disadvantaged	0.95*	(0.91; 1.00)	0.95*	(0.91; 0.99)	0.96	(0.84; 1.09)
Moderate disadvantage	0.95	(0.90; 1.00)	0.94*	(0.89; 0.99)	0.86*	(0.76; 0.97)
Less disadvantage	0.98	(0.93; 1.03)	0.97	(0.92; 1.02)	0.95	(0.82; 1.10)
Least disadvantage	0.93**	(0.88; 0.98)	0.90***	(0.86; 0.95)	0.94	(0.81; 1.09)
Accessibility						
Very remote	1	(1; 1)	1	(1; 1)	1	(1; 1)
Remote	1.00	(0.87; 1.13)	1.00	(0.88; 1.13)	0.76*	(0.59; 0.96)
Moderate	0.97	(0.88; 1.08)	0.98	(0.88; 1.08)	0.84	(0.64; 1.09)
Accessible	0.92	(0.83; 1.03)	0.92	(0.82; 1.02)	0.73*	(0.57; 0.95)
Highly accessible	0.89*	(0.82; 0.98)	0.90*	(0.83; 0.99)	0.97	(0.78; 1.21)
Duration of diabetes (years)	1.03***	(1.03; 1.04)	1.04***	(1.03; 1.04)	1.05***	(1.04; 1.06)
Complication severity level						
No complication	1	(1; 1)	1	(1; 1)	1	(1; 1)
1 complication	1.33***	(1.27; 1.40)	1.27***	(1.21; 1.33)	1.05	(0.94; 1.18)
2 complications	1.68***	(1.60; 1.77)	1.58***	(1.51; 1.66)	1.57***	(1.37; 1.80)
3+ complications	2.12***	(2.02; 2.22)	1.90***	(1.81; 2.00)	2.72***	(2.34; 3.15)
Number of comorbidities	1.07***	(1.06; 1.07)	1.04***	(1.03; 1.04)	1.07***	(1.05; 1.09)
Number of specialist services	1.01***	(1.01; 1.01)	0.99***	(0.98; 0.99)	0.97***	(0.96; 0.98)
Non-diabetes related hospitalisation	1.05***	(1.02; 1.09)	0.99	(0.96; 1.02)	0.99	(0.90; 1.10)
Diabetes related hospitalisation lag1			1.36***	(1.31; 1.40)	4.65***	(3.94; 5.49)
Diabetes related hospitalisation baseline			1.11***	(1.07; 1.14)	1.14*	(1.02; 1.27)
Group mean number of specialist visits			1.04***	(1.04; 1.05)	1.06***	(1.05; 1.08)
Group mean non-diabetes related hospitalisations			1.60***	(1.50; 1.72)	1.89***	(1.52; 2.36)
AIC	191782.6		190686.5		202182.5	
BIC	192075.6		191019.9		202515.9	

Exponentiated coefficients = "*p < 0.05 **p < 0.01 ***p < 0.001".

by the number of GP visits [6]. Thus, use of a more complex measure of GP use, such as that developed in our study which incorporates several dimensions may be better suited to understand the risk of hospitalisation and help predict and contain the costs of healthcare for diabetes.

Our findings support the hypotheses that GP contact reduces the risk of hospitalisation. However, the effect was not linear for each additional level of GP usage, with the highest effect observed among those with moderate GP usage cluster. This may be explained by characteristics of GP usage cluster, those with moderate usage were likely to be younger, have fewer complications and comorbidities than those with high and very high GP usage. The results were also supported by the health demand model of Grossman where health is considered as a durable capital stock that depreciates with age and can be increased through investment in healthcare [36]. Thus, a finite lifetime increase in the depreciation rate of health may lead to an increase in demand for both preventive care and curative care [36,37]. However, if primary health care can provide early treatment and prevention of illness, it would still be a substitute for hospital care in some instances [37].

Table 5 – Margin incident rate of diabetes related PPH.

GP usage	Incidence rate	95% CI	
No GP usage	0.38	0.36	0.40
Moderate GP usage	0.25	0.24	0.27
High GP usage	0.26	0.26	0.27
Very high GP usage	0.29	0.28	0.30

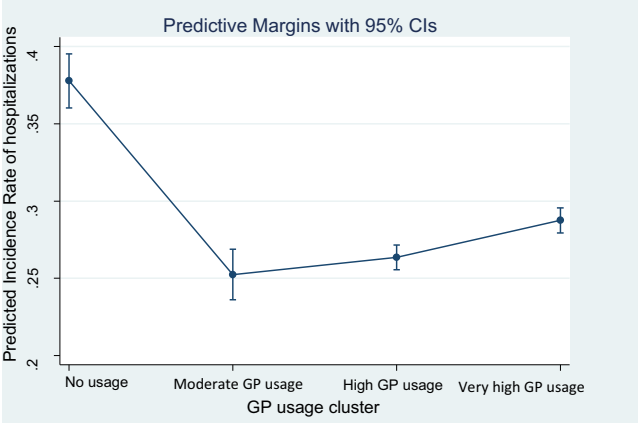


Fig. 2 – Predictive margins the incident rate of diabetes related PPH.

Strengths and limitations of the study

The major strength of our study is that it was based on a large set of linked administrative data at the individual level that encompassed the whole-population and a comprehensive range of health care services. The linked whole-of-population data allowed us to assess changes in both exposure and outcomes at the individual level over the follow-up period. The panel data structure contained information on both within and between individual variations enabling us to control for the effect of unobserved covariates [38]. Our study also applied a novel advanced analytic approach, cluster analysis, and customer relationship management framework to reveal previously hidden patterns of primary health care utilisation. These approaches allowed us to examine primary health care utilisation across multiple attributes simultaneously, and thus characterise a measure of GP utilisation that may facilitate a better understanding of the influence of primary health care in reducing the risk of hospitalisations among people with diabetes.

Our study has some limitations. Comorbidity was accessed by a simple count of conditions which may not well capture actual health care needs although the measure is frequently used in the literature [6,34,39]. The analyses were limited to Australian citizens in one Australian State, due to the reliance on the WA Electoral Roll, and those with a previous diagnosis of diabetes captured by our data. Thus, the result may not be fully generalizable to all individuals living with diabetes, since the Electoral Roll is known to under-represent some groups such as Indigenous Australians and those aged under 21 years of age [40]. However, the use of longitudinal Electoral Roll data provided the ability to accurately capture person-time at risk, due to capturing movement in and out of the state [40]. Limiting the study to a single Australian State is unlikely to have significantly influenced the findings, since Australia has a single public health system, Medicare. Similarly, our reliance on linked administrative health data to identify those diagnosed with diabetes limited the study to those who have previously accessed health services pathognomonic of diabetes and thus people living with diabetes who have never accessed diabetes-related health services are not represented. Individuals not included in our data are likely to be the lower severity patients who are less likely to need hospital care. These limitations are common and well-known in administrative datasets and, because of the features of the excluded patients, are likely to have limited effect on our examination of the pattern of primary care utilisation and the relationship between the patterns of utilisation on the risk of hospitalisation in previously diagnosed diabetes.

Through combining both temporal factors with measures of frequency of use of GP services our study revealed a latent pattern of primary health care utilisation. Incorporation of multiple attributes that go beyond a simplistic frequency-based approach may better characterise the complex relationship between use of GP services and diabetes-related hospitalisation. The study has demonstrated the ability of cluster analyses to provide a systematic formalised approach for exploring complex patterns of health service utilisation in large administrative datasets. Application the cluster analysis approach to other chronic conditions would be useful for accurate understanding patterns of service utilisation. Future studies should further examine temporal factors in the provision of primary health care and evaluate what combination of time between visits, regularity and frequency of access to primary care would best improve health outcome and contain costs.

Acknowledgements

The authors wish to thank the staff at the Western Australian Data Linkage Branch and Commonwealth Department of Health and Aging for providing the linked data for this project.

Funding

This work was supported by the National Health and Medical Research Council, project grant APP1078345.

Appendix A

ICD-9-CM, ICD-10-AM and procedure codes for identifying diabetes related hospitalisations

Conditions	ICD-9-CM principle diagnosis and procedure codes	ICD-10-AM principle diagnosis and procedure codes
Diabetes/diabetes complications	250	E10–E14
Circulatory disorders		
Hypertension	401–405	I10–I13, I15
Ischemic heart disease	410–414	I20–I22, I24, I25
Cerebrovascular disease	430–438, 362.34, 784.3	I60–I67, I69, G45, H34.0, R47.0
Heart failure	428, 429.2–429.3, 429.9	I50.0–I50.1, I50.9, I51.6–I51.7, I51.9
Atherosclerosis	440	I70
Peripheral vascular disease	443, 459.8–459.9, 444, 447.1	I73, I87.2, I99, I74, I77.1
Visual disorders		
Glaucoma	365	H40, H42.8
Cataract	366	H25–H26, H28.0
Blindness	369	H54
Other disorders		
Nephropathy	580–586, V45.1, V56	N00, N01, N03–N05, N07, N08, N16–N19, Z49, Z99.2
Other renal complications		
Infections of kidney	590	N10, N11.8–N11.9, N12, N15.1, N15.9, N28.8
Cystitis, urinary tract infection	595, 599.0	N30, N39.0
Proteinuria	791.0	R80
Neuropathy/other neurologic symptoms	354, 355, 356.8, 729.2	G56–G57, G58.7, G60.8, M79.2, M54.10, M54.11, M54.19
Chronic skin ulcer	707	L89, L97, L98.4
Gangrene	785.4	R02
Non-traumatic lower-extremity amputation or revision	84.1, 84.3	44338-00, 44358-00, 44361-00, -01, 44364-00,-01, 44367-00, -01, -02, 44376-00
Other complications		
Candidiasis of vulva and vagina	112.1	B37.3 N77.1
Chronic osteomyelitis of the foot	730.17	M86.37, M86.47, M86.57, M86.67, M86.87
Cellulitis	681, 682	L03
Non-diabetes related	All other codes	All other codes

REFERENCES

[1] Van Loenen T, Faber MJ, Westert GP, Van den Berg MJ. The impact of primary care organization on avoidable hospital admissions for diabetes in 23 countries. Scand J Prim Health Care 2016;34:5–12.

[2] Tamayo T, Rosenbauer J, Wild SH, Spijkerman AM, Baan C, Forouhi NG, et al. Diabetes in Europe: an update. Diabetes Res Clin Pract 2014;103:206–17.

[3] Centers for disease control and prevention. 2014 National diabetes statistics report. Centers for disease control and prevention; 2014.

[4] AIHW. How many Australians have diabetes? Canberra Australian Institute of Health and Welfare; 2017.

[5] Erny-Albrecht K, Bywood P, Oliver-Baxter J. The role of primary care in primary and secondary prevention of diabetes and related complications: PHCRIS Policy Issue Review. Adelaide primary health care research & information service; 2015.

[6] Comino EJ, Islam MDF, Tran DT, Jorm L, Flack J, Jalaludin B, et al. Association of processes of primary care and hospitalisation for people with diabetes: a record linkage study. Diabetes Res Clin Pract 2015;108:296–305.

[7] Gibson OR, Segal L, McDermott RA. A systematic review of evidence on the association between hospitalisation for chronic disease related ambulatory care sensitive conditions and primary health care resourcing. BMC Health Serv Res 2013;13:336.

[8] van Loenen T, van den Berg MJ, Westert GP, Faber MJ. Organizational aspects of primary care related to avoidable hospitalization: a systematic review. Fam Pract 2014;31:502–16.

[9] Einarsdottir K, Preen DB, Emery JD, Kelman C, Holman CD. Regular primary care lowers hospitalisation risk and mortality in seniors with chronic respiratory diseases. J Gen Intern Med 2010;25:766–73.

[10] Wolters RJ, Braspenning JCC, Wensing M. Impact of primary care on hospital admission rates for diabetes patients: a systematic review. Diabetes Res Clin Pract 2017;129:182–96.
[11] Gibson D, Moorin R, Preen D, Emery J, Holman DA. Effects of the Medicare enhanced primary care program on primary care physician contact in the population of older Western Australians with chronic diseases. Australian Health Rev 2011;35:334–40.
[12] Liao M, Li Y, Kianifard F, Obi E, Arcona S. Cluster analysis and its application to healthcare claims data: a study of end-stage renal disease patients who initiated hemodialysis. BMC Nephrol 2016;17:25.
[13] Conry MC, Morgan K, Curry P, McGee H, Harrington J, Ward M, et al. The clustering of health behaviours in Ireland and their relationship with mental health, self-rated health and quality of life. BMC Public Health 2011;11:692.
[14] Clatworthy J, Buick D, Hankins M, Weinman J, Horne R. The use and reporting of cluster analysis in health psychology: a review. Brit J Health Psychol 2005;10:329–58.
[15] Eisen MB, Spellman PT, Brown PO, Botstein D. Cluster analysis and display of genome-wide expression patterns. PNAS 1998;95:14863–8.
[16] Holman CD, Bass AJ, Rouse IL, Hobbs MS. Population-based linkage of health records in Western Australia: development of a health services research linked database. Aust N Z J Public Health 1999;23:453–9.
[17] Ha NT, Harris M, Robinson S, Preen D, Moorin R. Stratification strategy for evaluating the influence of diabetes complication severity index on the risk of hospitalization: a record linkage data in Western Australia. J Diabetes Complications 2017;31:1175–80.
[18] Australian Institute of Health and Welfare. A set of performance indicators across the health and aged care system. Canberra: Australian Institute of Health and Welfare; 2008.
[19] Davis WA, Knuiman MW, Hendrie D, Davis TM. Determinants of diabetes-attributable non-blood glucose-lowering medication costs in type 2 diabetes: the Fremantle Diabetes Study. Diabetes Care 2005;28:329–36.
[20] Hughes AM. Strategic database marketing. McGraw-Hill Pub. Co.; 2005.
[21] Lee EW. Data mining application in customer relationship management for hospital inpatients. Healthcare Inform Res 2012;18:178–85.
[22] Australian Bureau of Statistics. Census of population and housing: socio-economic indexes for areas Canberra: Australian Bureau of Statistics; 2001 2006 & 2011.
[23] Australian Bureau of Statistics. Census of population and housing: socio-economic indexes for areas. Canberra: Australian Bureau of Statistics; 1981–2006.
[24] Young BA, Lin E, Von Korff M, Simon G, Ciechanowski P, Ludman EJ, et al. Diabetes complications severity index and risk of mortality, hospitalization, and healthcare utilization. Am J Manage Care 2008;14:15–23.
[25] Holman CD, Preen DB, Baynham NJ, Finn JC, Semmens JB. A multipurpose comorbidity scoring system performed better than the Charlson index. J Clin Epidemiol 2005;58:1006–14.
[26] Caliński T, Harabasz J. A dendrite method for cluster analysis. Commun Stat 1974;3:1–27.
[27] Chamberlain G. Multivariate regression models for panel data. J Economet 1982;18:5–46.
[28] Mundlak Y. On the pooling of time series and cross section data. Econometrica 1978;46:69–85.
[29] Nuti LA, Lawley M, Turkcan A, Tian Z, Zhang L, Chang K, et al. No-shows to primary care appointments: subsequent acute care utilization among diabetic patients. BMC Health Serv Res 2012;12:304.
[30] Bywood P, Katterl R, Lunnay B. Disparities in primary health care utilisation: Who are the disadvantaged groups? How are they disadvantaged? What interventions work?. PHCRIS Policy Issue Review. Adelaide: Primary Health Care Research & Information Service; 2011.
[31] Davy C, Harfield S, McArthur A, Munn Z, Brown A. Access to primary health care services for Indigenous peoples: a framework synthesis. Int J Equity Health 2016;15:163.
[32] Struijs JN, Baan CA, Schellevis FG, Westert GP, van den Bos GA. Comorbidity in patients with diabetes mellitus: impact on medical health care utilization. BMC Health Serv Res 2006;6:84.
[33] van Oostrom SH, Picavet HSJ, de Bruin SR, Stirbu I, Korevaar JC, Schellevis FG, et al. Multimorbidity of chronic diseases and health care utilization in general practice. BMC Family Pract 2014;15:61.
[34] Fisher K, Griffith L, Gruneir A, Panjwani D, Gandhi S, Sheng L, et al. Comorbidity and its relationship with health service use and cost in community-living older adults with diabetes: a population-based study in Ontario, Canada. Diabetes Res Clin Pract 2016;122:113–23.
[35] Booth GL, Hux JE. Relationship between avoidable hospitalizations for diabetes mellitus and income level. Arch Intern Med 2003;163:101–6.
[36] Grossman M. On the concept of health capital and the demand for health. J Polit Econ 1972;80:223–55.
[37] Tian W-H, Chen C-S, Liu T-C. The demand for preventive care services and its relationship with inpatient services. Health policy (Amsterdam, Netherlands) 2010;94:164–74.
[38] Hsiao C. Panel data analysis—advantages and challenges. TEST 2007;16:1–22.
[39] Calderón-Larrañaga A, Abad-Díez JM, Gimeno-Feliu LA, Marta-Moreno J, González-Rubio F, Clerencia-Sierra M, et al. Global health care use by patients with type-2 diabetes: does the type of comorbidity matter? Eur J Internal Med 2015;26:203–10.
[40] Youens D, Preed D, Harris M, Moorin R. The importance of historical address information in longitudinal studies using administrative health data. Int J Epidemiol 2017. In press.

Appendix D Manuscript 3

A time-duration measure of continuity of care to optimise utilisation of primary health care: A threshold effects approach among people with diabetes

Author names and affiliations

1) Ninh Thi Ha

Health systems and Health economics, School of Public Health, Curtin University, Perth, Western Australia 6845, Australia

thininh.ha@student.curtin.edu.au

2) Mark Harris

School of Economics and Finance, Curtin University, Perth, Western Australia 6845, Australia

mark.harris@curtin.edu.au

3) David Preen

Centre for Health Services Research, School of Population and Global Health, The University of Western Australia, 35 Stirling Highway, CRAWLEY WA 6009, Australia

david.preen@uwa.edu.au

4) Suzanne Robinson

Health Systems and Health Economics, School of Public Health, Curtin University, Perth, Western Australia 6845, Australia

Suzanne.robinson@curtin.edu.au

5) Rachael Moorin

Health Systems and Health Economics, School of Public Health, Curtin University, Perth, Western Australia 6845, Australia

School of Population and Global Health, The University of Western Australia, 35 Stirling Highway, CRAWLEY WA 6009, Australia

r.moorin@curtin.edu.au; rachael.moorin@uwa.edu.au

Corresponding author

Rachael Moorin - Email: r.moorin@curtin.edu.au

School of Population and Global Health, The University of Western Australia, 35 Stirling Highway, CRAWLEY WA 6009, Australia

Health Systems and Health Economics, School of Public health, Curtin University, Perth, Western Australia 6845, Australia

Abstract

Background: Literature highlighted the importance of timely access and ongoing care provided at primary care settings in reducing hospitalisation and health care resource uses. However, the effect of timely access to primary care has not been fully captured in most of the current continuity of care indices. This study aimed to develop a time-duration measure of continuity of primary care ("cover index") capturing the proportion of time an individual is under the potentially protective effect of primary health care contacts.

Methods: An observational study was conducted on 36 667 individuals aged 45 years or older with diabetes mellitus extracted from Western Australian linked administrative data. Threshold effect models were used to determine the maximum time interval between general practitioner (GP) visits that afforded a protective effect against avoidable hospitalisation across complication cohorts. The optimal maximum time interval was used to compute a cover index for each individual. The cover was evaluated using descriptive statistics stratified by population socio-demographic characteristics.

Results: The optimal maximum time between GP visits was 9-13 months for people with diabetes with no complication, 5-11 months for people with diabetes with 1-2 complications, and 4-9 months for people with diabetes with 3+ complications. The cover index was lowest among those aged 75+ years, males, Indigenous people, socio-economically disadvantaged and those in very remote areas.

Conclusions: This study developed a new measure of continuity of primary care that adds a time parameter to capturing longitudinal continuity. Cover has the potential to better capture underuse of primary care and will significantly contribute to the sparsely available methods for analysis of linked administrative data in evaluating continuity of care for people with chronic conditions.

Keywords: cover index, continuity of care, optimal time interval, diabetes mellitus, primary care, potentially preventable hospitalisation

Background

Given current pressures experienced by most health systems improvements in care delivery are needed to make the system more effective, efficient and sustainable. Over recent years the focus in many countries has been the enhancement of primary health care to reduce potentially preventable hospitalisations (PPH) which are often costly and undesirable for patients (van Loenen et al. 2014). The rationale behind this is that timely utilisation and effective treatment in primary health care (PHC) settings for people with chronic conditions could afford a protective effect in preventing complications and adverse health events (Caminal et al. 2004; Sanderson and Dixon 2000). For common chronic conditions such as diabetes, heart failure and asthma, a shift in focus from acute to primary care has the potential to delay or even prevent the onset of complications and reduce PPH. This theory surrounding 'ambulatory care sensitive condition' has been the driver of many policies aimed at increasing long-term ongoing, rather than sporadic or episodic, contact with a General Practitioner (GP).

The Australian government has set a focus on strengthening the PHC system to address inequities and future challenges of chronic diseases (Department of Health and Ageing 2010a). One of the ways this is being undertaken is by providing financial incentives for aspects of PHC and general practitioner (GP) behaviour, such as the introduction of Primary Health Networks, Integrated Care Models, Service/Practice Incentive Payments, Health Care Homes, Chronic Disease Management Medicare Benefits Scheme items and Home Medication Reviews (Kecmanovic and Hall 2015). Although GPs act as the gatekeeper of the health care system in Australia, it is not required that individuals register with a single practitioner or general practice. People are free to visit any GP they wish and can visit multiple GPs and general practices simultaneously. The role of GPs has been emphasised that GPs are the only physicians appropriate for taking the leading roles in the primary health care team and coordinating with other health care professionals into providing the best patient centred care including diagnosis, treatment and management (Authority 2015).

Continuity of care (COC) is an important component of high-quality primary care as it is associated with increased patient satisfaction, quality of life and health outcomes (Guthrie et al. 2008; Menec et al. 2006; Pereira Gray et al. 2018; Saultz and Albedaiwi 2004). New models of care often rely on the theoretical link between COC and better health outcomes. A well-known conceptual framework of continuity of care proposed that continuity of care is a combination of three essential components: interpersonal continuity, management continuity and informational continuity (Guthrie et al. 2008; Haggerty et al. 2003). Interpersonal continuity is defined as an ongoing relationship between a patient and the same provider where the relationship between patients and providers are strengthen through mutual familiarity and personal trust (Haggerty et al. 2003). Informational continuity is a link between providers to share comprehensive information about patients' history of care and circumstances that helps to reduce duplicative and wasteful resources (Haggerty et al. 2003). Management continuity is a collaboration between providers to ensure services delivered regularly and complementary and especially important in chronic and complex conditions which require management from multiple providers (Haggerty et al. 2003). A sufficient continuity of care requires a presence of both care of an individual and proper management of care linked over time (Barker, Steventon, and Deeny 2017; Haggerty et al. 2003).

Although interpersonal continuity of care can be easily measured and widely used in literature (Barker et al. 2017; Bentler et al. 2014; Cho et al. 2015; Dreiher et al. 2012; Menec et al. 2006), it is becoming more difficult to sustain due to the changing size of practices over time and to the recent evolution of large multi-partner (or corporate) practices rather than the solo-practice model common in previous decades (Gulliford, Naithani, and Morgan 2006; Haggerty et al. 2003). In the current context of a high burden of complex and multiple chronic conditions, health care for people with complex needs is now extended to a wide range of skills and settings to better manage chronic conditions (Gulliford et al. 2006; Guthrie et al. 2008). Thus, the view of continuity of care is concerned with management continuity - the extent of health care provided over time in a

coordinated manner with appropriate response to patients' needs (Gulliford et al. 2006). While continuity of care is a complex multi-dimensional concept, current measures of continuity of care mostly reflect interpersonal continuity of care (Barker et al. 2017; Bentler et al. 2014; Jackson and Ball 2018; Jee and Cabana 2006). Development of measures which can integrate management aspect of continuity would be useful to support comprehensive evaluations on continuity of care and optimising efficiency in management of chronic disease.

Few recent studies have considered management aspect of continuity of care in term of regularity of visiting GPs which captures the degree of regular contact with PHC providers (Einarsdóttir et al. 2011; Einarsdóttir et al. 2010; Gibson et al. 2012). Studies reported that regularity of contact is more important than the frequency of contact for reducing number and costs of hospitalisations (Youens and Moorin 2017a; Youens and Moorin 2017b). Greater regularity of visits more likely indicates care which is planned and proactive, while visits on an irregular basis (even if frequent/numerous) likely indicate care which is unplanned or reactive and thus not indicative of good ongoing management (Moorin 2015). Current evidence also shows that use of the Enhanced Primary Care Medicare items increases regular PHC contact in the following year (Gibson et al. 2012; Youens and Moorin 2017a), suggesting that regularity is suitable as a target for health policy intervention (Gibson et al. 2011, 2012).

Our new time-duration concept extends on the concept of regularity by adding a time component. This is important as care can be regular if a patient sees their GP once per year, but this might not be sufficient (i.e. the time-duration may be too long between visits) to provide adequate management of the patient's condition and therefore some of the protective effects of regular care may be lost. Although the concept of time duration between services is relative new in health care services research, it has been integrated in other research areas such as customer relationship management (Hong-kit Yim, Anderson, and Swaminathan 2004; Lee 2012; Ling and Yen 2001; Reinartz and Kumar 2003) and pharmaceutical studies to capture medication persistence – a proportion of time duration

under adequate medication supply (Caetano, Lam, and Morgan 2006; Santoleri et al. 2013). Our new metric – the Cover Index is defined as the proportion of days, within a fixed ascertainment period (preferably one year since this is the time period that current chronic disease management plans are based (The Department of Health 2014)) that a patient is considered under the 'protective effect' of their PHC contact and at reduced risk of PPH. In contrast to drug utilisation studies where medication protective effect is well defined, in primary care, no data exist providing the duration over which a GP visit has the potential to protect a patient from an adverse event or complication of their chronic disease.

We hypothesise that interaction with a GP can protect a patient from experiencing a diabetes-related potentially preventable hospitalisation and that this protective effect can be maintained if GP interactions fall within a particular maximum time interval (i.e. do not exceed this time) named the "optimal maximum time interval". Our study aimed to develop a methodology for determining "cover" of primary care using individual-level linked administrative data by (i) estimating the optimal maximum time interval over which primary care affords an increased protection from PPH using threshold effects models; and (ii) using the derived optimal time period to operationalise "cover" at the individual level.

Methods

Time-duration index of continuity of primary care (Cover) development

The proposed time-duration index, which we call "Cover", is defined as the proportion of time that an individual is under the potentially protective effect of PHC (via contact with their GP) over a pre-specified ascertainment period. Construction of the index relies on first determining a period of time between GP visits that a patient with a stated set of socio-demographic and clinical characteristics has a reduced probability of PPH. We term this the 'optimal maximum time interval'. Once this optimal time period has been determined cover can be calculated as shown in Figure 1. Briefly, the actual time

interval (in days) between each GP attendance within the ascertainment period is first determined. This time is then compartmentalised into within and outside of the pre-defined optimal maximum time interval for persons with pre-defined characteristics in that year. The number of days within the optimal maximum time interval (i.e. days covered) are then aggregated over an ascertainment period for each individual in the complication cohort and the proportion of the total number of days eligible for cover over the ascertainment period calculated. This provides the cover index, which has a value between 0 and 1, for each individual in each year in our scenario (or some other time period chosen based on specific clinically or policy based rationale). A higher score reflects a greater proportion of time 'covered'. Although methods used to calculate the cover score were demonstrated in complication cohorts of people with diabetes, the methods are applicable to other ambulatory care sensitive conditions.

Estimation of the optimal time interval for GP services in people living with diabetes

Data sources

Western Australia (WA) whole-of-population administrative health data linked at the individual level for adults aged 18 years or older enrolled to vote in WA at any time between 1 July 1990 and 30 June 2004 were used for this study. The data included four datasets: WA Hospital Morbidity Data System (HMDS); Medicare Benefits Scheme (MBS) claim records; WA Electoral Roll (ER) records and WA mortality records. The HMDS provided information on diagnosis, date of admission and date of discharge from all WA hospitals. The MBS provided information on services provided outside the hospital (for example GP services) and included the date of service and type of medical service. The ER provided information on dates of migration in and out of WA or changes in a residential address while living in WA. Mortality records provided date and cause of death. WA data were linked and extracted via the WA Data Linkage System (WADLS)(Holman et al. 1999) and MBS data by the Commonwealth Department of Health and Ageing using a linkage key provided by the WADLS.

Study population

The study population consisted of people living with diabetes aged 45 years and older in WA for the years 1998/99 to 2003/04. Individuals with diabetes mellitus were determined using the International Classification of Disease, 9th edition-clinical modification (ICD-9-CM) codes in HMDS records and MBS claims indicative of the presence of diabetes using all the available data and has been described previously (Ha et al. 2017). Three diabetes complication cohorts were constructed for this study depending on level of disease at each observed year: no diabetes complications, 1-2 complications and 3+ complications. Complication severity level was assessed using the complication severity index suggested by Young et al. (2008) and stratified into three groups as outlined previously (Ha et al. 2017).

All individuals were observed annually from the baseline year to 30 June 2004, or last year living in WA or death with the data constructed as a panel (with years nested within a person). Only individuals who were alive and resident in WA for at least two consecutive years were included in the study. Individuals could move to a higher complication cohort if their complication status changed as ascertained at the end of each observed year. Within each complication cohort, we measured individual characteristics including GP utilisation, hospitalisations, complications, comorbidities and socio-demographic characteristics in each observed year, and GP utilisation and hospitalisations in the following year. A similar design has been applied in other studies (Comino et al. 2015; Ha et al. 2017).

Ethical approval was provided by The University of Western Australia and Curtin University Human Research Ethics Committees.

Dependent variable

The number of diabetes-related potentially preventable hospitalisations during each follow-up year was the main outcome of the study. Diabetes-related hospitalisations were identified using ICD-9-

CM and ICD-10-AM codes suggested by the National Health Performance Framework (AIHW 2008) and hospitalisations where diabetes was identified as a significant risk factor by Davis et al (Davis et al. 2005).

Independent variables

GP utilisation including frequency of GP services and the time interval between GP services were focal measures in this study. For each individual, the date of GP services within a financial year was identified in MBS data. The time between GP visits was determined by number of days: (1) between GP visits within a financial year and; (2) between the date of first GP visit of a financial year and the date of the last GP visit in the previous financial year(s) looking back up to 3 financial years. In the case where a hospitalisation was observed, time was counted either to the first GP visit post-hospitalisation provided that the GP visit was within 14 days of discharge or from day 14 after hospital discharge date and the next GP visit (Jackson et al. 2015). The 14 day rule was applied based on a large scale study which suggests that timely follow-up within 14 days of discharge may be considered to reduce the risk of readmission for patient with multiple complex chronic conditions such as diabetes, heart disease and chronic obstructive pulmonary disease (Jackson et al. 2015) and that time in excess of that would be deemed “out of cover”. The time intervals within a financial year were used to calculate the mean time interval for a GP visit, the variance of the time intervals and maximum time interval to a GP visit in months (or part thereof) of the financial year for each individual.

As mean time interval reflects central tendency of time intervals between services, two individuals can have the same mean time interval but their maximum time interval may be entirely different. In addition, the maximum time interval is more likely to capture the period of time that people were not covered by any protective effect of GP service contact than mean time interval. Thus, the maximum time interval to a GP visit in the following year was used as the main predictor of the

number of hospitalisation in all analyses while mean time interval, frequency and regularity in the same year as well as mean time interval and regularity in the last year comprised covariates.

The variance of the time intervals was used to calculate the annual regularity of GP visits as [1/(1+variance)] for each individual, described in detail elsewhere (Einarsdóttir et al. 2011; Einarsdóttir et al. 2010; Gibson et al. 2012). This regularity score was then converted into quintiles for each complication cohort. The frequency of GP usage was defined as a total number of GP visits within a financial year excluding those GP visits occurring within 14 days of the previous GP visit. This exclusion was to minimise over counting GP service utilisation as the visits within 14 days were thought by our expert primary care clinicians more likely to be associated with the existing episode of care rather than being indicative of a new episode (e.g. returning for the results of tests) , recommended in the literature (Donabedian 2005).

A number of individual socio-demographic and clinical characteristics were also measured. Demographic characteristics included were age groups (45-59 years, 60-74 years and ≥75 years), gender, and Indigenous status. Socio-economic status was assessed annually using quintiles of the Census specific Socio-Economic Indexes for Areas (SEIFA) Index of Relative Socioeconomic Disadvantage (Australian Bureau of Statistics 2011). Service accessibility was measured annually classified as very remote, remote, moderate, accessible and highly accessible (Australian Bureau of Statistics 1981-2006). The number of comorbidities was summed using MACSS index (Holman et al. 2005), excluding conditions classified as complications of diabetes. Duration of diabetes was calculated in years from the first identification in WA linked data. Other use of health services was accounted for by capturing the number of specialist visits and the number of non-diabetes related hospitalisations in each financial year.

Average cost per hospitalisation was calculated and used to describe the characteristics of each complication cohort but not used as a controlling variable in regression models. Costs were assigned using Australian Refined Diagnostic Related Group costs from the National Hospital Cost Data

collection and National Efficient Price of the Independent Hospital Pricing Authority (Department of Health and Ageing 2010b). All costs were adjusted to 2014 Australian dollar using the Consumer Price Index.

Statistical Analyses

The data for each complication cohort were constructed as a panel data structure with multiple measures for each individual, such that response and control variables could vary over the study period. Panel data were complex and unbalanced as individuals could move in and out of WA, die or move to higher complication level cohort during the study period. Characteristics of the population were described for each complication cohort at the time entering to the cohort.

To estimate the optimal maximum time interval we employed threshold effects model proposed by (Gannon, Harris, and Harris 2014) to examine how the relationship between GP service and diabetes-related potentially preventable hospitalisation varies with the length of the time interval (the maximum time interval) between GP services. The model proceeded by searching for sample heterogeneity in the response of diabetes-related potentially preventable hospitalisation to variation in the time interval between GP services across populations in each complication cohort. The information criteria approach including Bayes Information Criterion (BIC) and Akaike Information Criterion (AIC) statistics was used to select the optimal model. The selected model was used to identify a number of subpopulations defined in terms of length of the time interval between GP services. The optimal model was used to suggest the maximum optimal time interval between GP services where the number of diabetes-related potentially preventable hospitalisations was minimal. The threshold effects model evaluates all subpopulations simultaneously rather than sequentially and therefore extends towards a non-linear model (Frühwirth-Schnatter 2006; Gannon et al. 2014; Gonzalo and Pitarakis 2002) that allows more flexibility in examining the relationship between GP service and the risk of diabetes-related potentially preventable hospitalisation. This approach has been applied in previous studies (Gannon et al. 2015; Ha et al. 2017).

The threshold effects model in our study was an extension of the random effects negative binomial model for panel data which accounts for time-variant factors and unbalance in the data structure. The general form of the model for individual *i* in year *t* presented as follows:

$$HOSP_{it} = \sum_{m=1}^{M} \gamma_m R_{m,i} * (TInt_{i,t} * GPsvc_{i,t} | GPsvc_{i,t} = 1 \,\&\, TInt_{i,t} \leq 18)$$

$$+ \beta_1 (D1 = 1 \,|GPsvc_{i,t} = 0) + \beta_2 (D2 = 1 |\, TInt_{i,t} > 18) * Tint_{i,t} + \beta_1 X_{i,t}$$

$$+ \beta_2 \bar{x}_{i,t} + \alpha_i + HOSP_{t0} + U_{i,t} + \beta_0$$

$$, i = 1,2 \dots N; t = 1,2 \dots, T$$

The equation is the hypothesised differential effect of GP services ($GPsvc_{i,t}$) on diabetes-related PPH ($HOSP_{it}$) with respect to an individual's position with regard to the maximum time interval ($TInt_{i,t}$) to the next GP service. The threshold model allows the coefficient γ_m on GP service to vary according to the time interval to a GP service (in month) indicated by subpopulation indicators: $R_{m,i} = 1 \; if \; \{\tau_{m-1} < Tint_{i,t} \leq \tau_m\}$, and 0 otherwise, where *m* is the number of subpopulation and τ is the threshold parameters. The number of subpopulation m (1, 2, 3 … M) and the threshold parameters τ was estimated from the data. The model splits the data into M subpopulations. The M = 1 setting gives the constant coefficient as a standard negative binomial model.

The threshold variable R_i only took values from 1 to 18 for two reasons: 1) 99% of the population in each complication cohort had a maximum time interval to a GP service ≤18 months, the sample size for the time interval >18 months was relatively small (about 90 or less records for each time interval); 2) it was more computationally feasible as we could reduce the searching time. However, we still included the cases with the time interval >18 months as a controlling variable (D2) with value of 1 if the maximum time interval >18 months, and 0 otherwise.

The threshold effects model included a dummy variable (D1) for any observation with no GP service in a financial year to control for, rather than excluding, the observation. The model also included

demographic and clinical characteristics in the observed years and GP utilisation in both observed and follow-up years in the notation $X_{i,t}$ to control for any confounding. Endogeneity due to a correlation between the error term and the maximum time interval has been minimized by adding Mundlak variables $\bar{x}_{i,t}$, which are group means of time-varied variables including frequency of GP visits, regularity of GP visits and comorbidities. The group mean of time-varied variables relax the assumption of the random-effects estimator that unobserved factors were independent with the observed factors (Chamberlain 1982; Mundlak 1978). In addition, the model also included initial conditions (history of hospitalisation at the baseline year, and GP utilisations in the previous years) to adjust for effects of unobserved heterogeneity (Wooldridge 2005).

All competing models were compared using their BIC and AIC statistics. The preferred model was the one which minimised the appropriate information criteria (AIC and BIC) (Gannon et al. 2014). Within each diabetes complication cohort, the preferred model indicated the maximum time interval to a GP service which had minimal risk of diabetes-related potentially preventable hospitalisations and suggested the maximum optimal time interval to a GP service corresponding to each diabetes complication cohort that was subsequently used to operationalise the cover index.

All analyses were conducted using STATA for Window version SE14.1.

Operationalizing the Cover index in the diabetes cohort

In this demonstration, the cover index was calculated for each financial year (July 1st to June 30th) for the studied period of 1998 to 2004, date of death or date of leaving WA which ever came first. The year of death was excluded from the analysis. Thus, part-years were not considered in the Cover Index calculation. For each financial year, the ascertainment days were the total number of days that people were living in the community (i.e. not in hospital).

Days out of GP cover (DOC) were calculated by subtraction of the pre-defined optimal maximum time interval (updated according to diabetes severity level) from the actual time interval between a

GP service and the next health care service (either GP or hospital admission). Thus, by definition DOC values were positive. Any time interval that was shorter than the optimal maximum time interval was deemed as "under cover", thus, DOC was counted as zero.

The cover index= [∑ascertainment days - ∑DOC] / ∑ascertainment days] was calculated for each individual annually. As the optimal maximum time interval was identified as a range of values from the threshold effects model, the cover index was calculated with low, middle and upper values bounds corresponding to low, middle and upper values of the optimal maximum time interval identified for each complication cohort.

Values of cover were reported by socio-demographic characteristics of the cohort to explore the range of scores and serve to evaluate the face validity of the cover index in capturing vulnerable groups which traditionally have poor continuity of primary care.

Results

Characteristics of diabetes complication cohorts at the time entering the cohort

A total of 36,667 individuals aged 45 years or older were classified as living with diabetes in WA in this study. Since individuals could change complication cohorts (i.e. move to a higher complication group) throughout the study the total number of individuals shown in Table 1 reflects the number of individuals who were classified in that particular complication cohort at any time and is thus larger than the total number of individuals in the study. The complication cohorts are not mutually exclusive over the entire study period but are mutually exclusive within individual years (i.e. an individual cannot be in more than one complication cohort in the same financial year). During the studied period, 8,968 individuals changed complication cohorts.

Characteristics of the individuals at the time of entry into each complication cohort is presented in Table 1. Compare with individuals in the cohort with no complication, individuals in cohorts with

higher complications were older (38.7% of those in three complication cohort and 25.8% of those in one or two complication cohort aged 75 years or older vs. 10.8% among those with no complication); had a higher number of comorbidities (average of 8.3 and 5.7 vs. 3.0 comorbidities, respectively); a longer duration of diabetes (9.2 years and 7.2 years vs. 5.4 years, respectively), a higher number of hospitalisations (1.8 and 0.53 hospitalisation per year vs. 0.03 hospitalisation per year, respectively) and higher average cost per hospitalisation (AU$ 7756.2 and AU$ 5637.4 per hospitalisation vs. AU$ 3993.2). However, other characteristics such as gender, socio-economic status and accessibility to services and GP usage did not vary between complication cohorts.

Estimation of the optimal maximum time intervals for each diabetes complication cohort

Table 2 shows the results of the threshold effects model which presents how the relationship between GP service and the risk of diabetes-related PPH varies across the length of the maximum time interval between GP services by complication cohort. Based on both BIC and AIC, the preferred models indicated a non-linear relationship between maximum time interval between GP visits and the number of hospitalisations with five subpopulations in both no complication cohort and one or two complication cohort and four subpopulations in three or more complication cohort (Table 2). Overall, the expected number of diabetes related PPH was observed lowest in a maximum time interval between GP visits of 9 months to 13 months for diabetes with no complication; 5 months to 11months for diabetes with one or two complications; and 4 months to 9 months for diabetes with three or more complications. For no complication cohort, the average number of predicted diabetes related potentially preventable hospitalisation within the optimal maximum time interval was 0.044 (95%CI, 0.043-0.045) admissions while the number was significantly higher among the sub-optimal time intervals (0.127 (95%CI, 0.126- 0.128)). For one or two complication cohort, the average number of predicted diabetes related potentially preventable hospitalisation within the optimal maximum time interval was 0.159 (95%CI, 0.158-0.160) admissions while the number of hospitalisation was significantly higher among sub-optimal time interval (0.314 (95%CI, 0.311-

372 0.316)). For three or more complication cohort, the predicted number of diabetes related potential
373 preventable hospitalisations within the optimal maximum time interval was 0.589 (95%CI, 0.583-
374 0.595) admissions while the number of hospitalisations was significantly higher among the sub-
375 optimal time interval (1.15, 95%CI 1.14- 1.16). The change in the number of predicted diabetes-
376 related potentially preventable hospitalisations across the maximum time interval between GP visits
377 using spline function is also presented in Figure 2.

378 **Cover index and its distributions**

379 Table 3 shows the annual average cover index score overall for the whole studied population and by
380 socio-demographic characteristics. Overall, the average cover score was 0.85 (upper bound) (95%CI
381 0.80 to 0.85) indicating that on average, in this cohort, 85% of the year people with diabetes were
382 under the potentially protective effect of PHC via contact with their GP. However, only 83% of the
383 time period was covered if the lower boundary of the optimal maximum time interval was
384 considered rising to 84% of the time interval covered if the middle bound of the optimal maximum
385 time interval was considered. The cover index score changed by socio-demographic characteristics.
386 The lowest average cover index scores across low, middle and upper bounds was observed among
387 those aged 75 years or older (0.77 - 0.78 - 0.79, respectively), males (0.80 - 0.82 - 0.83, respectively),
388 indigenous (0.60 - 0.63 - 0.64, respectively), having highest disadvantage (0.81 - 0.82 - 0.83,
389 respectively) and living in very remote areas (0.48 - 0.51 - 0.52, respectively).

390 **Discussion**

391 Our study aimed to develop and operationalise the cover index, a novel measurement of continuity
392 of primary care that represents an improvement in existing measurements of regularity of primary
393 care through accounting for a time-limited protective effect achieved from interaction with a GP.
394 This study presented an empirical approach to estimate the optimal time period for GP cover in a
395 diabetes patient population in order to demonstrate its operationalisation, however, we suggest

that the cover index could be flexibly operationalised with a range of a priori optimal time periods, such as those based on expert opinion or clinical guidelines, if applicable, to aid in both the development and evaluation of policies incentivizing provider-patient interactions. Differences in the cover index score operationalised in this way could be used as to evaluate the impact of such opinion, guidelines or policy on potentially preventable hospitalisations. The tremendous growth in the availability and range of whole-of-population administrative health datasets provide opportunities to measure the performance of health systems and evaluate the impact of health policy. However, currently available metrics are limited in their sophistication regarding the domains within utilisation they capture. The cover metric would significantly contribute to the advancement of available methods for the analysis of these data.

In these data, the threshold model indicated the optimal maximum time interval of 9-13 months for diabetes without complication, 5-11 months for one or two complications and 4-9 months for three or more complication where the risk of hospitalisation was minimised. This finding is in line with the recommendation in primary care guidelines for diabetes (American Diabetes Association 2003; The Royal Australian College of General Practitioners 2014) which suggest people with diabetes should receive primary care at regular intervals of 3-12 months depending on the complexity of individual needs. In addition, our findings are consistent with growing evidence that optimised primary care use may improve health outcomes and reduce resources used (Ha et al. 2018; Zhao et al. 2013). However, current evidence does not clearly indicate specific time intervals for different disease severity levels, which may limit the ability to effectively measure primary care performance and utilisation. In addition to facilitating the operationalisation of cover our findings provide an important insight into primary care needs of people with diabetes corresponding to their severity level that may provide evidence for improvement of primary care performance.

Recent studies show various approaches such as counting a number of GP services in the short term or long term prior hospitalisation (Vuik et al. 2017) or visualizing the density of GP services (Falster,

421 Jorm, and Leyland 2016) to examine utilisation of GP services. In countries where GPs are the
422 gatekeepers to access for most medical services, using these approaches may not capture
423 underutilisation of GP services. Our study suggests using the maximum time interval between health
424 care services in examining the relationship with the risk of hospitalisation since the maximum time
425 interval drives attention towards the "long overdue period" likely to reflect discontinuity of GP care
426 and lost opportunities for early treatment in the primary care setting.

427 Results of the variation in the average cover score show disparities in GP cover that are associated
428 with socio-economic disadvantage, even though the results are only exploratory. The results are
429 consistent with the literature showing poor access to primary care services among people from the
430 low socio-economic background, Indigenous, and living in remote areas (Bywood, Katterl, and
431 Lunnay 2011) and thus provide some face validity that the cover score performs in the way
432 expected. The results also provide a quantification of the disparities in GP cover that is important
433 information to target health care resources and provide a tool to accurately quantify the
434 improvement in primary care resulting from interventions. Given the high burden of hospitalisation,
435 improvement in GP cover would offer a cost-effective opportunity to reduce the costs of
436 hospitalisation, especially among those with multiple complications. While not explored in this
437 paper, in addition to capturing periods that are not covered, the metric could also be adapted to
438 capture periods of "over cover" and thus be used to measure over as well as under servicing.

439 *Strengths and limitation of the study*

440 The major strength of our study was using a threshold effects model, an advanced and flexible
441 approach to comprehensively estimate the optimal time interval for a GP visit. A further strength of
442 this study is the large population and comprehensive range of linked databases used in the empirical
443 analysis that allowed us to measure and control any changes in both outcomes and exposures over
444 the studied period.

445 The cover metric developed in this paper does not incorporate the number of GPs or GP practices
446 visited. Since the purpose of the metric is to determine the influence of the time between visits
447 adjusting for other dimensions of continuity (e.g. via the usual provider index, the frequency of visits
448 and the number of practices visited) in models would be superior to incorporating these dimensions
449 of continuity in the metric. Therefore, inclusive measure of time duration in the design of the Cover
450 Index is a strength, since using the cover metric with separate adjustment for other dimensions of
451 continuity allows the impact of the time duration component to be separated from other
452 components. This is more valuable to practitioners and policy makers than a metric that reports a
453 combined impact. Interaction terms could be used for evaluating various combinations of
454 dimensions if required.

455 Our study has some limitations to consider when interpreting the results. The empirical analyses
456 were conducted using data from 1990 to 2004, hence it cannot provide evidence regarding current
457 utilisation of GP services. However, for the purposes of this paper, which sought to develop and
458 operationalise the cover metric, the lack of contemporaneous data is unimportant. The cover metric
459 could have been developed solely using synthetic data; however the use of these historical data is a
460 strength because they allowed us to develop the metric using real world relationships between GP
461 visits and other covariates and also afforded us the opportunity undertake face validity of the metric
462 during the development stage. In addition, the use of these historical data could be considered a
463 strength because this particular time period incorporates a period in Australia with little intervention
464 aimed at increasing provision of primary care for people with chronic conditions. Thus, the data in
465 this period could, with appropriate control of confounding factors, provide the baseline needed to
466 identify the incremental impact of policies aimed at supporting continuity of primary care, via
467 changes in the cover score and associated impact on PPHs.

468 Administrative data are not collected for research purposes, hence, they do not include some details
469 about severity of disease. Our data also did not have information about whether individuals visited

the same or different GPs which may have improved the threshold modelling of our estimation of the maximum optimal time period. As the same provider is a potential factor for a holistic approach to continuity of care, future work may wish to expend on the current metric with inclusion of such data. The empirical results were limited to those who were clinically diagnosed with diabetes and incur health care resource utilisation through hospitals or Medicare claims that may affect generalisation of the maximal optimal time period estimated. Although the covered time interval found in our study relates only to diabetes at particular severity levels, the cover metric has application to other ambulatory care sensitive chronic conditions.

Conclusions

Our study adds to the current literature by developing and operationalizing a new approach to measuring continuity of primary care which incorporates time-duration protective effects of primary care. This study used novel threshold modelling to determine the impact of maximum duration between GP services on preventable hospitalisation and used the estimated value to operationalise cover. However, the operationalisation of cover is flexible and allows for use of a priori time intervals, which makes it ideal to evaluate clinical guidelines and policies that recommend specified durations between GP visits.

List of abbreviations

PHC Primary health care

COC continuity of care

GP General Practitioner

PPH Potentially Preventable Hospitalisation

WA Western Australia

DOC Days out of Cover

BIC Bayes Information Criterion

AIC Akaike Information Criterion

WADLS Western Australian Data Linkage System

HMDS Hospital Morbidity Data System

MBS Medicare Benefits Scheme

ER Western Australian Electoral Roll

Declarations

Ethical approval

Ethical approval was provided by The University of Western Australia and Curtin University Human Research Ethics Committees.

Consent for publication

All authors agreed to submission of this manuscript for publication.

Availability of data and material

The data that support the findings of this study are available from the relevant data custodians of the study datasets. Restrictions by the data custodians mean that the data are not publicly available or able to be provided by the authors. Researchers wishing to access the datasets used in this study should refer to the WA data linkage application process (https://www.datalinkage-wa.org.au/access-and-application)

Competing of interests

No competing or conflict of interests

Funding

514 This work was supported by the National Health and Medical Research Council, project grant
515 APP1078345. The study funders had no role in the study design, conduct, manuscript writing or
516 decision to submit for publication.

517 **Author contribution**

518 TNH, RM and MH conceived the idea and study design for the manuscript. TNH conducted data
519 analyses and drafted the manuscript. RM and MH provided supervision and contributed in analysis,
520 interpreting the results, drafting and revising the manuscript. DP and SR involved in drafting and
521 revising critically for important intellectual content of the manuscript. All authors read and approved
522 the final version of the manuscript for publication

523 **Acknowledgements**

524 The authors wish to thank the staff at the Western Australian Data Linkage Branch and
525 Commonwealth Department of Health and Aging for providing the linked data for this project.

526

527 **References**

528 AIHW. 2008. " A set of performance indicators across the health and aged care system." Canberra:
529 Australian Institute of Health and Welfare.
530 American Diabetes Association. 2003. "Standards of medical care for patients with diabetes
531 mellitus." *Diabetes Care* 26 Suppl 1: S33-50.
532 Australian Bureau of Statistics. 1981-2006. "Census of Population and Housing: Socio-Economic
533 Indexes for Areas." Canberra: Australian Bureau of Statistics.
534 Australian Bureau of Statistics. 2011. "Census of Population and Housing: Socio-Economic Indexes
535 for Areas ". Canberra: Australian Bureau of Statistics.
536 Authority, T. n. H. P. 2015. "Healthy communities: Potentially preventable hospitalisations in 2013-
537 14." Sydney: The national Health Performance Authority.
538 Barker, I., A. Steventon, and S. R. Deeny. 2017. "Association between continuity of care in general
539 practice and hospital admissions for ambulatory care sensitive conditions: cross sectional
540 study of routinely collected, person level data." *BMJ* 356.
541 Bentler, S. E., R. O. Morgan, B. A. Virnig, and F. D. Wolinsky. 2014. "The Association of Longitudinal
542 and Interpersonal Continuity of Care with Emergency Department Use, Hospitalization, and
543 Mortality among Medicare Beneficiaries." *PLoS ONE* 9(12): e115088.
544 Bywood, P., R. Katterl, and B. Lunnay. 2011. "Disparities in primary health care utilisation: Who are
545 the disadvantaged groups? How are they disadvantaged? What interventions work? ." *PHCRIS*
546 *Policy Issue Review.* Adelaide: Primary Health Care Research & Information Service.
547 Caetano, P. A., J. M. Lam, and S. G. Morgan. 2006. "Toward a standard definition and measurement
548 of persistence with drug therapy: Examples from research on statin and antihypertensive
549 utilization." *Clin Ther* 28(9): 1411-24; discussion 10.
550 Caminal, J., B. Starfield, E. Sanchez, C. Casanova, and M. Morales. 2004. "The role of primary care in
551 preventing ambulatory care sensitive conditions." *Eur J Public Health* 14(3): 246-51.
552 Chamberlain, G. 1982. "Multivariate regression models for panel data." *Journal of Econometrics*
553 18(1): 5-46.
554 Cho, K. H., S. G. Lee, B. Jun, B.-Y. Jung, J.-H. Kim, and E.-C. Park. 2015. "Effects of continuity of care
555 on hospital admission in patients with type 2 diabetes: analysis of nationwide insurance data."
556 *BMC Health Services Research* 15: 107.
557 Comino, E. J., M. D. F. Islam, D. T. Tran, L. Jorm, J. Flack, B. Jalaludin, M. Haas, and M. F. Harris. 2015.
558 "Association of processes of primary care and hospitalisation for people with diabetes: A
559 record linkage study." *Diabetes Research and Clinical Practice* 108(2): 296-305.

560 Davis, W. A., M. W. Knuiman, D. Hendrie, and T. M. Davis. 2005. “Determinants of diabetes-
561 attributable non-blood glucose-lowering medication costs in type 2 diabetes: the Fremantle
562 Diabetes Study.” *Diabetes Care* 28(2): 329-36.
563 Department of Health and Ageing. 2010a. “Building a 21st Century Primary Health Care System:
564 Australia's First National Primary Health Care strategy.” *Commonwealth of Australia*.
565 Department of Health and Ageing. 2010b. "National Hospital Cost Data Collection: Cost report Round
566 13 (2008–2009)" [accessed on 15 Feb, 2010b]. Available at:
567 http://www.health.gov.au/internet/main/publishing.nsf/Content/health-casemix-data-
568 collections-about_NHCDC.
569 Donabedian, A. 2005. “Evaluating the quality of medical care. 1966.” *Milbank Q* 83(4): 691-729.
570 Dreiher, J., D. S. Comaneshter, Y. Rosenbluth, E. Battat, H. Bitterman, and A. D. Cohen. 2012. “The
571 association between continuity of care in the community and health outcomes: a population-
572 based study.” *Isr J Health Policy Res* 1(1): 21.
573 Einarsdóttir, K., D. B. Preen, J. D. Emery, and C. D. A. J. Holman. 2011. “Regular Primary Care Plays a
574 Significant Role in Secondary Prevention of Ischemic Heart Disease in a Western Australian
575 Cohort.” *Journal of General Internal Medicine* 26(10): 1092-97.
576 Einarsdóttir, K., D. B. Preen, J. D. Emery, C. Kelman, and C. D. A. J. Holman. 2010. “Regular Primary
577 Care Lowers Hospitalisation Risk and Mortality in Seniors with Chronic Respiratory Diseases.”
578 *Journal of General Internal Medicine* 25(8): 766-73.
579 Falster, M. O., L. R. Jorm, and A. H. Leyland. 2016. “Visualising linked health data to explore health
580 events around preventable hospitalisations in NSW Australia.” *BMJ Open* 6(9): e012031.
581 Frühwirth-Schnatter, S. 2006. *Finite Mixture and Markov Switching Models*: Springer Series in
582 Statistics.
583 Gannon, B., D. Harris, and M. Harris. 2014. “THRESHOLD EFFECTS IN NONLINEAR MODELS WITH AN
584 APPLICATION TO THE SOCIAL CAPITAL-RETIREMENT-HEALTH RELATIONSHIP.” *Health*
585 *Economics* 23(9): 1072-83.
586 Gannon, B., D. Harris, M. Harris, L. Magnusson, B. hollingsworth, B. Lnder, and L. Munford. 2015.
587 “New approaches to estimating the child health-patental income relationship ” *Economics*
588 *Discussion* 15-31.
589 Gibson, D., R. Moorin, D. Preen, J. Emery, and C. D. Holman. 2011. “Effects of the Medicare
590 enhanced primary care program on primary care physician contact in the population of older
591 Western Australians with chronic diseases.” *Australian Health Review* 35: 334-40.

592 Gibson, D., R. Moorin, D. Preen, J. Emery, and C. D. Holman. 2012. “Enhanced Primary Care improves
593 GP service regularity in older patients without impacting on service frequency.” *Australian*
594 *Journal of Primary Health* 18(4): 295-303.
595 Gonzalo, J. and J.-Y. Pitarakis. 2002. “Estimation and model selection based inference in single and
596 multiple threshold models.” *Journal of Econometrics* 110(2): 319-52.
597 Gulliford, M., S. Naithani, and M. Morgan. 2006. “What is 'continuity of care'?” *Journal of Health*
598 *Services Research & Policy* 11(4): 248-50.
599 Guthrie, B., J. W. Saultz, G. K. Freeman, and J. L. Haggerty. 2008. “Continuity of care matters.” *BMJ*
600 337.
601 Ha, N. T., M. Harris, D. Preen, S. Robinson, and R. Moorin. 2018. “Identifying patterns of general
602 practitioner service utilisation and their relationship with potentially preventable
603 hospitalisations in people with diabetes: The utility of a cluster analysis approach.” *Diabetes*
604 *Research and Clinical Practice*.
605 Ha, N. T., M. Harris, S. Robinson, D. Preen, and R. Moorin. 2017. “Stratification strategy for
606 evaluating the influence of diabetes complication severity index on the risk of hospitalization:
607 a record linkage data in Western Australia.” *J Diabetes Complications* 31(7): 1175-80.
608 Haggerty, J. L., R. J. Reid, G. K. Freeman, B. Starfield, C. E. Adair, and R. McKendry. 2003. “Continuity
609 of care: a multidisciplinary review.” *BMJ* 327(7425): 1219.
610 Holman, C. D., A. J. Bass, I. L. Rouse, and M. S. Hobbs. 1999. “Population-based linkage of health
611 records in Western Australia: development of a health services research linked database.”
612 *Aust N Z J Public Health* 23(5): 453-9.
613 Holman, C. D., D. B. Preen, N. J. Baynham, J. C. Finn, and J. B. Semmens. 2005. “A multipurpose
614 comorbidity scoring system performed better than the Charlson index.” *J Clin Epidemiol*
615 58(10): 1006-14.
616 Hong-kit Yim, F., R. E. Anderson, and S. Swaminathan. 2004. “Customer Relationship Management:
617 Its Dimensions and Effect on Customer Outcomes.” *Journal of Personal Selling & Sales*
618 *Management* 24(4): 263-78.
619 Jackson, C. and L. Ball. 2018. “Continuity of care is vital but how do we measure it.” *Australian*
620 *Journal for General Practitioners* 47: 662-64.
621 Jackson, C., M. Shahsahebi, T. Wedlake, and C. A. DuBard. 2015. “Timeliness of outpatient follow-up:
622 an evidence-based approach for planning after hospital discharge.” *Ann Fam Med* 13(2): 115-
623 22.
624 Jee, S. H. and M. D. Cabana. 2006. “Indices for continuity of care: a systematic review of the
625 literature.” *Med Care Res Rev* 63(2): 158-88.

626 Kecmanovic, M. and P. J. Hall. 2015. “The use of financial incentives in Australian general practice.”
627 *The Medical Journal of Australia* 202(9): 488-91.
628 Lee, E. W. 2012. “Data Mining Application in Customer Relationship Management for Hospital
629 Inpatients.” *Healthcare Informatics Research* 18(3): 178-85.
630 Ling, R. and D. C. Yen. 2001. “Customer Relationship Management: An Analysis Framework and
631 Implementation Strategies.” *Journal of Computer Information Systems* 41(3): 82-97.
632 Menec, V. H., M. Sirski, D. Attawar, and A. Katz. 2006. “Does continuity of care with a family
633 physician reduce hospitalizations among older adults?” *Journal of Health Services Research &*
634 *Policy* 11(4): 196-201.
635 Moorin, R. 2015. “Symposium: Measuring the influence of regularity of GP contact on diabetic
636 potentially preventable hospitalisations.” *Health Services & Policy Research Conference.*
637 Melbourne: Health Services Research Association of Australia & New Zealand.
638 Mundlak, Y. 1978. “On the Pooling of Time Series and Cross Section Data.” *Econometrica* 46(1): 69-
639 85.
640 Pereira Gray, D. J., K. Sidaway-Lee, E. White, A. Thorne, and P. H. Evans. 2018. “Continuity of care
641 with doctors—a matter of life and death? A systematic review of continuity of care and
642 mortality.” *BMJ Open* 8(6).
643 Reinartz, W. J. and V. Kumar. 2003. “The Impact of Customer Relationship Characteristics on
644 Profitable Lifetime Duration.” *Journal of Marketing* 67(1): 77-99.
645 Sanderson, C. and J. Dixon. 2000. “Conditions for Which Onset or Hospital Admission is Potentially
646 Preventable by Timely and Effective Ambulatory Care.” *Journal of Health Services Research &*
647 *Policy* 5(4): 222-30.
648 Santoleri, F., P. Sorice, R. Lasala, R. C. Rizzo, and A. Costantini. 2013. “Patient adherence and
649 persistence with Imatinib, Nilotinib, Dasatinib in clinical practice.” *PLoS ONE* 8(2): e56813.
650 Saultz, J. W. and W. Albedaiwi. 2004. “Interpersonal continuity of care and patient satisfaction: a
651 critical review.” *Ann Fam Med* 2(5): 445-51.
652 The Department of Health. 2014. "Chronic Disease Management (formerly Enhanced Primary Care or
653 EPC) — GP services" [accessed on 2014]. Available at:
654 http://www.health.gov.au/internet/main/publishing.nsf/content/mbsprimarycare-
655 chronicdiseasemanagement.
656 The Royal Australian College of General Practitioners. 2014. “General practice management of type 2
657 diabetes 2014-2015.” Melbourne: The Royal Australian College of General Practitioners.

van Loenen, T., M. J. van den Berg, G. P. Westert, and M. J. Faber. 2014. “Organizational aspects of primary care related to avoidable hospitalization: a systematic review.” *Fam Pract* 31(5): 502-16.

Vuik, S. I., G. Fontana, E. Mayer, and A. Darzi. 2017. “Do hospitalisations for ambulatory care sensitive conditions reflect low access to primary care? An observational cohort study of primary care usage prior to hospitalisation.” *BMJ Open* 7(8).

Wooldridge, J. M. 2005. “Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity.” *Journal of Applied Econometrics* 20(1): 39-54.

Youens, D. and R. Moorin. 2017a. “The impact of regular General Practitioner visits on diabetic hospitalisation costs.” *International Health Economics Association World Congress.* Boston: International Health Economics Association

Youens, D. and R. Moorin. 2017b. “Regularity of General Practitioner contact – analysis of methods for measurement using administrative data.” *Health Services Research & Policy Conference.* Brisbane: Health Services Research Association of Australia & New Zealand.

Young, B. A., E. Lin, M. Von Korff, G. Simon, P. Ciechanowski, E. J. Ludman, S. Everson-Stewart, L. Kinder, M. Oliver, E. J. Boyko, and W. J. Katon. 2008. “Diabetes Complications Severity Index and Risk of Mortality, Hospitalization, and Healthcare Utilization.” *Am J Manag Care* 14(1): 15-23.

Zhao, Y., J. Wright, S. Guthridge, and P. Lawton. 2013. “The relationship between number of primary health care visits and hospitalisations: evidence from linked clinic and hospital data for remote Indigenous Australians.” *BMC Health Serv Res* 13: 466.

List of Figures

Tables

Table 1. Characteristics of studied population at the time entering each complication cohort

Characteristics	No complication (N, (%))	One or two complications (N, (%))	Three complications or more (N, (%))
N	20039	14866	10730
Age group (years)			
45-59	9223 (46.0)	3849 (25.9)	1,869 (17.4)
60-74	8650 (43.2)	7178 (48.3)	4,708 (43.9)
≥75	2166 (10.8)	3839 (25.8)	4,153 (38.7)
Gender			
Female	9741 (48.6)	7263 (48.8)	5000 (46.6)
Male	10298 (51.4)	7603 (51.1)	5,730 (53.4)
Indigenous status			
No	17911 (95.9)	13,937(93.7)	9,880 (92.1)
Yes	771 (4.1)	929 (6.2)	850 (7.9)
SEIFA			
Highest Disadvantage	3951 (19.8)	3,232 (21.9)	2,445 (22.9)
High disadvantaged	5540 (27.8)	4,302(29.1)	3,128 (29.3)
Moderate disadvantage	2792 (14.0)	2,126 (14.4	1,496 (14.0)
Less disadvantage	3205 (16.1)	2,226 (15.1)	1,582 (14.8)
Least disadvantage	4412 (22.2)	2876 (19.5)	2,005 (18.8)
Accessibility			
Very remote	553 (2.8)	606 (4.1)	525 (4.9)
Remote	359 (1.8)	277 (2.0)	186 (1.7)
Moderate	945 (4.7)	772 (5.2)	603 (5.6)
Accessible	1039 (5.2)	843 (5.7)	627 (5.9)
Highly accessible	17004 (85.4)	12265 (83.0)	8,716 (81.9)
Number of comorbidity			
Mean (SD)	3.0 (2.9)	5.7 (3.1)	8.3 (3.1)
Duration of diabetes (years)			
Mean (SD);	5.4 (3.8)	7.2 (4.2)	9.2 (4.7)
Regularity quantiles			
No regularity	4765 (23.8)	3,150 (21.2)	2,382 (22.2)
Quantile 1	3833 (19.1)	2,776 (18.7)	2,082 (19.4)
Quantile 2	3850 (19.2)	2,873(19.3)	2,070 (19.3)
Quantile 3	3772 (18.8)	2,975 (20.0)	2,116 (19.7)
Quantile 4	3819 (19.0)	3,092 (20.8)	2,080 (19.4)
Average time to a GP visit (months) Mean (SD)	3.6 (3.2)	2.8 (2.5)	2.4 (2.1)
Frequency of GP visits Mean (SD)	4.7 (2.8)	5.1 (3.0)	5.2 (3.2)
Number of specialist visits Mean (SD)	2.4 (4.1)	4.5 (6.5)	5.5 (9.2)
Number of non-diabetes related hospitalization	0.35 (1.57)	0.72 (2.3)	1.04 (1.85)
Number of diabetes related hospitalization	0.03 (1.06)	0.53 (1.7)	1.8 (10.8)

Average costs per diabetes related hospitalizations (2014 A$) (Mean (SD))	4381.2 (3828.7)	5185.5 (5492.7)	8192.7 (8992.6)
Min-Max	800.8-38842.4	748.8-128552.6	598.2-144061.3
Average costs per non-diabetes related hospitalizations (2014 A$) (Mean (SD))	3993.3 (4132.2)	5637.4 (7964.4)	7756.2 (12172.2)
Min-Max	393.4-61680.1	393.4-142694.4	662.2 -227080.1

Table 2 Threshold search for max time to a GP visits by complications for people aged 45 years or older

Complication cohorts	**No complication [(a)]**						**One or two complications [(b)]**						**Three or more complications [©]**				
Number of subpopulations	2	3	4	5	6	18	2	3	4	5	6	18	2	3	4	5	18
AIC	45169.0	45091.2	45049.5	45020.4	45017.6	45018.7	53464.2	53413.6	53360.2	53346.5	53408.3	53340.3	69875.6	69812.3	69774.9	69769.4	69777.3
BIC	45398.5	45329.9	45297.3	45277.4	45283.8	45450.1	53683.6	53641.8	53597.2	53592.3	53662.8	53752.9	70086.1	70031.2	70002.3	70005.2	70173.0
Threshold parameters																	
τ_1	8	8	2	2	2	-	10	2	2	2	3	-	9	2	2	2	-
τ_2		13	8	3	3	-		10	3	3	6	-		3	3	3	-
τ_3			13	8	8	-			11	4	7	-			9	9	-
τ_4				13	10	-				11	9	-				13	-
τ_5					13	-					11	-					
Coefficients																	
γ_1	-0.229***	-0.249***	-0.040	0.134**	0.123**	-	-0.194***	-0.015	0.194***	0.323***	-0.165***	-	-0.128***	0.289***	0.196***	0.190***	-
	(0.01)	(0.01)	(0.03)	(0.05)	(0.05)	-	(0.01)	(0.03)	(0.04)	(0.05)	(0.03)	-	(0.01)	(0.03)	(0.03)	(0.03)	-
γ_2	-0.083***	-0.126***	-0.199***	-0.057	-0.064*	-	-0.053***	-0.157***	0.006	0.087**	-0.216***	-	-0.014	0.115***	0.054*	0.050*	-
	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)	-	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	-	(0.01)	(0.02)	(0.02)	(0.02)	-
γ_3		-0.013	-0.101***	-0.148***	-0.152***	-		-0.039**	-0.099***	-0.023	-0.188***	-		-0.001	-0.046**	-0.048**	-
		(0.01)	(0.01)	(0.02)	(0.02)	-		(0.01)	(0.01)	(0.02)	(0.02)	-		(0.01)	(0.02)	(0.02)	-
γ_4			0.004	-0.072***	-0.089***	-			-0.000	-0.071***	-0.162***	-			0.028*	0.013	-
			(0.01)	(0.01)	(0.02)	-			(0.01)	(0.02)	(0.02)	-			(0.01)	(0.01)	-
γ_5				0.024	-0.057***	-				0.016	-0.116***	-				0.062***	-
				(0.01)	(0.02)	-				(0.01)	(0.02)	-				(0.02)	-
γ_6					0.022	-					-0.039**	-					
					(0.01)	-					(0.01)	-					

For one subpopulation (a): AIC= 45401.0; BIC= 45676.3; (b) AIC=53622.8; BIC=53886.1; (c) AIC= 69969.5; BIC=70222.1

Table 3. Average yearly cover score across maximal optimal time interval boundary over the studied period

Characteristics	Low bound cover			Middle bound cover			Upper bound cover		
	mean	95% CI		mean	95% CI		mean	95% CI	
Overall									
Mean	0.83	(0.83 ;	0.83)	0.84	(0.84 ;	0.85)	0.85	(0.80 ;	0.85)
Median (IQR)	0.98	(0.81 ;	1.00)	1.00	(0.86 ;	1.00)	1.00	(0.87 ;	1.00)
Age group (years)									
45-59	0.82	(0.81 ;	0.82)	0.84	(0.83 ;	0.84)	0.85	(0.84 ;	0.85)
60-74	0.87	(0.87 ;	0.87)	0.88	(0.88 ;	0.89)	0.89	(0.89 ;	0.89)
≥75	0.77	(0.77 ;	0.77)	0.78	(0.78 ;	0.79)	0.79	(0.78 ;	0.79)
Gender									
Female	0.86	(0.86 ;	0.86)	0.87	(0.87 ;	0.87)	0.88	(0.88 ;	0.88)
Male	0.80	(0.80 ;	0.80)	0.82	(0.82 ;	0.82)	0.83	(0.83 ;	0.83)
Indigenous status									
No	0.84	(0.84 ;	0.84)	0.86	(0.86 ;	0.86)	0.86	(0.86 ;	0.86)
Yes	0.60	(0.59 ;	0.61)	0.63	(0.62 ;	0.64)	0.64	(0.63 ;	0.65)
SEIFA									
Highest Disadvantage	0.81	(0.80 ;	0.81)	0.82	(0.82 ;	0.83)	0.83	(0.83 ;	0.83)
High disadvantaged	0.83	(0.83 ;	0.84)	0.85	(0.85 ;	0.85)	0.86	(0.85 ;	0.86)
Moderate disadvantage	0.83	(0.83 ;	0.84)	0.85	(0.85 ;	0.85)	0.86	(0.85 ;	0.86)
Less disadvantage	0.84	(0.84 ;	0.84)	0.86	(0.85 ;	0.86)	0.86	(0.86 ;	0.87)
Least disadvantage	0.84	(0.84 ;	0.84)	0.86	(0.85 ;	0.86)	0.86	(0.86 ;	0.87)
Accessibility									
Very remote	0.48	(0.47 ;	0.49)	0.51	(0.50 ;	0.52)	0.52	(0.51 ;	0.53)
Remote	0.74	(0.73 ;	0.76)	0.77	(0.76 ;	0.78)	0.78	(0.77 ;	0.79)
Moderate	0.79	(0.79 ;	0.80)	0.82	(0.81 ;	0.82)	0.82	(0.82 ;	0.83)
Accessible	0.81	(0.81 ;	0.82)	0.83	(0.83 ;	0.84)	0.84	(0.84 ;	0.85)
Highly accessible	0.85	(0.85 ;	0.85)	0.86	(0.86 ;	0.87)	0.87	(0.87 ;	0.87)

Figure 1: Calculation of cover index

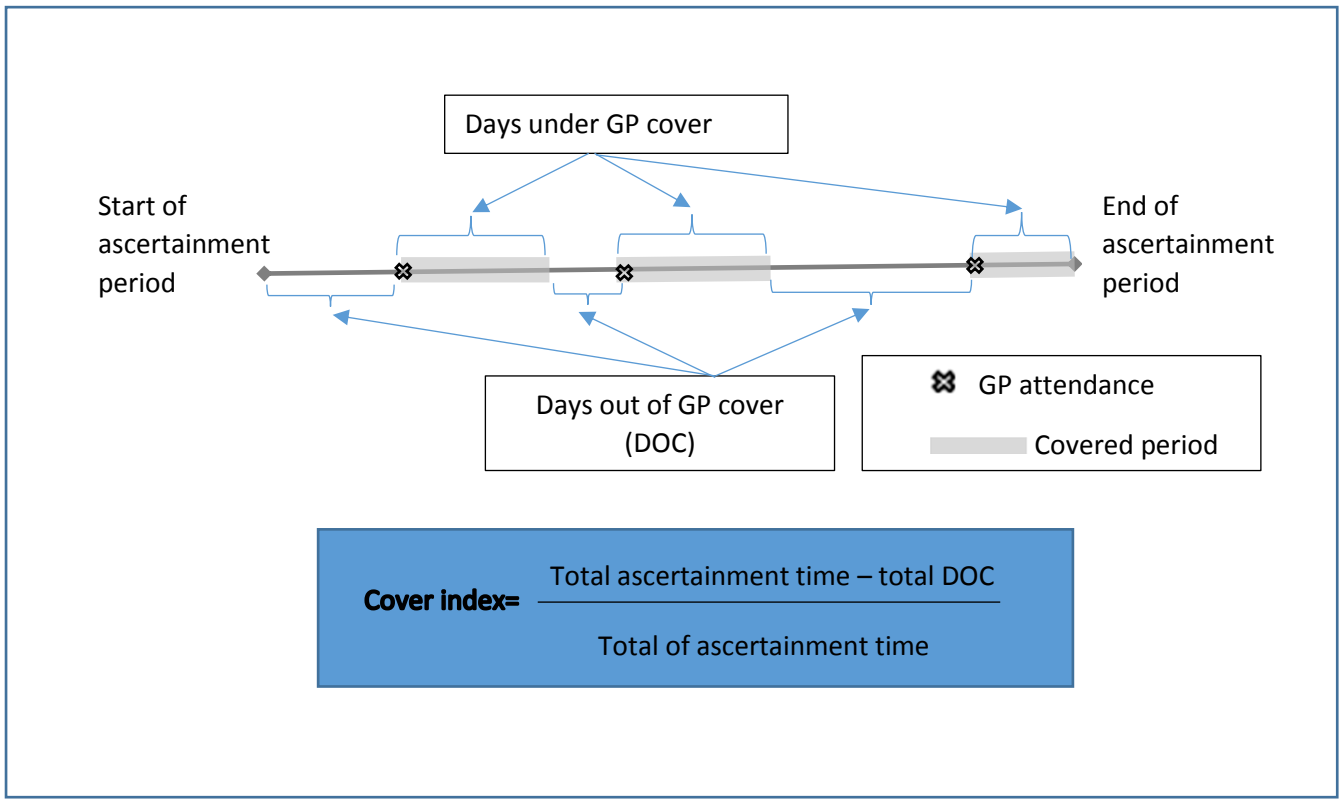
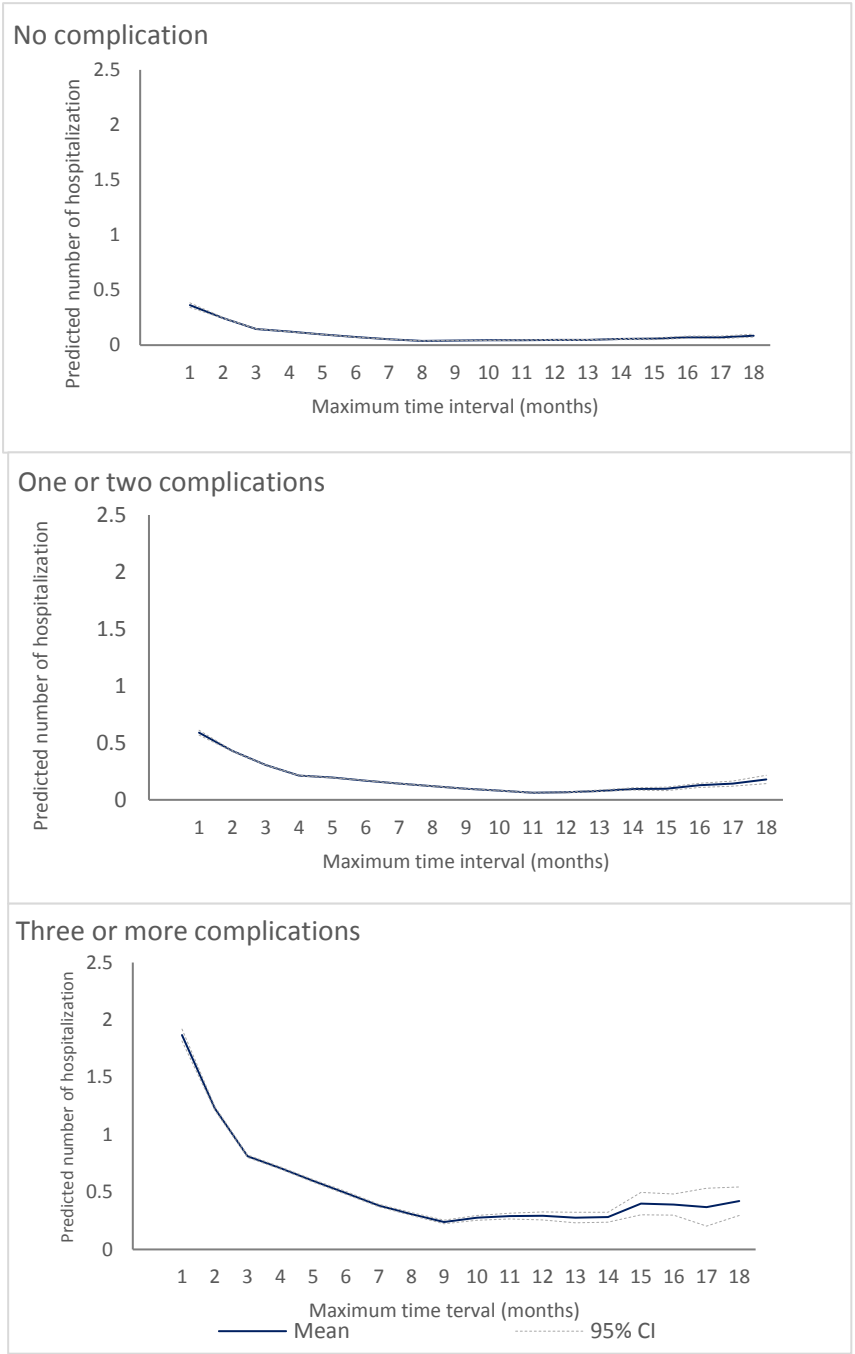


Figure 2: Changes in number of hospitalisations across maximum time interval between GP visits by complication cohort



Appendix E Manuscript 4

The Cover Index – Evaluating continuity of care incorporating a time-duration effect of general practitioner care on diabetic-related potentially preventable hospitalisations

Author names and affiliations

1) Ninh Thi Ha

Health systems and Health economics, School of Public Health, Curtin University, Perth, Western Australia 6845, Australia

thininh.ha@student.curtin.edu.au

2) Mark Harris

School of Economics and Finance, Curtin University, Perth, Western Australia 6845, Australia

mark.harris@curtin.edu.au

3) David Preen

Centre for Health Services Research, School of Population and Global Health, The University of Western Australia, 35 Stirling Highway, CRAWLEY WA 6009, Australia

david.preen@uwa.edu.au

4) Rachael Moorin

Health Systems and Health Economics, School of Public Health, Curtin University, Perth, Western Australia 6845, Australia and School of Population and Global Health, The University of Western Australia, 35 Stirling Highway, CRAWLEY WA 6009, Australia

r.moorin@curtin.edu.au

Corresponding author

Ninh Thi Ha

Email: thininh.ha@student.curtin.edu.au

Health Systems and Health Economics, School of Public health, Curtin University, Perth, Western Australia 6845, Australia

Abstract

Objectives: To evaluate continuity of care incorporating a time duration effect using the Cover Index and its association with diabetes related potentially preventable hospitalisation (PPH) among people with diabetes.

Design: A retrospective, observational study

Setting: A total of 26 602 individuals aged 45 years and older identified with diabetes in the 45 and Up Study in New South Wales (NSW), Australia

Main outcome measures: Diabetes-related PPH, unplanned diabetes related PPH and length of stay (LOS).

Methods: Linked hospitalisations, out of hospital service utilisation, medication and population survey data were used to create a diabetes cohort stratified by complication severity. For each severity cohort, threshold effect models were conducted to identify the maximum optimal time interval between GP visits offering the lowest number of diabetes related PPH to use for calculating time under cover of GP care. Negative binomial models and dose-response functions adjusted using a generalised propensity score were used to examine the association of the coverage of GP care with diabetes related PPH/unplanned PPH and LOS.

Results: On average the percentage of the year spent under cover of a GP was 93.6% (95%CI, 93.4-93.8%). However, time under cover of GP care was significantly lower among males (92.8 (95%CI 92.5-93.2%), individuals aged 85 years or older (79.5%, 95%CI 77.0-82.1%), those living in very remote areas (77.5%, 95%CI 65.1-90.0%) and those with a severe level of limitations (92.8%, 92.3-93.3%). Individuals with higher GP cover had a significantly lower number of diabetes related PPHs (Coef. -2.3, 95%CI -2.6; -2.0), unplanned diabetes related PPHs (Coef. -1.8, 95%CI -2.3; -1.4) and shorter lengths of stay (Coef. -5.5, 95%CI -5.9; -5.1 and Coef. -3.9, 95%CI -4.7; -3.2, respectively). Incrementally increasing GP cover was associated with increasing reduction in the number of diabetes related PPHs, unplanned diabetes related PPHs and LOS.

Conclusions: Our study provides a more comprehensive view of continuity of care. Measuring longitudinal continuity in terms of time under cover of GP care may offer opportunities to optimise the performance of primary health care and reduce secondary care costs in the management of diabetes.

What is already known on this topic

Continuity of care with a GP is of vital importance for management of chronic conditions including diabetes due to its ability to provide proactive care leading to opportunities for early action to be taken to prevent or delay progression.

Continuity is a multi-dimensional concept but has mostly been measured in terms of interpersonal relationships between providers and patients with limited exploration of other dimensions

What this study adds

This study suggests that longitudinal continuity of care measured by time under the protection of a GP (cover) may be an important factor associated with reduction in PPHs and length of stay independent of other measures of longitudinal continuity.

Continuity with GP care integrating the time-duration dimension may offer opportunities to improve quality of care, reduce burden of secondary care and costs.

Incorporation of time covered by a GP could present new options for development of policies aimed at optimising management of diabetes.

Introduction

Primary health care has become a cornerstone of health systems in many countries due to its contribution to optimise population health and minimise inequity across subpopulations [1 2]. In Australia, approximately 85% of the general population received at least one consultation per year from a general practitioner (GP) [2]. In many countries GPs are responsible for the first contact of care, gatekeeping access to other parts of the health system, and coordinating and integrating primary and community care with services provided in secondary care settings including speciality, allied health and hospital care [2]. With the growing proportion of elderly due to ageing of the population resulting in an increase in the number of people living with chronic and complex conditions, care offered by GPs has been identified as being of vital importance for management of chronic conditions[3]. GPs are able to provide long-term and comprehensive care that is not solely focused on a single condition but rather focusses on the condition within the context of a patients' other health and social situation [1 4]. Thus, GPs have an important contribution to high quality care and efficient use of scarce health care resources [1].

Continuity of care is the centrepiece of high quality primary care, especially for people living with long-term and complex conditions who are often faced with a wide range of challenges such as medical crises, symptom control and social isolation [5]. The connection of care from past to current and future in which GPs play a central role is essential to ensure a sufficient provision of care, minimise unnecessary or harmful care and to promote self-management for people with the chronic conditions [6 7]. Continuity of care has been described as incorporating three main dimensions including interpersonal relationships, information and management [6 8]. Previous studies found that more continuity of care in terms of higher continuity of provider[9 10], greater regularity of GP visits[11-13] or greater density of visits [14] is associated with better patient satisfaction, and fewer avoidable hospitalisations.

For people with ambulatory care sensitive conditions (ACSC), early disease management and treatment provided in primary care settings has been shown to reduce potentially preventable hospitalisation (PPH) [15 16]. To be efficient in managing a chronic ACSC such as diabetes, shifting care to a proactive or predictive approach instead of reactive care, which is both expensive and ineffective, can be an effective strategy [17]. Proactive care offers an opportunity for early and sufficient action to be taken to prevent the onset and delay progression of degenerative diseases [17]. Recent evidence examining patterns of GP utilisation has demonstrated that the time interval between GP visits was associated with a reduction in a number of potentially preventable hospitalisations. The importance of the time duration between services has been suggested in customer relationship management frameworks [18], and used with a similar form in measuring medication persistence [19 20], and continuity of medication management [21]. This concept is integrated into a new continuity of care metric named "the Cover Index" capturing the proportion of time people are under the potentially protective effect of GP care [22]. To aid in the development of policies and behaviours that support proactive care by GPs, examining the cover of GP services accounting for other facets of continuity of care including continuity of provider, regularity and frequency of GP contact would be useful. This study aimed to assess time under the protection of GP care as measured by the Cover Index among people with diabetes and its relationship with diabetes related potentially preventable hospitalisation while simultaneously accounting for continuity of provider, regularity and frequency of GP contact.

Methods

Data sources

This was a retrospective observational study using data from the Sax Institute's 45 and Up Study in New South Wales; details of the cohort profile have been previously reported [23]. The Sax Institute's 45 and Up Study was sampled from the Department of Humans Services (formerly Medicare Australia) enrolment data base. The study comprises of over 267 000 people aged 45 years and over

with individual information on demographics, socioeconomic status, lifestyle factors, health status and well-being collected from the survey between 2006 and 2009. Survey data were linked with administrative health records from i) the New South Wales Admitted Patient Data Collection (APDC)(2005 to 2015), ii) the Medicare Benefits Schedule (MBS) (2005 to 2015), iii) the Pharmaceutical Benefit Scheme (PBS) (2005 to 2015) and (iv) the NSW Register of Births Deaths and Marriages (RBDM) (2006 to 2015). The NSW Centre for Health Record Linkage (CHeReL) conducted the linkage for APDC and RBDM. CHeReL linkages are probablistic. The MBS and PBS data are linked deterministically by the Sax Insititute using a unique identifier provided by the Australian Government Department of Human Services. The privacy of individual patients is conserved using probabilistically linked technique with very low false-positive and false-negative rates of <0.5 and <0.1%, respectively [24]. All individual data were de-identified and assigned a unique project person number.

The APDC data comprised dates of admission and separation, diagnoses (primary and secondary), procedures performed and other details of individual episodes of hospitalisation such as type of admission, transfer and discharged status from all private and public hospitals in NSW. Details of diagnoses were recorded using 10th revision Australian Modification codes (ICD-10-AM) in the principal diagnosis and up to 54 additional diagnoses [25]. The MBS records consisted of claim items, date of services and de-identified provider codes for medical and diagnostic services provided out of hospital under Australia's universal health insurance scheme. The PBS records comprised claims for subsidised prescription medicines and included item code, Anatomical Therapeutic Chemical (ATC) code, quantity and date supplied. The death registry had information on the date and cause of death and were used to identify participants in the study population who died during the study period.

Study population

The study population included people aged 45 years and older identified with diabetes between 2005 and 2009 using information from self-report, APDC and PBS data. People were identified as

having diabetes if they answered yes to the question "has the doctor ever told you that you have diabetes?; or they had an APDC record with ICD-10-AM codes for diabetes (E10, E11, E13, E14) in any field of diagnoses and/or a PBS claim indicating a dispensing between 2005 and 2009 using ATC code of A10A (insulins and analogues) or A10B (blood glucose lowering drugs excluding insulins. A total of 29 007 individuals were identified with diabetes by 1 July 2009. We then excluded those who died within two-year after the baseline year (2009) (n=2 310, 7.9%) to allow a minimum of two-year follow-up for every individual. Individuals who did not have any hospitalisation and general practitioner encounter in the whole studied period from 1 July 2009 to 30 June 2016 were also excluded (n=95, 0.3 %). Finally, we excluded a small number (n=1 755, 6.0 %) of individuals without details of age, sex, and/or socioeconomic characteristics.

Ethics approval was obtained from Curtin University Human Research Ethics Committee (RD-42-14) and the NSW Population and Health Services Research Ethics Committee (HREC/17/CIPHS/37). Consent was given by all participants in the Sax Institute's 45 and Up Study for their information to be used in approved studies, and for follow-up and data linkage. The conduct of the Sax Institute's 45 and Up Study was approved by the University of NSW Human Research Ethics Committee.

Outcome measures

The main outcome was the number of diabetes-related PPHs measured in each financial year using ICD-10-AM codes suggested by the National Health Performance Framework [26] and hospitalisation where diabetes was identified as a significant risk factor [27]. We excluded routine hospitalisations for kidney dialysis and inter-hospital transfers were counted as a single episode of care. We also measured unplanned diabetes-related PPHs which included only those diabetes-related PPHs with emergency admission status recorded on the APDC record.

Annual and three-year period total length of stay (LOS) were calculated for diabetes related PPHs and unplanned diabetes related PPHs with same day episodes counted as one day.

Independent measures

Cover Index

The main predictor was the estimated Cover Index, which is a metric that captures the proportion of time over the ascertainment period in which an individual is considered under the 'protective effect' ie cover of a GP contact, developed in the previous study [22] (See Appendix 1 for the calculation of Cover Index). The time under GP cover was determined using the optimal maximum time interval following a GP consultation during which people with diabetes were found to have the lowest number of hospitalisations. In this study, the optimal maximum time interval was estimated among candidates of the maximum time intervals between GP visits using threshold effect modelling stratified by severity level of diabetes. Further details of its estimation using threshold effects models are presented in the statistical analysis section below and have been previously reported [22].

The Cover Index was calculated for each financial year (ie 1 July to 30 June) ascertained from the number of days within each year that the individual remained alive and not in hospital (i.e., was living in the community and therefore eligible for a GP visit). The annual number of days under GP cover was the number of days following each GP visit that were within the defined optimal maximum time interval with special consideration given to the start of each year and time following a hospitalisation, as follows. For the start of each year the days from the last GP visit in the preceding year that were within the optimal maximum time period and fell within the financial year of interest were counted. Following a hospitalisation, determination of cover re-started on the earliest of either the 15th day post-separation date or the date of the first GP visit. A three-year Cover Index was then calculated using the average of the annual Cover Index over the three-year exposure ascertainment period.

Other indices of continuity of care by a GP

Frequency of GP contact was calculated as the number of GP contacts within each financial year, excluding visits within 14 days of the previous visit to avoid over-counting GP episodes of care [28]. The

regularity index was used to measure the distribution of GP visits over each year and was calculated annually as [1/(1+standard deviation of the days between visits)], described in detail elsewhere [12 13 29]. The regularity index ranges from 0 to 1 with 1 representing perfect regularity and close to 0 being lower regular. Continuity of provider was measured using the usual provider of care index, which measures the proportion of GP contacts within the ascertainment period that were provided by the same GP [10]. All indices were aggregated into the three-year ascertainment period when examining the association with the hospitalisation.

Other covariates

This study also measured demographic and socioeconomic characteristics including age classified as 45-54, 55-64, 65-74, 75-84 or 85+ years; sex, Indigenous status, education, residential remoteness classified according to Accessibility Remoteness of Australia index (ARIA) [30], and quintiles of the Census-specific Socio-economic Indexes for Areas (SEIFA) index of relative socioeconomic disadvantage [31]. Duration of diabetes was counted from self-reported age, first date of diagnosis recorded in APDC, or incident diabetes-related PBS record, whichever came first, and classified as 1-5 years, 6-10 years and 11+ years. The number of self-reported comorbidities was the sum of all self-reported conditions including cancers, heart disease, high blood pressure, stroke, blood clot, asthma or hay fever, depression and anxiety, and Parkinson's disease. The number of comorbidities was also counted in the APDC using the Multipurpose Australian Comorbidity Scoring System (MACSS) with a five-year look-back period [32 33]. Diabetes complications were identified using ICD-10-AM codes in the APDC data and classified into three severity level groups: no complication, 1-2 complications and 3+ complications as used elsewhere [34 35]. Levels of limitation in terms of the ability to perform daily activities such as walking, bending, dressing and bathing were measured using the Medical Outcome Study Physical Function Scale [36], and classified into four groups: no limitation, minor limitation, mild limitation and severe limitation. The number of out of hospital specialist visits were identified using MBS claims data, counted in each financial year and then aggregated over a three-year period.

Statistical methods

Estimating the optimal maximum time interval using the threshold effect model

Descriptive analyses were conducted for all characteristics of the study population at the baseline year followed by the analyses on annual panel data to calculate cover of primary care.

The study population were stratified into three cohorts (i) individuals with no complications of diabetes, (ii) those with one or two complications of diabetes and (iii) those with three or more complications of diabetes to account for disease severity levels [35]. The data in each complication cohort were constructed in a panel structure with annual measures of the maximum time interval to GP visits, average time interval between GP visits, GP regularity, GP frequency and GP usual provider index, diabetes related PPHs, comorbidities between 2009/2010 to 2015/2016 financial years.

Threshold effect based on random effects negative binomial models were conducted to identify the optimal maximum time interval to GP visit in which the number of diabetes related PPHs were minimal for each complication cohort. This approach was proposed by Gannon, et al. [37] and applied previously [35 38]. Briefly, the model searched for subpopulations in which the association between diabetes related PPHs and the maximum time interval between GP visits was homogeneous and used information criteria Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to select the optimal model. In addition to the covariates previously specified above the models incorporated Mundlak variables, (group means of time-varying variables including frequency of GP contact, regularity of GP contact and comorbidities) to allow for arbitrary correlation between observed and unobserved heterogeneity terms in the model [39 40]. The initial condition – history of diabetes-related hospitalisations at the baseline year – was also included to allow for any endogeneity arising from the dynamic set-up of the approach [41]. The optimal maximum time intervals identified from the threshold effect models in each cohort were used to calculate the Cover Index which is defined as the proportion of time in a financial year people with diabetes were under cover of primary care (via their GP) as previously described above.

Examining the association between the Cover Index and Diabetes related PPHs and LOS

The association of cover of primary care with diabetes related PPH, unplanned diabetes related PPH and LOS was examined using the data structured into two distinct three-year periods (2009/10-2011/12 and 2012/13-2014/15). A total of 21 965 individuals with full follow-up in the two periods were included in the analyses. The average of the Cover Index over three-year period was the main predictor. As high proportion of the hospital count outcomes contained zero value, in addition to standard multivariable negative binomial models (NB) we also used zero inflated negative binomial models (ZINB) with the inflated constant to examine the association between the Cover Index and the hospital outcomes. Vuong non-nested tests and information criteria (AIC and BIC) were used to indicate the appropriate model.

We further examined the dose-response function of cover of primary health care on diabetes related PPHs, unplanned diabetes related PPHs and LOS adjusting for the generalised propensity score (GPS). The GPS of the Cover Index was predicted using a generalised linear regression model with family binomial and link logit for a fractional treatment variable [42]. The GPS model included individual demographic, socioeconomic characteristics at the baseline year, comorbidities, and complication status at the start of the three-year period, the frequency of GP contact, regularity, usual provider index of the current and previous three period and history of Diabetes related PPHs. Model fit for predicting the propensity score was assessed by plotting the propensity score distribution against the actual Cover Index distribution. Then, the balance of propensity score across four treatment intervals with cut-off points at 0.75, 0.85 and 0.95 were examined by plotting the overlap of GPS between the treatment levels against the rest of the study population in term of the frequency distribution [43]. The covariate balance was assessed by comparing an improvement in t-test statistics and the standardised mean difference between the treatment intervals and the rest of the study population with a threshold of 1.96 and 0.20, respectively to indicate if covariate balance was achieved [42 44]. We excluded individuals whose GPS was not among the common support region for all treatment groups [43]. Finally, we used the dose-response function to evaluate the treatment effect function of the Cover Index on PPHs and LOS [42].

All analyses were conducted using STATA for Windows version MP14.

Results

A total of 24 874 individuals aged 45 years and older were identified as having diabetes in the Sax Institute's 45 and Up Study population. The characteristics of the individuals at the baseline year are presented in Table 1. Individuals with no complications of diabetes were characterised by only a relatively small proportion of people aged 75+ years (17.6 %), and less than a quarter living with severe limitations (22.1 %) and having been diagnosed with diabetes 10+ years previously (24.4%). In contrast, individuals in the cohorts with 1-2 and 3+ complications were characterised by a higher proportion of people in aged 75+ years (28.5% and 44.5%, respectively), and more than a quarter living with severe level of limitations (29.3% and 42.3%, respectively) and diagnosed with diabetes more than 10 years previously (31.7% and 44.9%, respectively).

The optimal maximum time interval estimated from the threshold effect models was 13 months for diabetes with no complications, 8 months for diabetes with 1-2 complications and 6 months for 3+ complications (Table 2). Those optimal time intervals were considered as the time interval under GP cover corresponding to individuals' complication level and used to calculate the Cover Index. On average, the proportion of time in each year that people with diabetes were under cover of primary care was approximately 90% for the first three-year period increasing to 93.6% for the second three-year period. The distribution of the time covered varied across subpopulations and remained significantly lower among people aged 85+ years and older (79.5%, 95% CI 77.0%-82.1%), being male (92.8%, 95%CI 92.5%-93.2%) and living in very remote areas (77.5%, 95%CI 65.1%- 90.0%) across the first and the second three-year period (Table 3).

The association between the Cover Index and the outcomes were examined using both NB and ZINB. The results were similar between the standard NB model and the ZINB model, although AIC and BIC suggested the NB model was most appropriate for both hospitalisations and LOS while the Vuong test suggested ZINB for LOS. Thus, we focus on the results of the standard NB model. When

adjusting for demographic and socioeconomic characteristics at the baseline year; duration of diabetes; disease severity including comorbidities and complication level at beginning of the study period; current and history of specialist visits, frequency of GP visits, usual provider index, and regularity of GP visits; and history of diabetes related PPH, a higher Cover Index was significantly associated with fewer number of diabetes related PPH (Coef. -2.3, 95%CI -2.6;-2.0) and shorter LOS (Coef. -5.5, 95%CI -5.9; -5.1) (Table 4). Similar results were found when unplanned diabetes related PPH (Coef. -1.8, 95%CI -2.3; -1.4) and their LOS were considered (Coef. -3.9, 95%CI -4.7; -3.2) (Table 5).

All of the above covariates were used to predict the GPS of the Cover Index. Figure A2 (Appendix 2) shows good overlap between the GPS of the Cover Index and the actual distribution of the Cover Index suggesting a good fit of the GPS model. The common support, in terms of frequency distribution between each cover interval and the rest of the study population, is presented in Figure A3 (Appendix 2). About 5% of the study population were excluded as lacking of supporting distribution overlapping of GPS distribution with other treatment intervals. The covariate balance adjusting for propensity score using blocking on quintiles of the GPS is presented in Figure A4 (Appendix 2). The covariate balance was achieved for most of the demographic characteristics and diabetes severity levels when using the standardised mean difference threshold at 0.2 and t-test critical values at 1.96. Few subgroups of covariates did not achieve the expected balance, although the balance was improved compared with not adjusting for GPS. Using T-test critical values, the appropriate covariate balance increased from 15 to 29/43 sub-covariates after adjusting for GPS. A similar balance achievement was obtained after adjusting for GPS when using standardised mean difference threshold values (from 33 to 38/43). A total of 1 951 records, 8.8% not in a common support region of GPS distribution across different treatment levels were excluded from estimating dose-response function.

The results of the dose-response function of the Cover Index, adjusting for the GPS, are presented in Figures 1 and 2. The results show that the average number of predicted diabetes related PPH and LOS significantly reduced when the Cover Index increased. The treatment effect function shows a higher effect on the diabetes related PPH and LOS among those with a higher Cover Index. Similar results were observed in the unplanned diabetes related PPH and its LOS.

Discussion

Although timely and early treatment and prevention is important for people with chronic conditions to prevent adverse health events such as complications and potentially preventable hospitalisation, to our knowledge no previous study has examined the temporal aspect of continuity of GP care for people with chronic conditions, especially diabetes. Our study provides a comprehensive view of how well people with diabetes living in community settings are covered by care provided by a GP across different subpopulations. We also evaluate the impact of continuity of GP care in terms of its time duration protective effect, as distinct from other facets of longitudinal continuity such as provider and regularity, on potentially preventable hospitalisation. Overall, our study found that most people with diabetes had an average of 93.6% of time living in the community under cover of a GP over the three-year study period between 2012/13 and 2014/15. However, the proportion of time under cover of a GP care was significantly lower among males, individuals aged 85 years or older, those living in very remote areas, and those with a severe level of limitations. We also found that individuals with a higher Cover Index had a significantly lower number of diabetes related PPHs and shorter length of stay. Similar findings were observed when hospitalisation was limited to unplanned diabetes related PPHs and their length of stay. Analysis of the dose-response function suggested that the effect of GP cover on hospitalisation and length of stay was negative and linear which means that incrementally increasing GP cover offers a higher reduction in the number of admissions and length of stay for both diabetes related PPHs and unplanned diabetes related PPHs.

Strengths and limitations of this study

Our study used a large population based cohort linked with individuals' health care service records that enabled us to account for differences across a wide range of demographic, socioeconomic and clinical characteristics. The self-report data provided an opportunity to include individuals at the early stage of diabetes prior to any hospitalisation for the condition which makes our study population more likely to be representative of the general population living with diabetes. The data were linked with historical administrative data from 2005, which allowed us to capture the history of complications and comorbidities to better capture health related factors, which may have a strong effect on health service utilisation. By using advanced analytic approaches, the study was able to explore latent patterns of primary care utilisation and unpack further dimensions of longitudinal continuity of primary care.

In this study, we excluded days spent in hospital from the calculation of GP cover so as to correctly capture person time in the community (ie eligible for a GP contact). We allowed a maximum of 14 days post separation from hospital to observe the first post discharge GP contact to more accurately capture the person time eligible for cover by a GP without unduly penalising initial days post hospitalisation. A 14 day window was used based on advice from our GP clinical experts who determined that 14 days was the maximum time following discharge from hospital that a person with diabetes should go without seeing their GP. Thus, if a GP contact was not observed by day 15, that day and subsequent days until a GP contact was observed were classed as not under cover of GP care. We included the total number of specialist visits in the study period and also the previous 3 year period to control for the impact of specialist care. GPs are considered as the cornerstone for coordinating and integrating disease management for people with chronic and/complex conditions such as diabetes [45 46]. Long gaps between GP contact, even with or without specialist visits, may suggest insufficiency of comprehensive disease management for patients.

As this is a cross sectional observational study, cautionis required when interpreting any causal relationship between cover of GP care and diabetes related PPHs since both were measured over

the same time period. To partially counteract this the study controlled for history of clinical characteristics and prior health service utilisation. It could be argued that the outcome- diabetes related PPH may not all be truly avoidable by effective GP care and this may lead to difficulty interpreting the association between the Cover Index and the number of DPPHs. To explore this, we evaluated a second outcome, unplanned diabetes related PPHs which, because of their emergency admissions status are more likely to represent hospitalisations that are unexpected and result from uncontrolled clinical events. We found that the association remained significant when we limited the outcome to unplanned diabetes related PPHs confirming that increasing GP cover reduces unplanned hospitalisation, likely via better management of the condition.

The Cover Index was lower across certain subpopulations including males, people aged 85 years or older, and severe level or limitation. Except for people living in the remote areas, the other subgroups had significantly higher number of specialist visits and it may be that specialist care substituting for GP care partially explains this finding. However our results are consistent with literature on the prominence of the role of primary care in planning and coordinating care, which shows an absence among people with older age and complex conditions [46]. Despite financial incentives subsidising multidisciplinary care referred by GPs to encourage patient involvement in chronic disease management, less improvement in access to multidisciplinary care has been reported among males and people living in the remote areas [47].

Best practice care for people with chronic complex conditions, including diabetes, recognises the critical role of GPs in providing effective health management and high quality of care [45 46]. GPs are in the best position to manage care, coordinate with appropriate specialists and continuously review and updating care plans because of their deep-knowledge and close relationship with the patient [45]. In addition, GPs rather than other specialists can offer a superior care by not primarily focussing on the condition but on the condition in the context of the patients' other health problems [1]. Appropriate management of disease in the primary care setting can better connect care, reduce the

risk of adverse drug effect and duplicative interactions with the health care system that in turn can reduce PPHs [47]. These statements are consistent with our findings that better cover of primary care (ie increased time covered by a GP) was associated with a reduction of diabetes related PPHs and length of stay after controlling for frequency of GP visits, regularity, usual provider index and specialist visits.

Our results are in line with the previous studies which looked at primary care MBS re-imbursement items which contain time components such as the annual cycle of care item, review of GP management plan item and team care arrangement item and found that use of these items were associated with reduce in risk of hospitalisation among people with diabetes [25 48]. Our findings are also consistent with our previous finding that the time interval between GP services is inversely associated with the risk of hospitalisation [49]. Thus, we suggest that time under cover of a GP is more likely to directly relate to the reduction of hospitalisations among people with diabetes than other measures of longitudinal continuity of care. The Cover Index is also easier to interpret than indices such as regularity, which has no natural units, as it expresses the proportion of time under cover of GP care and therefore can indicate absolute levels of insufficiency of primary care utilisation. The metric can be applied at the individual, subpopulation or whole population level and therefore is suitable for both development of financial levers via payment incentives (eg an MBS item) or monitoring utilisation of primary care. The index can also be calculated for individuals with single or no GP visits, which is better than other continuity care metrics such as regularity and usual provider index which can only calculated when at least two GP visits were observed within a time frame [10 13] thus unlike these two metrics the Cover Index can comprehensively capture the whole population.

The cover period in this study was calculated using a data-driven approach to determine the maximum time interval used, however this could be derived a prior from expert opinion, existing clinical guidelines or funding arrangements. In this context the Cover Index has the ability to explore the impact of pre-specified temporal arrangements on health outcomes.

Conclusions

Our study found that longitudinal continuity of care in terms of a time duration protective effect of GP contact is associated with admissions and LOS of both diabetes related PPH and unplanned diabetes related PPH. Importantly the proportion of time under cover of GP care acts independently of other facets of longitudinal continuity such as continuity of provider, regularity and frequency of GP contact. The Cover Index provides an important advance in capturing longitudinal continuity that has superior properties to exiting metrics and can be ascertained using either data driven or a priori approaches. These results provide a more comprehensive view of continuity of primary care and provide information valuable for the design interventions and policy levers aimed at optimising disease management for people with diabetes, allocating health resources and improving quality and effectiveness of health care.

Data sharing

The data that support the findings of this study are available from the relevant data custodians of the study datasets. Restrictions by the data custodians mean that the data are not publicly available or able to be provided by the authors. Researchers wishing to access the datasets used in this study should refer to the Sax Institute's 45 and Up Study process (https://www.saxinstitute.org.au/our-work/45-up-study/)

Acknowledgements

This research was completed using data collected through the 45 and Up Study (www.saxinstitute.org.au). The 45 and Up Study is managed by the Sax Institute in collaboration with major partner Cancer Council NSW; and partners: the National Heart Foundation of Australia (NSW Division); NSW Ministry of Health; NSW Government Family & Community Services – Ageing, Carers and the Disability Council NSW; and the Australian Red Cross Blood Service. We thank the many thousands of people participating in the 45 and Up Study.

Competing of interests

No competing or conflict of interests

Funding

This work was supported by the National Health and Medical Research Council, project grant APP1078345.

References

1. Starfield B, Shi L, Macinko J. Contribution of primary care to health systems and health. *The Milbank quarterly* 2005;83(3):457-502. doi: 10.1111/j.1468-0009.2005.00409.x [published Online First: 2005/10/06]
2. Britt H, Miller G, Valenti L, et al. The changing face of Australian general practice across the decades. *Australian family physician* 2016;45:628-31.
3. WHO. Older people and Primary Health Care: WHO; 2004 [Available from: http://www.who.int/ageing/primary_health_care/en/4/10/2018.
4. The Lancet. Chronic disease management in ageing populations. *The Lancet* 2012;379(9829):1851. doi: 10.1016/S0140-6736(12)60790-9
5. Ridd M, Shaw A, Lewis G, et al. The patient–doctor relationship: a synthesis of the qualitative literature on patients' perspectives. *The British Journal of General Practice* 2009;59(561):e116-e33. doi: 10.3399/bjgp09X420248
6. Guthrie B, Saultz JW, Freeman GK, et al. Continuity of care matters. *BMJ* 2008;337
7. Dennis SM, Zwar N, Griffiths R, et al. Chronic disease management in primary care: from evidence to policy. *Med J Aust* 2008;188(8 Suppl):S53-6. [published Online First: 2008/06/17]
8. Van Servellen G, Fongwa M, Mockus D'Errico E. Continuity of care and quality care outcomes for people experiencing chronic conditions: A literature review. *Nursing & Health Sciences* 2006;8(3):185-95. doi: 10.1111/j.1442-2018.2006.00278.x
9. Rodriguez HP, Rogers WH, Marshall RE, et al. The Effects of Primary Care Physician Visit Continuity on Patients' Experiences with Care. *Journal of General Internal Medicine* 2007;22(6):787-93. doi: 10.1007/s11606-007-0182-8
10. Barker I, Steventon A, Deeny SR. Association between continuity of care in general practice and hospital admissions for ambulatory care sensitive conditions: cross sectional study of routinely collected, person level data. *BMJ* 2017;356
11. Youens D, Moorin R. Regularity of General Practitioner contact – analysis of methods for measurement using administrative data. Health Services Research & Policy Conference. Brisbane: Health Services Research Association of Australia & New Zealand, 2017.
12. Gibson DAJ, Moorin RE, Preen D, et al. Enhanced Primary Care improves GP service regularity in older patients without impacting on service frequency. *Australian Journal of Primary Health* 2012;18(4):295-303. doi: http://dx.doi.org/10.1071/PY11050
13. Einarsdóttir K, Preen DB, Emery JD, et al. Regular Primary Care Plays a Significant Role in Secondary Prevention of Ischemic Heart Disease in a Western Australian Cohort. *Journal of General Internal Medicine* 2011;26(10):1092-97. doi: 10.1007/s11606-011-1665-1
14. Jee SH, Cabana MD. Indices for continuity of care: a systematic review of the literature. *Medical care research and review : MCRR* 2006;63(2):158-88. doi: 10.1177/1077558705285294 [published Online First: 2006/04/06]
15. Ansari Z. The Concept and Usefulness of Ambulatory Care Sensitive Conditions as Indicators of Quality and Access to Primary Health Care. *Australian Journal of Primary Health* 2007;13(3):91-110. doi: https://doi.org/10.1071/PY07043
16. Ansari Z, Haider SI, Ansari H, et al. Patient characteristics associated with hospitalisations for ambulatory care sensitive conditions in Victoria, Australia. *BMC Health Services Research* 2012;12:475-75. doi: 10.1186/1472-6963-12-475
17. MacIntosh E, Rajakulendran N, Khayat Z, et al. Transforming health: Shifting from reactive to proactive and predictive care Canada: MaRS; 2016 [Available from: https://www.marsdd.com/news-and-insights/transforming-health-shifting-from-reactive-to-proactive-and-predictive-care/3/10/2018.
18. Ling R, Yen DC. Customer Relationship Management: An Analysis Framework and Implementation Strategies. *Journal of Computer Information Systems* 2001;41(3):82-97. doi: 10.1080/08874417.2001.11647013

19. Caetano PA, Lam JM, Morgan SG. Toward a standard definition and measurement of persistence with drug therapy: Examples from research on statin and antihypertensive utilization. *Clinical therapeutics* 2006;28(9):1411-24; discussion 10. doi: 10.1016/j.clinthera.2006.09.021 [published Online First: 2006/10/26]
20. Santoleri F, Sorice P, Lasala R, et al. Patient adherence and persistence with Imatinib, Nilotinib, Dasatinib in clinical practice. *PLoS One* 2013;8(2):e56813. doi: 10.1371/journal.pone.0056813 [published Online First: 2013/02/26]
21. Beadles CA, Voils CI, Crowley MJ, et al. Continuity of medication management and continuity of care: Conceptual and operational considerations. *SAGE Open Medicine* 2014;2:2050312114559261. doi: 10.1177/2050312114559261
22. Developing a new metric to capture continuity of primary care: The application of propensity score methods and threshold effects models using linked administrative data International Population Data Linkage conference; 2018; Banff. International Journal of Population Data Science
23. Up Study Collaborators. Cohort Profile: The 45 and Up Study. *International Journal of Epidemiology* 2008;37(5):941-47. doi: 10.1093/ije/dym184
24. Korda RJ, Du W, Day C, et al. Variation in readmission and mortality following hospitalisation with a diagnosis of heart failure: prospective cohort study using linked data. *BMC Health Services Research* 2017;17:220. doi: 10.1186/s12913-017-2152-0
25. Comino EJ, Islam MDF, Tran DT, et al. Association of processes of primary care and hospitalisation for people with diabetes: A record linkage study. *Diabetes Research and Clinical Practice* 2015;108(2):296-305. doi: http://dx.doi.org/10.1016/j.diabres.2015.02.003
26. AIHW. A set of performance indicators across the health and aged care system. Canberra: Australian Institute of Health and Welfare, 2008.
27. Davis WA, Knuiman MW, Hendrie D, et al. Determinants of diabetes-attributable non-blood glucose-lowering medication costs in type 2 diabetes: the Fremantle Diabetes Study. *Diabetes Care* 2005;28(2):329-36. [published Online First: 2005/01/29]
28. Donabedian A. Evaluating the quality of medical care. 1966. *The Milbank quarterly* 2005;83(4):691-729. doi: 10.1111/j.1468-0009.2005.00397.x [published Online First: 2005/11/11]
29. Einarsdóttir K, Preen DB, Emery JD, et al. Regular Primary Care Lowers Hospitalisation Risk and Mortality in Seniors with Chronic Respiratory Diseases. *Journal of General Internal Medicine* 2010;25(8):766-73. doi: 10.1007/s11606-010-1361-6
30. AIHW. Rural, regional and remote health: a guide to remoteness classifications: AIHW; 2004 [Available from: https://www.aihw.gov.au/reports/rural-remote-australians/guide-to-remoteness-classifications/formats26/9/2018.
31. Australian Bureau of Statistics. Census of Population and Housing: Socio-Economic Indexes for Areas Canberra: Australian Bureau of Statistics, 2001,2006&2011.
32. Holman CD, Preen DB, Baynham NJ, et al. A multipurpose comorbidity scoring system performed better than the Charlson index. *J Clin Epidemiol* 2005;58(10):1006-14. doi: 10.1016/j.jclinepi.2005.01.020 [published Online First: 2005/09/20]
33. Preen DB, Holman CD, Spilsbury K, et al. Length of comorbidity lookback period affected regression model performance of administrative health data. *J Clin Epidemiol* 2006;59(9):940-6. doi: 10.1016/j.jclinepi.2005.12.013 [published Online First: 2006/08/10]
34. Young BA, Lin E, Von Korff M, et al. Diabetes Complications Severity Index and Risk of Mortality, Hospitalization, and Healthcare Utilization. *The American journal of managed care* 2008;14(1):15-23.
35. Ha NT, Harris M, Robinson S, et al. Stratification strategy for evaluating the influence of diabetes complication severity index on the risk of hospitalization: a record linkage data in Western Australia. *J Diabetes Complications* 2017;31(7):1175-80. doi: 10.1016/j.jdiacomp.2017.03.015 [published Online First: 2017/04/22]

36. Ron HD, Sherbourne CD, Mazel R. User's Manual for the Medical Outcomes Study (MOS) Core Measures of Health-Related Quality of Life. *CA: RAND Corporation* 1995
37. Gannon B, Harris D, Harris M. THRESHOLD EFFECTS IN NONLINEAR MODELS WITH AN APPLICATION TO THE SOCIAL CAPITAL-RETIREMENT-HEALTH RELATIONSHIP. *Health Economics* 2014;23(9):1072-83. doi: 10.1002/hec.3088
38. Gannon B, Harris D, Harris M, et al. New approaches to estimating the child health-patental income relationship *Economics Discussion* 2015;15-31
39. Chamberlain G. Multivariate regression models for panel data. *Journal of Econometrics* 1982;18(1):5-46. doi: http://dx.doi.org/10.1016/0304-4076(82)90094-X
40. Mundlak Y. On the Pooling of Time Series and Cross Section Data. *Econometrica* 1978;46(1):69-85. doi: 10.2307/1913646
41. Wooldridge JM. Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of Applied Econometrics* 2005;20(1):39-54. doi: 10.1002/jae.770
42. Guardabascio B, Ventura M. Estimating the dose-response function through a generalized linear model approach. *Stata Journal* 2014;14(1):141-58.
43. Kluve J, Schneider H, Uhlendorff A, et al. Evaluating continuous training programmes by using the generalized propensity score. *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 2012;175(2):587-617. doi: 10.1111/j.1467-985X.2011.01000.x
44. Austin PC. Assessing covariate balance when using the generalized propensity score with quantitative or continuous exposures. *Statistical Methods in Medical Research* 2018;0(0):0962280218756159. doi: 10.1177/0962280218756159
45. Agency for Clinical Innovation. Building partnerships: a framework for integrating care for older people with complex health needs: Agency for Clinical Innovation; 2014 [Available from: https://www.aci.health.nsw.gov.au/__data/assets/pdf_file/0003/249483/Building_Partnerships_Framework.pdf28/9/2018.
46. Bartlett M, Wang J, Hay L, et al. Health service use in the older person with complex health needs. *Australian Health Review* 2017:-. doi: https://doi.org/10.1071/AH16286
47. McPake B, Mahal A. Addressing the Needs of an Aging Population in the Health System: The Australian Case. *Health Systems & Reform* 2017;3(3):236-47. doi: 10.1080/23288604.2017.1358796
48. Caughey GE, Vitry AI, Ramsay EN, et al. Effect of a general practitioner management plan on health outcomes and hospitalisations in older patients with diabetes. *Internal medicine journal* 2016 doi: 10.1111/imj.13286 [published Online First: 2016/10/09]
49. Ha NT, Harris M, Preen D, et al. Identifying patterns of general practitioner service utilisation and their relationship with potentially preventable hospitalisations in people with diabetes: The utility of a cluster analysis approach. *Diabetes Research and Clinical Practice* 2018 doi: https://doi.org/10.1016/j.diabres.2018.01.027

Appendix F Survey Questionnaire

Survey on temporal protective effect of a GP consultation

Dear General Practitioner,

Thank you for considering completing this survey.

I am a PhD student at Curtin University undertaking a project evaluating the impact of continuity of primary care in the management of diabetes.

I am currently conducting a very brief anonymous survey to help me better understand the optimal use of general practitioners' services for people with diabetes.

My study hypothesis is that a GP consultation may have a time limited/temporal protective effect against the risk of potentially avoidable hospitalisations and maintenance of wellbeing for people with diabetes.

This survey:

- Is about seeking your views on this hypothesised "time limited/temporal protective effect" for people with diabetes
- Has been approved by the Curtin University Human Research Ethics Committee (Approval number RD-42-14)
- Should take less than 5 minutes to complete
- Is voluntary and anonymous
- For more information, email the researchers at thininh.ha@postgrad.curtin.edu.au or moorin@curtin.edu.au or call Asso. Prof. Rachael Moorin at School of Public Health, Curtin University, on +61 8 9266 3536

I really appreciate your input.

Please select YES on the box bellow to indicate you agree to do the survey.

Kind regards,
Ninh Ha
PhD candidate, Curtin University
thininh.ha@postgrad.curtin.edu.au

□ **Yes, I agree to participate the survey.**

For each question, please select the option that best applies to you

Q1. How many years have you been practicing as a GP? _____ (years)

Q2. How often do you see patients with diabetes in last two years?

- ○ Very day (1)
- ○ Every week (2)
- ○ Every month (3)
- ○ Rarely (4)
- ○ Never (5)

Q3. Do you discuss a care plan with patients with diabetes?

- ○ Always (1)
- ○ Very often (2)
- ○ Sometimes (3)
- ○ Rarely (4)
- ○ Never (5)

Q4. How would you rate the importance of proactively planning follow-up care for patients with diabetes in maintaining their health and well-being?

- ○ Extremely important (1)
- ○ Very important (2)
- ○ Moderately important (3)
- ○ Slightly important (4)
- ○ Low importance (5)
- ○ Not at all important (6)

We define "time limited/ temporal protective effect" of a GP consultation as "the amount of time following a GP consultation that patients with diabetes would be expected to have a minimal risk of hospitalisations or developing complications of diabetes due to preventive effect of the GP consultation "

Q5. Do you believe that GP consultation would have **"time limited/ temporal protective effect"** on reducing potentially preventable hospitalisation for people with diabetes?

- ○ Very true of what I believe (1)
- ○ True of what I believe (2)
- ○ Somewhat true of what I believe (3)
- ○ Somewhat untrue of what I believe (4)
- ○ Untrue of what I believe (5)
- ○ No what I believe (6)
- ○ Any further comments on the "temporal protective effect" of a GP consultation? (7)

Q6. How important do you think the following known diabetes complications are in predicting the **"time/limited temporal protective effect**" of a GP?

	Extremely important (1)	Very important (2)	Moderate important (3)	Slightly important (4)	Low important (5)	Not at all important (6)
Existing of macrovascular complications (such as coronary artery disease, peripheral arterial disease or stroke) (1)	○	○	○	○	○	○
Existing of microvascular complications (such as diabetic nephropathy, neuropathy, or retinopathy) (2)	○	○	○	○	○	○
High number of diabetic complications (3)	○	○	○	○	○	○

Q7. Following is a list of other potential factors which may have an influence on predicting the length of **"time limited/ temporal protective effect"** of a GP care. How do you rate the level of influence of each factor?

	Extremely influence (1)	Very influence (2)	Moderately influence (3)	Slightly influence (4)	Low influence (5)	Not at all influence (6)
High number of comorbidities (1)	○	○	○	○	○	○
Long duration of diabetes (2)	○	○	○	○	○	○
Age (3)	○	○	○	○	○	○
Gender (4)	○	○	○	○	○	○
Indigenous status (5)	○	○	○	○	○	○
Low social economic status (6)	○	○	○	○	○	○
Smoking (7)	○	○	○	○	○	○
Obesity (8)	○	○	○	○	○	○
Previous history of hospitalisations (9)	○	○	○	○	○	○
Others, please specify (10)	○	○	○	○	○	○

For each question, please select the option that best applies to you

It may be possible that the "time limited/ temporal protective effect" of a GP consultation exists, irrespective and independent of any other factors. In the following questions, we ask you to estimate how long you think this "temporal protective effect" would last based on the specified patient criteria

Q8. If the diabetic patient has **some sort of macrovascular complications (**such as coronary artery disease, peripheral arterial disease or stroke), how long do you think "**the time limited/temporal protective effect**" would be for the patient regardless of other patients 'characteristics?

- ○ 1 month or less (1)
- ○ 2 to 3 months (2)
- ○ 4 to 5 months (3)
- ○ 6 to 7 months (4)
- ○ 8 to 9 months (5)
- ○ 10 to 12 months (6)
- ○ others, please specify (7) _____

Q9. If the diabetic patient has **some sort of microvascular complications** (such as diabetic nephropathy, neuropathy, or retinopathy), how long do you think "**the time limited/temporal protective effect**" would be for the patient regardless of other patients 'characteristics and diabetic type?

- ○ 1 month or less (1)
- ○ 2 to 3 months (2)
- ○ 4 to 5 months (3)
- ○ 6 to 7 months (4)
- ○ 8 to 9 months (5)
- ○ 10 to 12 months (6)
- ○ Others, please specify (7) _____

Q10. If the diabetic patient has **NOT had** any sort of complications, how long do you think "**the time limited/temporal protective effect**" would be for the patient regardless of other patients 'characteristics and diabetic type?

- ○ 1 month or less (1)
- ○ 2 to 3 months (2)
- ○ 4 to 5 months (3)
- ○ 6 to 7 months (4)
- ○ 8 to 9 months (5)
- ○ 10 to 12 months (6)
- ○ Others, please specify (7) _____

Q11. If the diabetic patient has previously been diagnosed with **ONE or TWO** complications, how long do you think "**the time limited/temporal protective effect**" would be for the patient regardless of other patients 'characteristics and diabetic type?

- ○ 1 month or less (1)
- ○ 2 to 3 months (2)
- ○ 4 to 5 months (3)
- ○ 6 to 7 months (4)
- ○ 8 to 9 months (5)
- ○ 10 to 12 months (6)
- ○ Others, please specify (7) _____

Q12. If the diabetic patient has been diagnosed with **MULTIPLE** (more than 2) complications, how long do you think "**the time limited/temporal protective effect**" would be for the patient regardless of other patients 'characteristics and diabetic type?

- ○ 1 month or less (1)
- ○ 2 to 3 months (2)
- ○ 4 to 5 months (3)
- ○ 6 to 7 months (4)
- ○ 8 to 9 months (5)
- ○ 10 to 12 months (6)
- ○ Others, please specify (7) _____

Q13. If the patient has other **comorbidities**, how long do you think "**the time limited/temporal protective effect"** of the GP consultation would be regardless of other factors?

- ○ 1 month or less (1)
- ○ 2 to 3 months (2)
- ○ 4 to 5 months (3)
- ○ 6 to 7 months (4)
- ○ 8 to 9 months (5)
- ○ 10 to 12 months (6)
- ○ Others, please specify (7) _____

Q14. Would you be prepared for an in-depth interview regarding your opinion about "**the time limited/temporal protective effect** " of a GP consultation for people with diabetes?

- ○ Yes (1)
- ○ No (2)

Q15. If yes, please provide us with your phone number and your preferred time to contact.

Phone number (1) _____

Best time to contact (2) _____

Thank you very much for completing the survey

Appendix G Lists of Covariates

Variables	Definition & Categories	Available to use in each chapter
Age	Age was measured in years using information from the 45 and Up baseline survey and classified as 45–54, 55–64, 65–74, 75–84 or 85+ years	Chapters 4 to 7
Gender	Males and females	Chapters 4 to 7
Indigenous status	Indigenous status was indicated if the answer was Aboriginal, Torres Strait Islander or Aboriginal and Torres Strait Islander, and no, otherwise	Chapters 4 to 7
SEIFA	The Census specific Socio-Economic Indexes for Areas (SEIFA) Index of Relative Socioeconomic Disadvantage SEIFA was classified into five levels with 1 for most disadvantaged to 5 for least disadvantaged (141)	Chapters 4 to 7
ARIA	ARIA is the Remoteness Areas Structure within the Australian Statistical Geography Standard, classified into 5 groups: very remote, remote, moderate, accessible, and highly accessible (142)	Chapters 4 to 7
Annual household income	Annual pre-tax household income was classified in Australian dollars as <$20,000, $20,000–$39,999, $40,000–$69,999, ≥ $70,00 (249)	Chapter 7 only
Married status	Married status was classified as married if being married or living with partner and no, otherwise (224)	Chapter 7 only
Education	Education was classified as <secondary school, secondary school graduation, trade/apprenticeship/certificate/diploma, university graduate (249)	Chapter 7 only
Smoking status	Smoking status was classified into three levels (249) Never smokers: participants who answered 'No' to the question, 'Have you ever been a regular smoker?' Current smokers: those who answered 'Yes' to this question and 'Yes' to being a smoker now. Past smokers: those who indicated that they had ever been a regular smoker but were not a smoker now.	Chapter 7 only
Alcohol consumption	Weekly alcohol consumption was classified as None, 1–14, ≥15 alcoholic drinks/week (249)	Chapter 7 only

Variables	Definition & Categories	Available to use in each chapter
Physical activities	Physical activity was measured in the 45 and Up baseline survey using the Active Australian Survey (250). The total of time for walking, moderate and vigorous activities was calculated, with double weight for vigorous activities, and classified into 5 categories: sedentary, low active, sufficiently active, highly active and very highly active (224).	Chapter 7 only
BMI	Self-reported weight and height was used to calculate Body Mass Index (BMI) in kg/m^2. This was then classified into four groups: underweight (<18.50 kg/m^2), normal weight (18.50–24.99 kg/m^2), overweight (25.00–29.99 kg/m^2) and obese (≥30.00 kg/m^2) categories (224).	Chapter 7 only
Levels of limitation (SF-36)	Levels of limitation were measured using SF-36 and transformed into a 100 score scale. It was then classified into four categories including No (100), minor (90-99), moderate (60-89), severe (0-59) (226).	Chapter 7 only
Anxiety and depression	This was measured using the Kessler psychological distress scale. The scale was classified into 4 categories: low (score 0–15), moderate (16–21), high (22–29) and very high (30 or higher) (226).	Chapter 7 only
Social support	Social support was measured using the Duke Social Support subscale with a scale of 12 points (227).	Chapter 7 only
Number of self-reported comorbidities	The number of self-reported comorbidities was the sum of all self-reported conditions, including cancers, heart disease, high blood pressure, stroke, blood clot, asthma or hay fever, depression and anxiety, and Parkinson's disease.	Chapter 7 only
Number of comorbidities	The number of comorbidities was counted in the APDC using the Multipurpose Australian Comorbidity Scoring System (MACSS) with a five-year look-back period (143, 144).	Chapter 4 to 7
Diabetes complications	Diabetes complications were identified using ICD-10-AM codes in the APDC data and classified into three severity level groups: no complication, 1-2 complications and 3+ complications as used elsewhere (130, 139).	Chapter 4 to 7
Number of	The number of out of hospital specialist visits	Chapter 4 to 7

Variables	Definition & Categories	Available to use in each chapter
specialist visits	were identified using MBS claims data, counted in each financial year and then aggregated over a three-year period.	
Non-diabetes-related PPHs	The number of non-diabetes-related PPH were a count of any hospitalisations which were not classified as diabetes-related PPH in HMDS or APDC.	Chapter 4 to 7
Duration of diabetes	The duration of diabetes in years was counted from self-reported age, first date of diagnosis recorded in APDC, or incident diabetes-related PBS record, whichever came first, and classified as 1-5 years, 6-10 years and 11+ years	Chapter 4 to 7
Usual provider index	The usual provider index was measured using de-identified provider codes in MBS which is only available in the MBS dataset in NSW. UPC measured proportion of GP contacts within each financial year that was provided by the same providers (24, 31).	Chapter 7 only
Regularity of GP contacts	Regularity of GP contacts was calculated using the standard deviation of time interval between GP visits in each financial year as [1/(1+standard deviation)] for each individual, described in detail elsewhere (33-35).	Chapter 4 to 7

Appendix H Model selections

Multivariable analyses using a random-effect negative binomial model were conducted to assess covariates associated with diabetes-related PPH and formed the base model for processing the threshold effects model. Time-variant covariates such as BMI, asocial support and alcohol consumption, were collected only once at the baseline survey of the '45 and Up Study' between February 2006 and the end of 2009 (125). However, the study period in this thesis was chosen as the most contemporary period between 1/7/2009 and 30/6/2016. Thus, to facilitate convergence of the models, the models of further analyses excluded covariates that were highly time variant and/or not significantly associated with diabetes-related PPHs. Thus, covariates including household income, married status, smoking status, alcohol consumption, physical activities, BMI, anxiety and depression and social support were excluded. However, important covariates including education and ARIA were still included.

From the based models with key covariates selected above, the final model for threshold effects model also included Mundlak variables, (group means of time-varying variables including frequency of GP contact, regularity of GP contact and comorbidities) to allow for arbitrary correlation between observed and unobserved heterogeneity terms in the model (147, 148). A reduction in both AIC and BIC indicated a better model fit when including the Mundlak variables (presented as Model 2 in Appendix H2).

Appendix H 1. Factors associated with diabetes-related PPH in panel data

Characteristics	Diabetes-related PPH	
	Coef.	95%CI
Maximum time interval (month)	-0.005	(-0.02; 0.010)
Mean time interval (month)	0.03***	(0.02; 0.04)
Mean time interval last year (month)	-0.08***	(-0.10; -0.06)
Regularity of GP contacts	-0.3***	(-0.3; -0.3)
Regularity of GP contacts last year	0.1***	(0.1; 0.2)
Frequency of GP visits	0.05***	(0.04; 0.05)
Age groups		
45–59years	Ref.	
60–74 years	0.4***	(0.3; 0.4)
75+ years old	0.6***	(0.5; 0.6)
Gender		
Male	Ref.	
Female	-0.2***	(-0.3; -0.2)
Indigenous status		
Not Indigenous	Ref.	
Indigenous	0.3***	(0.1; 0.4)
SEIFA		
Highest disadvantage	Ref.	
High disadvantage	-0.05*	(-0.10; -0.010)
Moderate	-0.05*	(-0.1; -0.002)
Less disadvantage	-0.09***	(-0.1; -0.04)
Least disadvantage	-0.06	(-0.1; 0.0009)
ARIA		
Very remote	Ref.	
Remote	0.1	(-0.4; 0.6)
Moderate	-0.2	(-0.7; 0.3)
Accessible	-0.2	(-0.7; 0.2)
Highly accessible	-0.3	(-0.8; 0.2)
Education		
Below secondary school	Ref.	
Secondary school	-0.009	(-0.06; 0.04)
Higher school/uni/tafe	-0.02	(-0.07; 0.02)
Self-reported number of multimorbidities	0.03***	(0.02; 0.04)
Level of limitation	0.1***	(0.10; 0.1)
Number of comorbidities (MACSS)	0.05***	(0.05; 0.06)
Usual Provider Index	0.07	(-0.004; 0.1)
Number of specialist visit	0.009***	(0.008; 0.01)
Diabetes-related PPH at the baseline year	0.4***	(0.3; 0.4)
Non-diabetes-related at the baseline year	0.05**	(0.02; 0.08)
Household income	0.00000007	(-0.0000003; 0.0000005)
Married status	-0.00000004	(-0.000002; 0.000002)

Smoking status	-0.0000005	(-0.000003; 0.000002)
Alcohol consumption	-0.000000009	(-0.0000009; 0.0000009)
Physical activities	-0.03***	(-0.04; -0.02)
BMI	0.0000003	(-0.0000003; 0.0000009)
Anxiety and depression	0.001	(-0.02; 0.02)
Social support	-0.003	(-0.01; 0.004)
AIC	143318.7	
BIC	143707.4	

*Notes: * if p-values<0.05; ** if p-values<0.01; *** if p-values<0.001*

Appendix H 2. Candidate models for processing threshold effect models

Characteristics	Model 1		Model 2	
	Coef.	95%CI	Coef.	95%CI
Maximum time interval (month)	-0.005	(-0.02; 0.009)	0.002	(-0.01; 0.02)
Mean time interval (month)	0.03***	(0.02; 0.04)	0.02***	(0.009; 0.03)
Mean time interval last year (month)	-0.08***	(-0.10; -0.06)	-0.009	(-0.03; 0.01)
Regularity of GP contacts	-0.3***	(-0.3; -0.3)	-0.3***	(-0.3; -0.2)
Regularity of GP contacts last year	0.1***	(0.1; 0.2)	0.2***	(0.2; 0.2)
Frequency of GP visits	0.05***	(0.04; 0.05)	0.04***	(0.04; 0.05)
Age groups				
45-59years	0	(0; 0)	0	(0; 0)
60-74 years	0.4***	(0.3; 0.4)	0.3***	(0.3; 0.4)
75+ years old	0.6***	(0.5; 0.6)	0.5***	(0.5; 0.6)
Gender				
Male	0	(0; 0)	0	(0; 0)
Female	-0.2***	(-0.3; -0.2)	-0.2***	(-0.2; -0.2)
Indigenous status				
Not Indigenous	0	(0; 0)	0	(0; 0)
Indigenous	0.3***	(0.1; 0.4)	0.2***	(0.1; 0.4)
SEIFA				
Highest disadvantage	0	(0; 0)	0	(0; 0)
High disadvantage	-0.06*	(-0.1; -0.01)	-0.05*	(-0.10; -0.007)
Moderate	-0.05*	(-0.1; -0.005)	-0.05*	(-0.1; -0.003)
Less disadvantage	-0.10***	(-0.2; -0.04)	-0.1***	(-0.2; -0.05)
Least disadvantage	-0.06*	(-0.1; -0.004)	-0.1***	(-0.2; -0.06)
ARIA				
Very remote	0	(0; 0)	0	(0; 0)
Remote	0.1	(-0.4; 0.6)	0.1	(-0.4; 0.6)
Moderate	-0.2	(-0.7; 0.3)	-0.2	(-0.7; 0.3)
Accessible	-0.2	(-0.7; 0.2)	-0.2	(-0.7; 0.2)
Highly accessible	-0.3	(-0.8; 0.2)	-0.3	(-0.8; 0.2)
Education				
Below secondary school	0	(0; 0)	0	(0; 0)
Secondary school	-0.01	(-0.06; 0.04)	0.0005	(-0.05; 0.05)
Higher school/uni/tafe	-0.03	(-0.08; 0.01)	-0.02	(-0.07; 0.02)
Self-reported number of multimorbidities	0.03***	(0.02; 0.04)	0.002	(-0.009; 0.01)

Level of limitation	0.1***	(0.1; 0.1)	0.07***	(0.06; 0.09)
Number of comorbidities (MACSS)	0.05***	(0.05; 0.06)	-0.08***	(-0.09; -0.07)
Usual Provider Index	0.07	(-0.004; 0.1)	0.1***	(0.05; 0.2)
Number of specialist visits	0.009***	(0.008; 0.01)	0.010***	(0.008; 0.01)
Diabetes-related PPH at the baseline year	0.4***	(0.3; 0.4)	0.2***	(0.2; 0.3)
Non-diabetes-related at the baseline year	0.05**	(0.02; 0.08)	0.03	(-0.002; 0.06)
Group mean frequency of GP contacts			-0.02**	(-0.04; -0.007)
Group mean of regularity of GP contacts			-0.2***	(-0.2; -0.1)
Group mean of comorbidities			0.2***	(0.2; 0.2)
AIC	143328.1		141193.2	
BIC	143637.1		141532.1	

Appendix I Association between the Cover Index and number of diabetes-related PPH and LOS

Characteristics	Diabetes-related PPH				LOS diabetes-related PPH			
	NB		Zero-inflated NB		NB		Zero-inflated NB	
	Coef.	95%CI	Coef.	95%CI	Coef.	95%CI	Coef.	95%CI
Cover index	-2.3***	(-2.6 ; -2.0)	-2.3***	(-2.6 ; -2.0)	-5.5***	(-5.9 ; -5.1)	-5.5***	(-5.9 ; -5.1)
Cover index in the last period	1.0***	(0.7 ; 1.3)	1.0***	(0.7 ; 1.3)	2.0***	(1.5 ; 2.4)	2.0***	(1.5 ; 2.4)
Gender (Females vs. males)	-0.1***	(-0.2 ; -0.09)	-0.1***	(-0.2 ; -0.09)	-0.4***	(-0.5 ; -0.3)	-0.4***	(-0.5 ; -0.3)
Age groups								
45–54 years	-0.2**	(-0.4 ; -0.07)	-0.2**	(-0.4 ; -0.07)	-1.2***	(-1.4 ; -0.9)	-1.2***	(-1.4 ; -0.9)
55–64 years	-0.05	(-0.2 ; 0.10)	-0.05	(-0.2 ; 0.10)	-1.2***	(-1.5 ; -1.0)	-1.2***	(-1.5 ; -1.0)
65–74 years	0.2**	(0.08 ; 0.4)	0.2**	(0.08 ; 0.4)	-0.9***	(-1.2 ; -0.7)	-0.9***	(-1.2 ; -0.7)
75–84 years	0.2**	(0.10 ; 0.4)	0.2**	(0.10 ; 0.4)	-0.5***	(-0.8 ; -0.3)	-0.5***	(-0.8 ; -0.3)
85+ years	Reference		Reference		Reference		Reference	
Area								
Very remote	0.1	(-0.6 ; 0.8)	0.1	(-0.6 ; 0.8)	1.6**	(0.5 ; 2.6)	1.6**	(0.5 ; 2.6)
Remote	0.2	(-0.05 ; 0.5)	0.2	(-0.05 ; 0.5)	3.2***	(2.7 ; 3.7)	3.2***	(2.7 ; 3.7)
Moderate	0.09*	(0.004 ; 0.2)	0.09*	(0.004 ; 0.2)	0.2**	(0.07 ; 0.3)	0.2**	(0.07 ; 0.3)
Accessible	0.02	(-0.04 ; 0.08)	0.02	(-0.04 ; 0.08)	0.008	(-0.08 ; 0.10)	0.008	(-0.08 ; 0.10)
Highly accessible	Reference		Reference		Reference		Reference	
SEIFA								
Highest disadvantage	0.09*	(0.0004 ; 0.2)	0.09*	(0.0004 ; 0.2)	0.3***	(0.1 ; 0.4)	0.3***	(0.1 ; 0.4)
High disadvantage	0.03	(-0.06 ; 0.1)	0.03	(-0.06 ; 0.1)	0.2**	(0.09 ; 0.4)	0.2**	(0.09 ; 0.4)
Moderate	0.04	(-0.06 ; 0.1)	0.04	(-0.06 ; 0.1)	0.1	(-0.01 ; 0.3)	0.1	(-0.01 ; 0.3)
Less disadvantage	0.002	(-0.10 ; 0.1)	0.002	(-0.10 ; 0.1)	0.3***	(0.1 ; 0.4)	0.3***	(0.1 ; 0.4)
Least disadvantage	Reference		Reference		Reference		Reference	
Indigenous								

No	-0.2*	(-0.4 ; -0.004)	-0.2*	(-0.4 ; -0.004)	-0.6***	(-1.0 ; -0.3)	-0.6***	(-1.0 ; -0.3)
Yes	Reference		Reference		Reference		Reference	
Education								
Below secondary school	0.004	(-0.07 ; 0.08)	0.004	(-0.07 ; 0.08)	-0.01	(-0.1 ; 0.1)	-0.01	(-0.1 ; 0.1)
Secondary school	0.03	(-0.03 ; 0.10)	0.03	(-0.03 ; 0.10)	0.1*	(0.006 ; 0.2)	0.1*	(0.006 ; 0.2)
Higher school/Uni/Tafe	Reference		Reference		Reference		Reference	
Levels of limitation								
No	-0.2***	(-0.3 ; -0.07)	-0.2***	(-0.3 ; -0.07)	-0.4***	(-0.5 ; -0.2)	-0.4***	(-0.5 ; -0.2)
Minor	-0.1**	(-0.2 ; -0.04)	-0.1**	(-0.2 ; -0.04)	-0.5***	(-0.6 ; -0.4)	-0.5***	(-0.6 ; -0.4)
Moderate	-0.02	(-0.09 ; 0.04)	-0.02	(-0.09 ; 0.04)	-0.2***	(-0.3 ; -0.08)	-0.2***	(-0.3 ; -0.08)
Severe	Reference		Reference		Reference		Reference	
Duration of diabetes								
1-5 years	-0.2***	(-0.2 ; -0.1)	-0.2***	(-0.2 ; -0.1)	-0.3***	(-0.4 ; -0.2)	-0.3***	(-0.4 ; -0.2)
6-10 years	-0.1***	(-0.2 ; -0.06)	-0.1***	(-0.2 ; -0.06)	-0.08	(-0.2 ; 0.03)	-0.08	(-0.2 ; 0.03)
11+ years	Reference		Reference		Reference		Reference	
Self-reported number of multimorbidities	0.01	(-0.004 ; 0.03)	0.01	(-0.004 ; 0.03)	-0.03	(-0.06 ; 0.0002)	-0.03	(-0.06 ; 0.0002)
Complication level baseline 2009	-0.4***	(-0.5 ; -0.4)	-0.4***	(-0.5 ; -0.4)	-0.4***	(-0.5 ; -0.3)	-0.4***	(-0.5 ; -0.3)
Complication level baseline 2012	0.7***	(0.6 ; 0.8)	0.7***	(0.6 ; 0.8)	0.8***	(0.7 ; 0.9)	0.8***	(0.7 ; 0.9)
Comorbidities baseline 2009	-0.003	(-0.02 ; 0.010)	-0.003	(-0.02 ; 0.010)	-0.02	(-0.04 ; 0.0010)	-0.02	(-0.04 ; 0.0010)
comorbidities baseline 2012	0.05***	(0.04 ; 0.06)	0.05***	(0.04 ; 0.06)	0.08***	(0.06 ; 0.10)	0.08***	(0.06 ; 0.10)
UPC index last 3 year period	-0.1	(-0.3 ; 0.08)	-0.1	(-0.3 ; 0.08)	-0.08	(-0.4 ; 0.2)	-0.08	(-0.4 ; 0.2)
UPC index	0.5***	(0.3 ; 0.7)	0.5***	(0.3 ; 0.7)	1.3***	(1.0 ; 1.6)	1.3***	(1.0 ; 1.6)
Number of specialist visits last 3 year period	-0.01***	(-0.01 ; -0.008)	-0.01***	(-0.01 ; -0.008)	-0.02***	(-0.02 ; -0.01)	-0.02***	(-0.02 ; -0.01)
Number of specialist visits	0.02***	(0.02 ; 0.02)	0.02***	(0.02 ; 0.02)	0.03***	(0.03 ; 0.04)	0.03***	(0.03 ; 0.04)

Number of GP visits	0.03***	(0.02 ; 0.03)	0.03***	(0.02 ; 0.03)	-0.01**	(-0.03 ; -0.004)	-0.01**	(-0.03 ; -0.004)
Number of GP visits last 3-year period	-0.02***	(-0.02 ; -0.008)	-0.02***	(-0.02 ; -0.008)	-0.01	(-0.02 ; 0.0006)	-0.01	(-0.02 ; 0.0006)
Regularity of GP visits last 3-year period	-0.9***	(-1.2 ; -0.5)	-0.9***	(-1.2 ; -0.5)	-1.5***	(-2.1 ; -1.0)	-1.5***	(-2.1 ; -1.0)
Regularity of GP visits	1.7***	(1.4 ; 2.0)	1.7***	(1.4 ; 2.0)	5.5***	(4.9 ; 6.0)	5.5***	(4.9 ; 6.0)
Number of PPH last 3-year period	0.1***	(0.09 ; 0.1)	0.1***	(0.09 ; 0.1)	0.2***	(0.1 ; 0.2)	0.2***	(0.1 ; 0.2)
Inflate constant			-16.7	(-793.6 ; 760.3)			-33.2	(-1825200.1 ; 1825133.6)
AIC	35350.9		35352.9		56357.6		56359.6	
BIC	35662.8		35672.7		56669.5		56679.5	
Vuong test	z= -0.01	p-values = 0.502			z=8.86	p-values <0.001		

*Note: * indicate p-values with * if p-value <0.05; ** if p-value <0.01; *** if p-value <0.001*

Appendix J Association between the Cover Index and number of unplanned diabetes-related PPHs and LOS

Characteristics	Unplanned diabetes-related PPH				LOS unplanned diabetes-related PPH			
	NB		Zero-inflated NB		NB		Zero-inflated NB	
	Coef.	95%CI	Coef.	95%CI	Coef.	95%CI	Coef.	95%CI
Cover Index	-1.8***	(-2.3 ; -1.4)	-1.8***	(-2.3 ; -1.4)	-3.9***	(-4.7 ; -3.2)	-3.9***	(-4.7 ; -3.2)
Cover Index in the last period	0.4	(-0.06 ; 0.9)	0.4	(-0.06 ; 0.9)	1.1**	(0.3 ; 1.9)	1.1**	(0.3 ; 1.9)
Gender (females vs. males)	-0.2***	(-0.3 ; -0.1)	-0.2***	(-0.3 ; -0.1)	-0.5***	(-0.6 ; -0.4)	-0.5***	(-0.6 ; -0.4)
Age groups								
45–54 years	-0.3*	(-0.5 ; -0.06)	-0.3*	(-0.5 ; -0.06)	-0.7**	(-1.1 ; -0.3)	-0.7**	(-1.1 ; -0.3)
55–64 years	-0.6***	(-0.8 ; -0.4)	-0.6***	(-0.8 ; -0.4)	-1.0***	(-1.4 ; -0.6)	-1.0***	(-1.4 ; -0.6)
65–74 years	-0.5***	(-0.7 ; -0.3)	-0.5***	(-0.7 ; -0.3)	-0.6**	(-1.0 ; -0.2)	-0.6**	(-1.0 ; -0.2)
75–84 years	-0.2	(-0.4 ; 0.05)	-0.2	(-0.4 ; 0.05)	0.04	(-0.3 ; 0.4)	0.04	(-0.3 ; 0.4)
85+ years	Reference		Reference		Reference		Reference	
Aria								
Very remote	0.3	(-0.7 ; 1.4)	0.3	(-0.7 ; 1.4)	-0.7	(-2.6 ; 1.1)	-0.7	(-2.6 ; 1.1)
Remote	0.3	(-0.1 ; 0.7)	0.3	(-0.1 ; 0.7)	1.8***	(1.0 ; 2.6)	1.8***	(1.0 ; 2.6)
Moderate	0.04	(-0.1 ; 0.2)	0.04	(-0.1 ; 0.2)	0.3*	(0.06 ; 0.5)	0.3*	(0.06 ; 0.5)
Accessible	-0.02	(-0.1 ; 0.08)	-0.02	(-0.1 ; 0.08)	0.08	(-0.08 ; 0.2)	0.08	(-0.08 ; 0.2)
Highly accessible	Reference		Reference		Reference		Reference	
SEIFA								
Highest disadvantage	0.5***	(0.3 ; 0.6)	0.5***	(0.3 ; 0.6)	0.6***	(0.4 ; 0.8)	0.6***	(0.4 ; 0.8)
High disadvantage	0.3***	(0.2 ; 0.5)	0.3***	(0.2 ; 0.5)	0.4**	(0.1 ; 0.6)	0.4**	(0.1 ; 0.6)
Moderate	0.3**	(0.1 ; 0.4)	0.3**	(0.1 ; 0.4)	0.4**	(0.1 ; 0.6)	0.4**	(0.1 ; 0.6)
Less disadvantage	0.1	(-0.04 ; 0.3)	0.1	(-0.04 ; 0.3)	0.4***	(0.2 ; 0.7)	0.4***	(0.2 ; 0.7)
Least disadvantage	Reference		Reference		Reference		Reference	

Indigenous								
No	-0.3*	(-0.6 ; -0.002)	-0.3*	(-0.6 ; -0.002)	-0.9**	(-1.5 ; -0.3)	-0.9**	(-1.5 ; -0.3)
Yes	Reference		Reference		Reference		Reference	
Education								
Below secondary school	0.05	(-0.06 ; 0.2)	0.05	(-0.06 ; 0.2)	0.2	(-0.04 ; 0.3)	0.2	(-0.04 ; 0.3)
Secondary school	0.07	(-0.04 ; 0.2)	0.07	(-0.04 ; 0.2)	0.2*	(0.05 ; 0.4)	0.2*	(0.05 ; 0.4)
Higher school/Uni/Tafe	Reference		Reference		Reference		Reference	
Levels of limitation								
No	-0.4***	(-0.6 ; -0.3)	-0.4***	(-0.6 ; -0.3)	-0.6***	(-0.9 ; -0.4)	-0.6***	(-0.9 ; -0.4)
Minor	-0.3***	(-0.5 ; -0.2)	-0.3***	(-0.5 ; -0.2)	-0.6***	(-0.8 ; -0.4)	-0.6***	(-0.8 ; -0.4)
Moderate	-0.1*	(-0.2 ; -0.03)	-0.1*	(-0.2 ; -0.03)	-0.3**	(-0.5 ; -0.10)	-0.3**	(-0.5 ; -0.10)
Severe	Reference		Reference		Reference		Reference	
Duration of diabetes								
1–5 years	-0.2***	(-0.3 ; -0.1)	-0.2***	(-0.3 ; -0.1)	-0.4***	(-0.5 ; -0.2)	-0.4***	(-0.5 ; -0.2)
6–10 years	-0.1**	(-0.2 ; -0.04)	-0.1**	(-0.2 ; -0.04)	-0.2*	(-0.4 ; -0.03)	-0.2*	(-0.4 ; -0.03)
11+ years	Reference		Reference		Reference		Reference	
Self-reported number of multimorbidities	0.005	(-0.02 ; 0.04)	0.005	(-0.02 ; 0.04)	-0.07**	(-0.1 ; -0.02)	-0.07**	(-0.1 ; -0.02)
Complication level baseline 2009	-0.2***	(-0.3 ; -0.1)	-0.2***	(-0.3 ; -0.1)	-0.3***	(-0.5 ; -0.1)	-0.3***	(-0.5 ; -0.1)
Complication level baseline 2012	0.7***	(0.6 ; 0.8)	0.7***	(0.6 ; 0.8)	0.9***	(0.7 ; 1.0)	0.9***	(0.7 ; 1.0)
Comorbidities baseline 2009	-0.01	(-0.03 ; 0.009)	-0.01	(-0.03 ; 0.009)	-0.02	(-0.05 ; 0.01)	-0.02	(-0.05 ; 0.01)
comorbidities baseline 2012	0.08***	(0.07 ; 0.1)	0.08***	(0.07 ; 0.1)	0.1***	(0.08 ; 0.1)	0.1***	(0.08 ; 0.1)
UPC index last 3-year period	0.01	(-0.3 ; 0.3)	0.01	(-0.3 ; 0.3)	-0.08	(-0.5 ; 0.4)	-0.08	(-0.5 ; 0.4)
UPC index	0.1	(-0.2 ; 0.4)	0.1	(-0.2 ; 0.4)	0.8***	(0.4 ; 1.3)	0.8***	(0.4 ; 1.3)
Number of specialist visits last 3-year period	-0.01***	(-0.02 ; -0.008)	-0.01***	(-0.02 ; -0.008)	-0.02***	(-0.03 ; -0.02)	-0.02***	(-0.03 ; -0.02)
Number of specialist visits	0.02***	(0.01 ; 0.02)	0.02***	(0.01 ; 0.02)	0.03***	(0.03 ; 0.04)	0.03***	(0.03 ; 0.04)

Number of GP visits	0.04***	(0.03 ; 0.05)	0.04***	(0.03 ; 0.05)	0.01	(-0.005 ; 0.03)	0.01	(-0.005 ; 0.03)
Number of GP visits last 3-year period	-0.02***	(-0.03 ; -0.01)	-0.02***	(-0.03 ; -0.01)	-0.01	(-0.03 ; 0.006)	-0.01	(-0.03 ; 0.006)
Regularity of GP visits last 3-year period	-0.7**	(-1.3 ; -0.2)	-0.7**	(-1.3 ; -0.2)	-0.8	(-1.7 ; 0.09)	-0.8	(-1.7 ; 0.09)
Regularity of GP visits	2.3***	(1.8 ; 2.8)	2.3***	(1.8 ; 2.8)	3.7***	(2.8 ; 4.6)	3.7***	(2.8 ; 4.6)
Number of unplanned PPH last 3-year period	0.4***	(0.4 ; 0.5)	0.4***	(0.4 ; 0.5)	0.4***	(0.3 ; 0.6)	0.4***	(0.3 ; 0.6)
Inflate constant			-24.8	(-70377.6 ; 70328.1)			-15.7	(-1457.8 ; 1426.4)
AIC	16711.1		16713.1		30861.4		30863.4	
BIC	17022.9		17032.9		31173.3		31183.3	
Vuong test	z=-0.00	p-values=0.5			z= -0.17	p-values=0.56		

*Note: * indicate p-values with * if p-value <0.05; ** if p-value <0.01; *** if p-value <0.001*

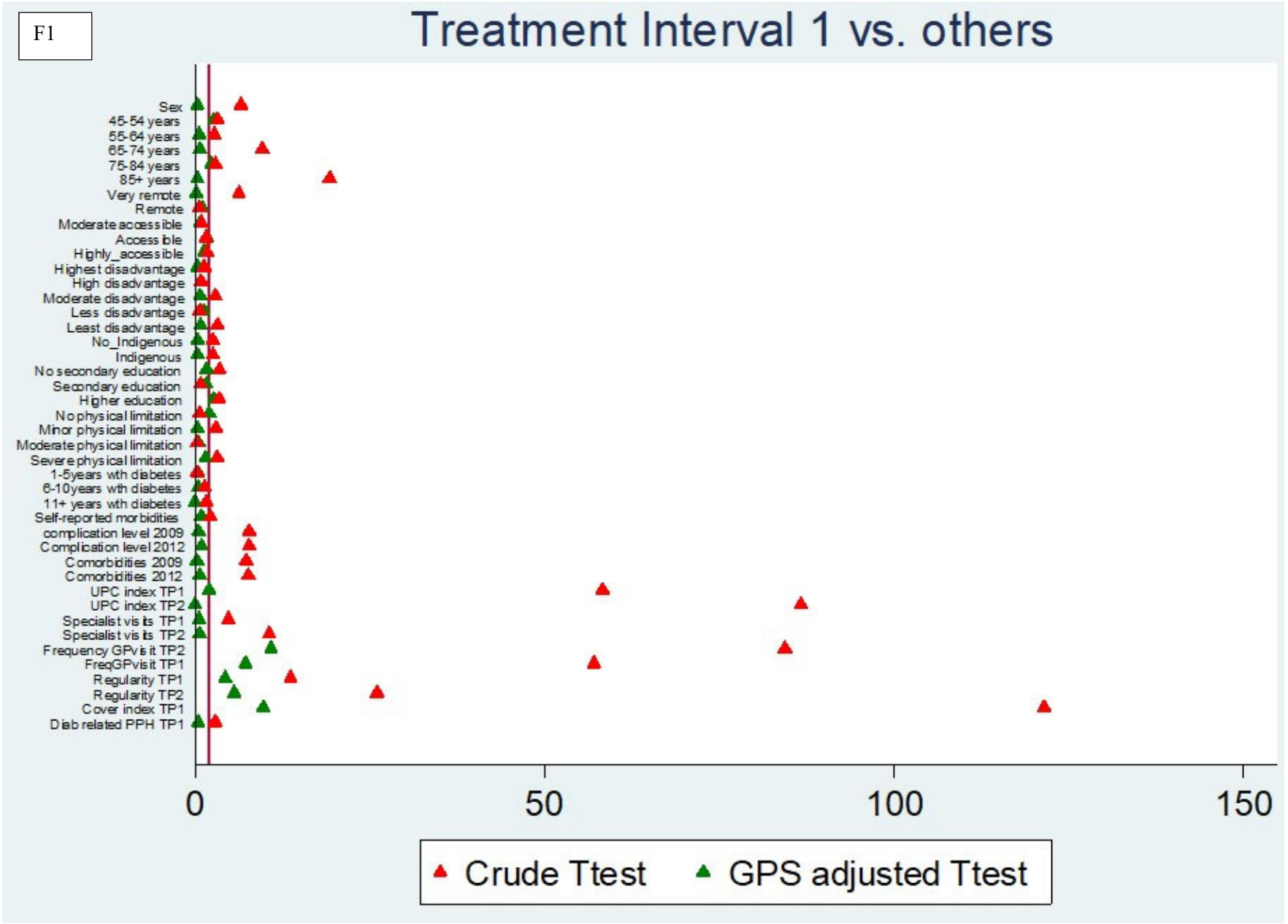
Appendix K Covariate balance between treatment intervals

Note:

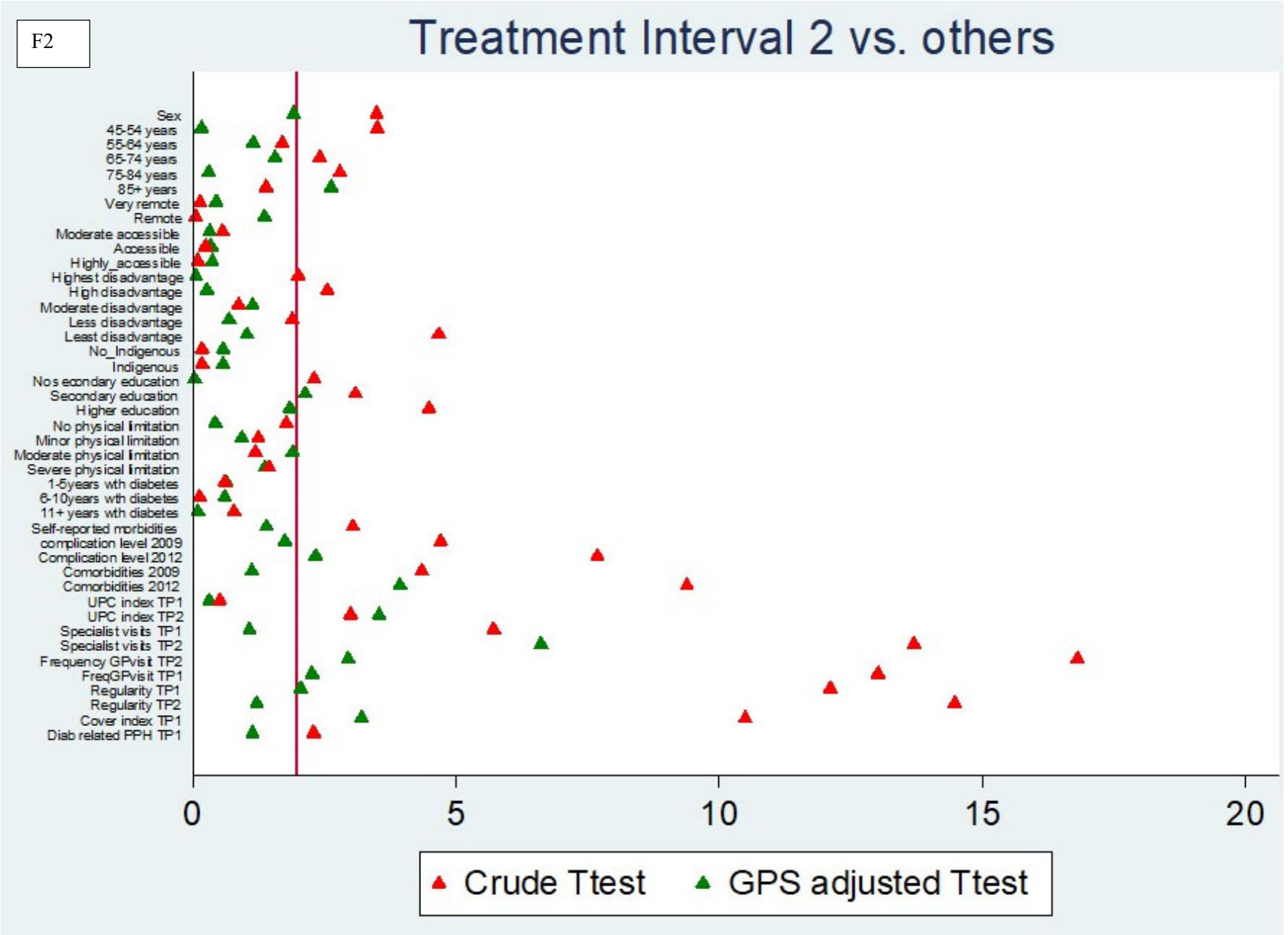
F1- F4 present covariate balance between treatment intervals using T-test with and without adjusted for generalised propensity score

F5- F8 present covariate balance between treatment intervals using standardised mean difference with and without adjusted for generalised propensity score

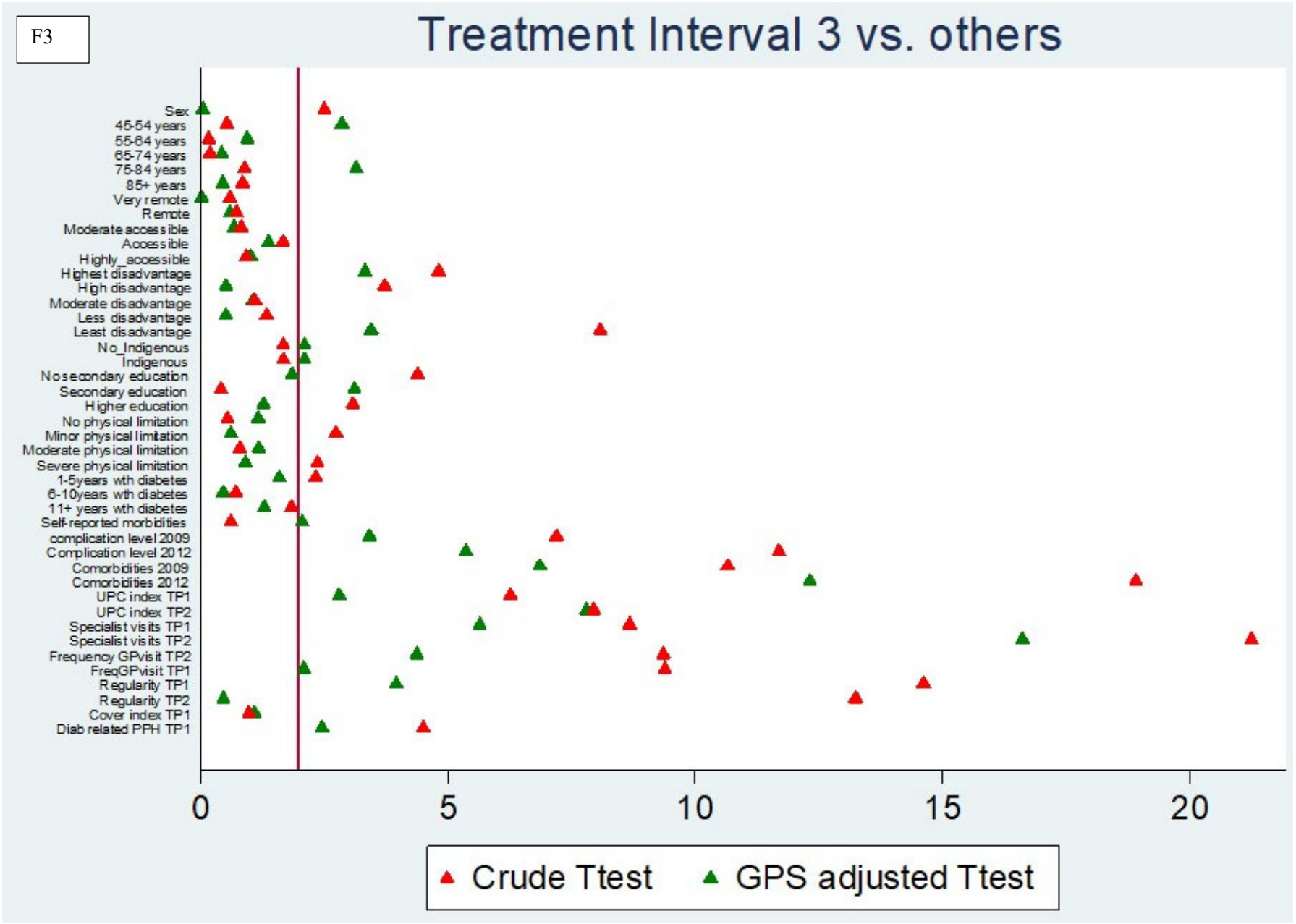
F1


Treatment Interval 1 vs. others
Sex
45-54 years
55-64 years
65-74 years
75-84 years
85+ years
Very remote
Remote
Moderate accessible
Accessible
Highly_accessible
Highest disadvantage
High disadvantage
Moderate disadvantage
Less disadvantage
Least disadvantage
No_Indigenous
Indigenous
No secondary education
Secondary education
Higher education
No physical limitation
Minor physical limitation
Moderate physical limitation
Severe physical limitation
1-5years wth diabetes
6-10years wth diabetes
11+ years wth diabetes
Self-reported morbidities
complication level 2009
Complication level 2012
Comorbidities 2009
Comorbidities 2012
UPC index TP1
UPC index TP2
Specialist visits TP1
Specialist visits TP2
Frequency GPvisit TP2
FreqGPvisit TP1
Regularity TP1
Regularity TP2
Cover index TP1
Diab related PPH TP1
0
50
100
150
Crude Ttest
GPS adjusted Ttest

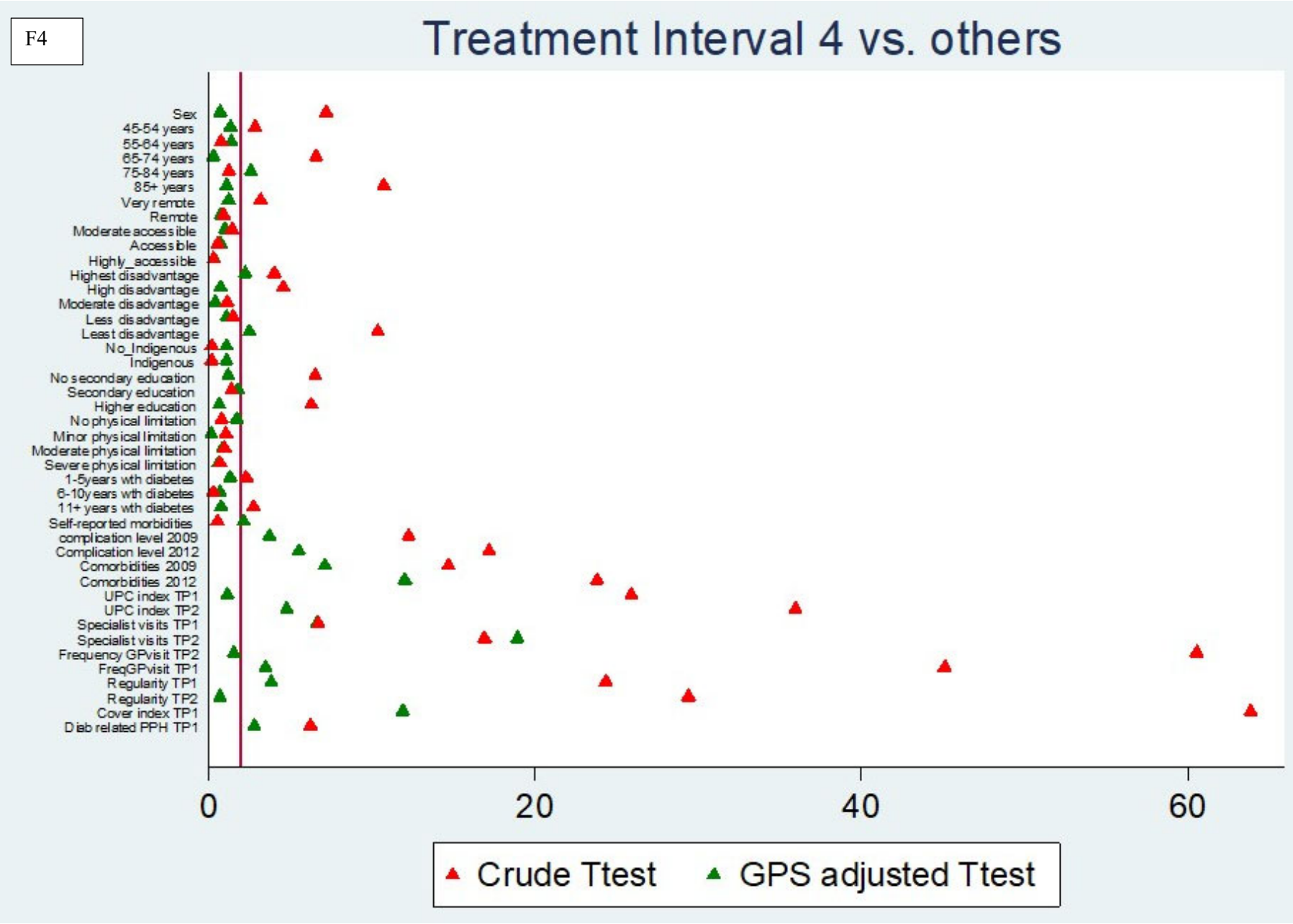
F2


Treatment Interval 2 vs. others
Sex
45-54 years
55-64 years
65-74 years
75-84 years
85+ years
Very remote
Remote
Moderate accessible
Accessible
Highly_accessible
Highest disadvantage
High disadvantage
Moderate disadvantage
Less disadvantage
Least disadvantage
No_Indigenous
Indigenous
Nos econdary education
Secondary education
Higher education
No physical limitation
Minor physical limitation
Moderate physical limitation
Severe physical limitation
1-5years wth diabetes
6-10years wth diabetes
11+ years wth diabetes
Self-reported morbidities
complication level 2009
Complication level 2012
Comorbidities 2009
Comorbidities 2012
UPC index TP1
UPC index TP2
Specialist visits TP1
Specialist visits TP2
Frequency GPvisit TP2
FreqGPvisit TP1
Regularity TP1
Regularity TP2
Cover index TP1
Disb related PPH TP1
0
5
10
15
20
Crude Ttest
GPS adjusted Ttest

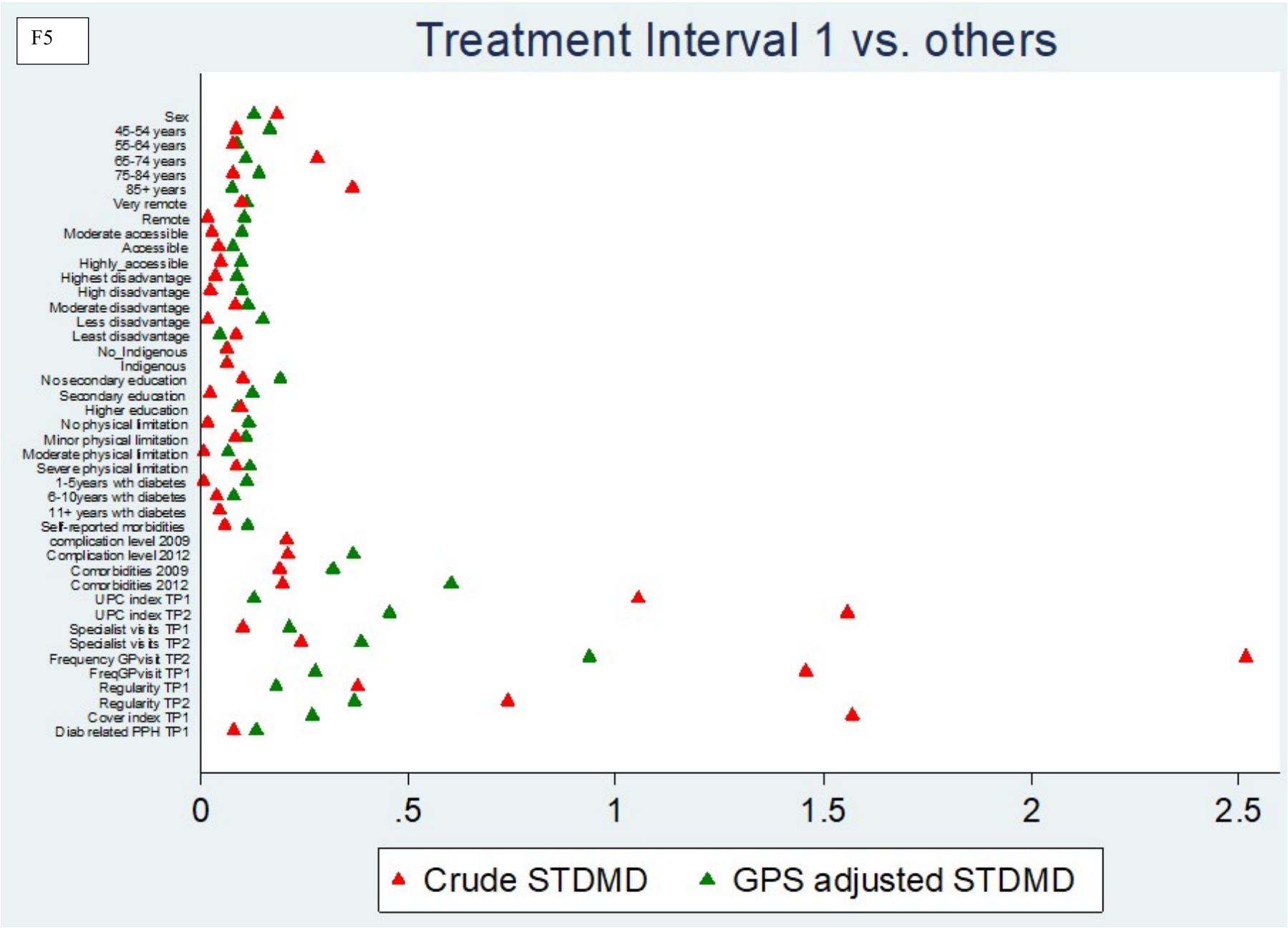
F3


Treatment Interval 3 vs. others
Sex
45-54 years
55-64 years
65-74 years
75-84 years
85+ years
Very remote
Remote
Moderate accessible
Accessible
Highly_accessible
Highest disadvantage
High disadvantage
Moderate disadvantage
Less disadvantage
Least disadvantage
No_Indigenous
Indigenous
No secondary education
Secondary education
Higher education
No physical limitation
Minor physical limitation
Moderate physical limitation
Severe physical limitation
1-5years wth diabetes
6-10years wth diabetes
11+ years wth diabetes
Self-reported morbidities
complication level 2009
Complication level 2012
Comorbidities 2009
Comorbidities 2012
UPC index TP1
UPC index TP2
Specialist visits TP1
Specialist visits TP2
Frequency GPvisit TP2
FreqGPvisit TP1
Regularity TP1
Regularity TP2
Cover index TP1
Diab related PPH TP1
0
5
10
15
20
Crude Ttest
GPS adjusted Ttest

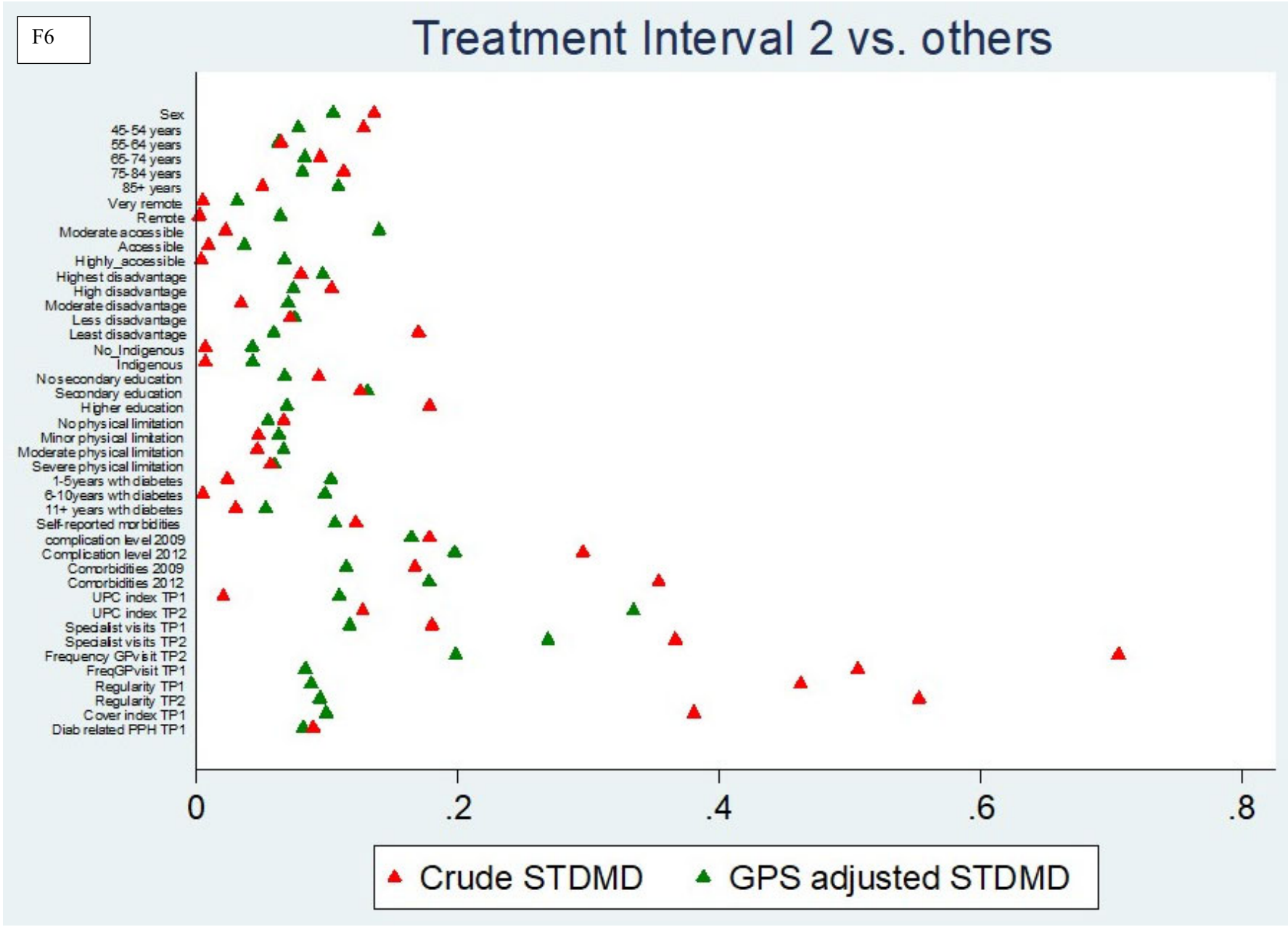
F4


Treatment Interval 4 vs. others
Sex
45-54 years
55-64 years
65-74 years
75-84 years
85+ years
Very remote
Remote
Moderate accessible
Accessible
Highly_accessible
Highest disadvantage
High disadvantage
Moderate disadvantage
Less disadvantage
Least disadvantage
No_Indigenous
Indigenous
No secondary education
Secondary education
Higher education
No physical limitation
Minor physical limitation
Moderate physical limitation
Severe physical limitation
1-5years wth diabetes
6-10years wth diabetes
11+ years wth diabetes
Self-reported morbidities
complication level 2009
Complication level 2012
Comorbidities 2009
Comorbidities 2012
UPC index TP1
UPC index TP2
Specialist visits TP1
Specialist visits TP2
Frequency GPvisit TP2
FreqGPvisit TP1
Regularity TP1
Regularity TP2
Cover index TP1
Diab related PPH TP1
0
20
40
60
Crude Ttest
GPS adjusted Ttest

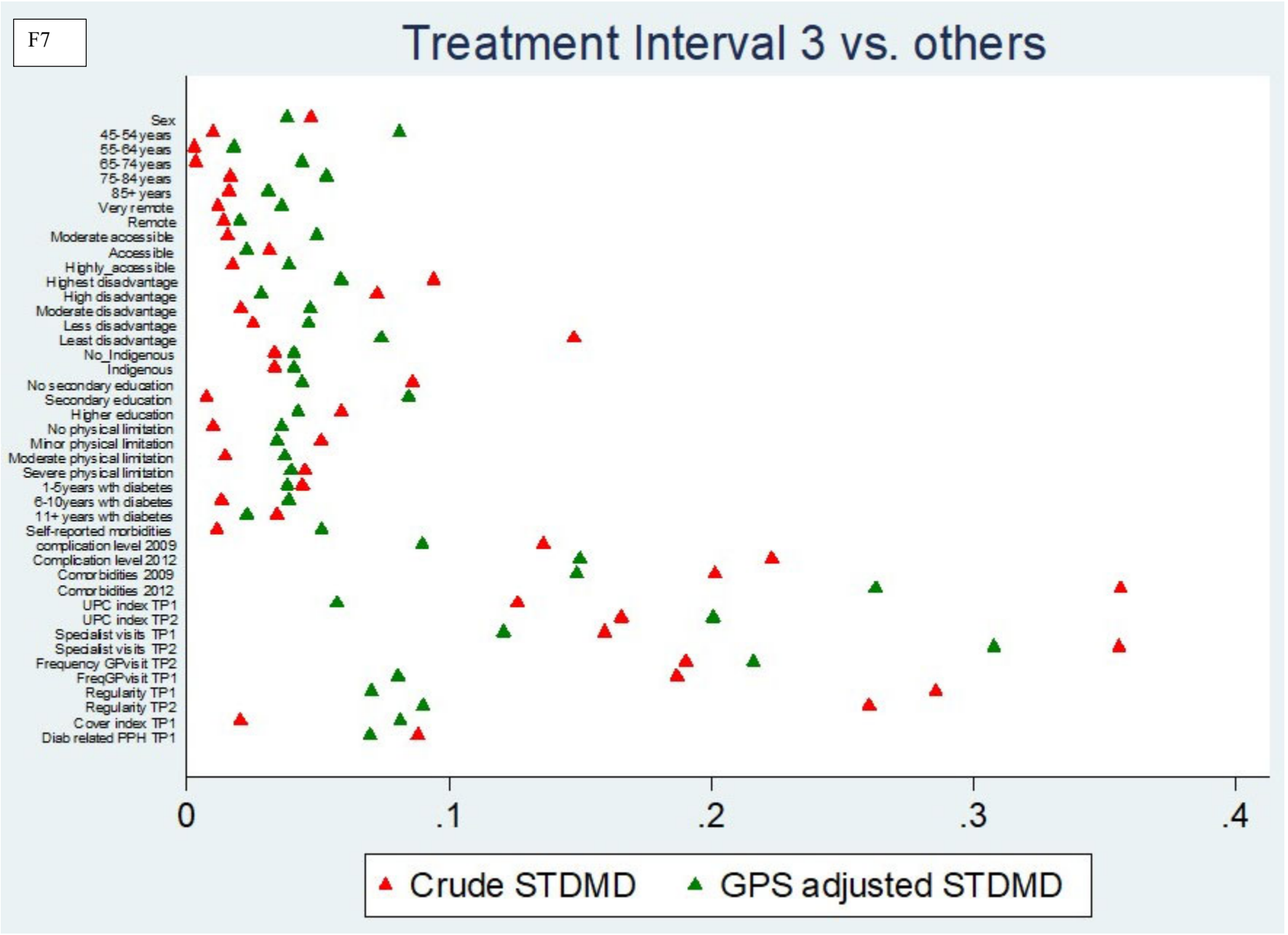
F5


Treatment Interval 1 vs. others
Sex
45-54 years
55-64 years
65-74 years
75-84 years
85+ years
Very remote
Remote
Moderate accessible
Accessible
Highly_accessible
Highest disadvantage
High disadvantage
Moderate disadvantage
Less disadvantage
Least disadvantage
No_Indigenous
Indigenous
No secondary education
Secondary education
Higher education
No physical limitation
Minor physical limitation
Moderate physical limitation
Severe physical limitation
1-5years wth diabetes
6-10years wth diabetes
11+ years wth diabetes
Self-reported morbidities
complication level 2009
Complication level 2012
Comorbidities 2009
Comorbidities 2012
UPC index TP1
UPC index TP2
Specialist visits TP1
Specialist visits TP2
Frequency GPvisit TP2
FreqGPvisit TP1
Regularity TP1
Regularity TP2
Cover index TP1
Diab related PPH TP1
0
.5
1
1.5
2
2.5
Crude STDMD
GPS adjusted STDMD

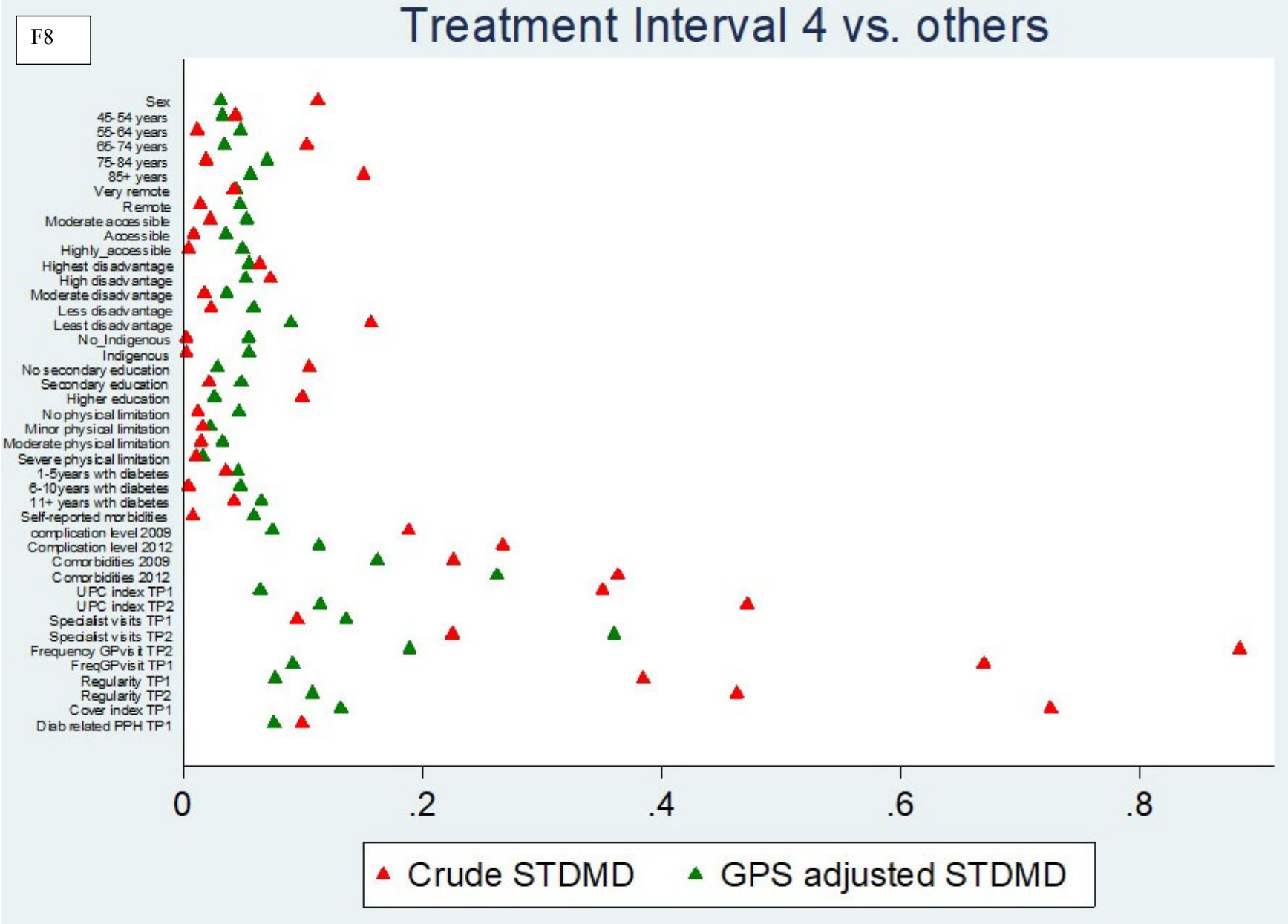
F6


Treatment Interval 2 vs. others
Sex
45-54 years
55-64 years
65-74 years
75-84 years
85+ years
Very remote
Remote
Moderate accessible
Accessible
Highly_accessible
Highest disadvantage
High disadvantage
Moderate disadvantage
Less disadvantage
Least disadvantage
No_Indigenous
Indigenous
No secondary education
Secondary education
Higher education
No physical limitation
Minor physical limitation
Moderate physical limitation
Severe physical limitation
1-5years wth diabetes
6-10years wth diabetes
11+ years wth diabetes
Self-reported morbidities
complication level 2009
Complication level 2012
Comorbidities 2009
Comorbidities 2012
UPC index TP1
UPC index TP2
Specialist visits TP1
Specialist visits TP2
Frequency GPvisit TP2
FreqGPvisit TP1
Regularity TP1
Regularity TP2
Cover index TP1
Diab related PPH TP1
0
.2
.4
.6
.8
Crude STDMD
GPS adjusted STDMD

F7


Treatment Interval 3 vs. others
Sex
45-54 years
55-64 years
65-74 years
75-84 years
85+ years
Very remote
Remote
Moderate accessible
Accessible
Highly_accessible
Highest disadvantage
High disadvantage
Moderate disadvantage
Less disadvantage
Least disadvantage
No_Indigenous
Indigenous
No secondary education
Secondary education
Higher education
No physical limitation
Minor physical limitation
Moderate physical limitation
Severe physical limitation
1-5years wth diabetes
6-10years wth diabetes
11+ years wth diabetes
Self-reported morbidities
complication level 2009
Complication level 2012
Comorbidities 2009
Comorbidities 2012
UPC index TP1
UPC index TP2
Specialist visits TP1
Specialist visits TP2
Frequency GPvisit TP2
FreqGPvisit TP1
Regularity TP1
Regularity TP2
Cover index TP1
Diab related PPH TP1
0
.1
.2
.3
.4
Crude STDMD
GPS adjusted STDMD

F8


Treatment Interval 4 vs. others
Sex
45-54 years
55-64 years
65-74 years
75-84 years
85+ years
Very remote
Remote
Moderate access ible
Access ible
Highly_access ible
Highest dis advantage
High dis adv antage
Moderate disadv antage
Less dis adv antage
Least dis adv antage
No_Indigenous
Indigenous
No secondary education
Secondary education
Higher education
No physical limitation
Minor physical limitation
Moderate physical limitation
Severe physical limitation
1-5years wth diabetes
6-10years wth diabetes
11+ years wth diabetes
Self-reported morbidities
complication level 2009
Complication level 2012
Comorbidities 2009
Comorbidities 2012
UPC index TP1
UPC index TP2
Specialist visits TP1
Specialist visits TP2
Frequency GPvis it TP2
FreqGPvis it TP1
Regularity TP1
Regularity TP2
Cover index TP1
Diab related PPH TP1
0
.2
.4
.6
.8
Crude STDMD
GPS adjusted STDMD

Appendix L Authors Contribution and Copyright Clearance

Curtin University

Health systems and Health economics
School of Public Health
Faculty of Health Sciences

GPO Box U1987
Perth Western Australia 6845

Telephone +61 416459789
Email thininh.ha@postgrad.curtin.edu.au

School of Public Health

Faculty of Health Sciences

GPO Box U1987

PERTH WESTERN AUSTRALIA 6845

To Whom It May Concern

I am, Thi Ninh Ha, a major contributor to the conceptualisation, coordination, and implementation of the research which resulted in the following paper:

> Thi Ninh Ha, Mark Harris, Suzanne Robinson, David Preen, & Rachael Moorin (2017). Stratification strategy for evaluating the influence of diabetes complication severity index on the risk of hospitalization: a record linkage data in Western Australia. *J Diabetes Complications, 31*(7), 1175-1180. http://dx.doi.org/10.1016/j.jdiacomp.2017.03.015

I contributed to a significant extent to the conceptualisation, data analysis, drafting, writing and editing of the paper above which is used for my PhD thesis. Accordingly I am lead author on this publication.

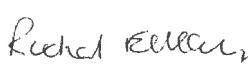
Thi Ninh Ha 

I, as co-author, endorse that this level of contribution by the candidate indicated above is appropriate.

Mark Harris 

Suzanne Robinson 

David Preen 

Rachael Moorin 

Curtin University

Health systems and Health economics
School of Public Health
Faculty of Health Sciences

GPO Box U1987
Perth Western Australia 6845

Telephone +61 416459789
Email thininh.ha@postgrad.curtin.edu.au

School of Public Health

Faculty of Health Sciences

GPO Box U1987

PERTH WESTERN AUSTRALIA 6845

To Whom It May Concern

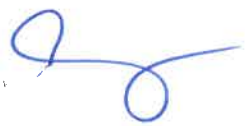
I am, Thi Ninh Ha, a major contributor to the conceptualisation, coordination, and implementation of the research which resulted in the following paper:

> Thi Ninh Ha, Mark Harris, David Preen, Suzanne Robinson, Rachael Moorin (2018). Identifying patterns of general practitioner service utilisation and their relationship with potentially preventable hospitalisations in people with diabetes: The utility of a cluster analysis approach. *Diabetes Research and Clinical Practice,* http://dx.doi.org/https://doi.org/10.1016/j.diabres.2018.01.027

I contributed to a significant extent to the conceptualisation, data analysis, drafting, writing and editing of the paper above which is used for my PhD thesis. Accordingly I am lead author on this publication.

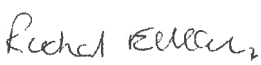
Thi Ninh Ha 

I, as co-author, endorse that this level of contribution by the candidate indicated above is appropriate.

Mark Harris 

David Preen 

Suzanne Robinson 

Rachael Moorin 

Curtin University

Health systems and Health economics
School of Public Health
Faculty of Health Sciences

GPO Box U1987
Perth Western Australia 6845

Telephone +61 416459789
Email thininh.ha@postgrad.curtin.edu.au

School of Public Health

Faculty of Health Sciences

GPO Box U1987

PERTH WESTERN AUSTRALIA 6845

To Whom It May Concern

I am, Thi Ninh Ha, a major contributor to the conceptualisation, coordination, and implementation of the research which resulted in the following paper:

> Thi Ninh Ha, Mark Harris, David Preen, Suzanne Robinson & Rachael Moorin. A time-duration measure of continuity of care to optimise utilisation of primary health care: A threshold effects approach among people with diabetes.

I contributed to a significant extent, to the conceptualisation, data analysis, drafting, writing and editing of the paper above which is used for my PhD thesis. Accordingly I am lead author on this publication.

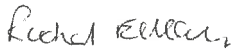
Thi Ninh Ha 

I, as co-author, endorse that this level of contribution by the candidate indicated above is appropriate.

Mark Harris 

David Preen 

Suzanne Robinson 

Rachael Moorin 

Curtin University

Health systems and Health economics
School of Public Health
Faculty of Health Sciences

GPO Box U1987
Perth Western Australia 6845

Telephone +61 416459789
Email thininh.ha@postgrad.curtin.edu.au

School of Public Health

Faculty of Health Sciences

GPO Box U1987

PERTH WESTERN AUSTRALIA 6845

To Whom It May Concern

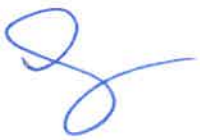
I am, Thi Ninh Ha, a major contributor to the conceptualisation, coordination, and implementation of the research which resulted in the following paper:

Ninh Thi Ha, Mark Harris, David Preen & Rachael Moorin. The Cover Index – Evaluating continuity of care incorporating a time-duration effect of general practitioner care on diabetic-related potentially preventable hospitalisations.

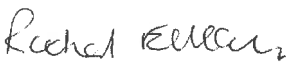
I contributed to a significant extent, to the conceptualisation, data analysis, drafting, writing and editing of the paper above which is used for my PhD thesis. Accordingly I am lead author on this publication.

Thi Ninh Ha 

I, as co-author, endorse that this level of contribution by the candidate indicated above is appropriate.

Mark Harris 

David Preen 

Rachael Moorin 

Title:	Stratification strategy for evaluating the influence of diabetes complication severity index on the risk of hospitalization: a record linkage data in Western Australia
Author:	Ninh Thi Ha,Mark Harris,Suzanne Robinson,David Preen,Rachael Moorin
Publication:	Journal of Diabetes and its Complications
Publisher:	Elsevier
Date:	July 2017

Title: Identifying patterns of general practitioner service utilisation and their relationship with potentially preventable hospitalisations in people with diabetes: The utility of a cluster analysis approach

Author: Ninh Thi Ha,Mark Harris,David Preen,Suzanne Robinson,Rachael Moorin

Publication: Diabetes Research and Clinical Practice

Publisher: Elsevier

Date: April 2018

References

1. Grover A, Joshi A. An Overview of Chronic Disease Models: A Systematic Literature Review. Global Journal of Health Science. 2015;7(2):210-27.
2. Reynolds R, Dennis S, Hasan I, Slewa J, Chen W, Tian D, et al. A systematic review of chronic disease management interventions in primary care. BMC Fam Pract. 2018;19(1):11.
3. Dexter PR, Miller DK, Clark DO, Weiner M, Harris LE, Livin L, et al. Preparing for an Aging Population and Improving Chronic Disease Management. AMIA Annual Symposium Proceedings. 2010;2010:162-6.
4. Comino EJ, Islam MDF, Tran DT, Jorm L, Flack J, Jalaludin B, et al. Association of processes of primary care and hospitalisation for people with diabetes: A record linkage study. Diabetes Research and Clinical Practice. 2015;108(2):296-305.
5. Diabetes Australia. Diabetes in Australia: Diabetes Australia; 2018 [Available from: https://www.diabetesaustralia.com.au/diabetes-in-australia.
6. Fisher K, Griffith L, Gruneir A, Panjwani D, Gandhi S, Sheng L, et al. Comorbidity and its relationship with health service use and cost in community-living older adults with diabetes: A population-based study in Ontario, Canada. Diabetes Research and Clinical Practice. 2016;122:113-23.
7. Forssas E, Arffman M, Manderbacka K, Keskimäki I, Ruuth I, Sund R. Multiple complications among people with diabetes from Finland: an 18-year follow-up in 1994–2011. BMJ Open Diabetes Research & Care. 2016;4(1).
8. WHO. Preventing chronic diseases: a vital investment. WHO; 2005.
9. Wagner EH. Chronic disease management: what will it take to improve care for chronic illness? Effective clinical practice : ECP. 1998;1(1):2-4.
10. The Lancet. Chronic disease management in ageing populations. The Lancet. 2012;379(9829):1851.
11. Davy C, Bleasel J, Liu H, Tchan M, Ponniah S, Brown A. Effectiveness of chronic care models: opportunities for improving healthcare practice and health outcomes: a systematic review. BMC Health Services Research. 2015;15(1):194.
12. Boehmer KR, Abu Dabrh AM, Gionfriddo MR, Erwin P, Montori VM. Does the chronic care model meet the emerging needs of people living with multimorbidity? A systematic review and thematic synthesis. PLoS ONE. 2018;13(2):e0190852.
13. Ansari Z. The Concept and Usefulness of Ambulatory Care Sensitive Conditions as Indicators of Quality and Access to Primary Health Care. Australian Journal of Primary Health. 2007;13(3):91-110.
14. Young Y, Barhydt NR, Broderick S, Colello AD, Hannan EL. Factors associated with potentially preventable hospitalization in nursing home residents in New York State: a survey of directors of nursing. J Am Geriatr Soc. 2010;58(5):901-7.
15. Passey ME, Longman JM, Johnston JJ, Jorm L, Ewald D, Morgan GG, et al. Diagnosing Potentially Preventable Hospitalisations (DaPPHne): protocol for a mixed-methods data-linkage study. BMJ Open. 2015;5(11).
16. Longman JM, Passey ME, Ewald DP, Rix E, Morgan GG. Admissions for chronic ambulatory care sensitive conditions - a useful measure of potentially preventable admission? BMC Health Services Research. 2015;15:472.
17. Britt H, Miller G, Henderson J, Bayram C, Harrison C, Valenti L, et al. General practice activity in Australia 2015-16. General practice. Sydney: Sydney University Press; 2016.
18. Rosano A, Loha CA, Falvo R, van der Zee J, Ricciardi W, Guasticchi G, et al. The relationship between avoidable hospitalization and accessibility to primary care: a systematic review. European journal of public health. 2013;23(3):356-60.
19. Starfield B, Shi L, Macinko J. Contribution of primary care to health systems and health. The Milbank quarterly. 2005;83(3):457-502.

20. The national Health Performance Authority. Healthy communities: Potentially preventable hospitalisations in 2013-14. Sydney: The national Health Performance Authority; 2015.
21. The Royal Australian College of General Practitioners. Vision for general practice and a sustainable healthcare system. Melbourne: RACGP; 2015. Contract No.: 978-0-86906-437-5.
22. Kecmanovic M, Hall PJ. The use of financial incentives in Australian general practice. The Medical Journal of Australia. 2015;202(9):488-91.
23. American Academy of Family Physicians. Continuity of Care, Definition of 2015 [Available from: https://www.aafp.org/about/policies/all/definition-care.html.
24. Barker I, Steventon A, Deeny SR. Association between continuity of care in general practice and hospital admissions for ambulatory care sensitive conditions: cross sectional study of routinely collected, person level data. BMJ. 2017;356.
25. Health Quality O. Continuity of Care to Optimize Chronic Disease Management in the Community Setting: An Evidence-Based Analysis. Ontario Health Technology Assessment Series. 2013;13(6):1-41.
26. Haggerty JL, Reid RJ, Freeman GK, Starfield B, Adair CE, McKendry R. Continuity of care: a multidisciplinary review. BMJ. 2003;327(7425):1219.
27. Jackson C, Ball L. Continuity of care is vital but how do we measure it. Australian Journal for General Practitioners. 2018;47:662-4.
28. Gulliford M, Naithani S, Morgan M. What is 'continuity of care'? Journal of Health Services Research & Policy. 2006;11(4):248-50.
29. Schers HJ, van den Bosch WJHM, Uijen AA, Schellevis FG. How unique is continuity of care? A review of continuity and related concepts. Family practice. 2011;29(3):264-71.
30. Medina-Mirapeix F, Oliveira-Sousa SL, Sobral-Ferreira M, Montilla-Herrador J, Jimeno-Serrano FJ, Escolar-Reina P. What Elements of the Informational, Management, and Relational Continuity Are Associated With Patient Satisfaction With Rehabilitation Care and Global Rating Change? Archives of Physical Medicine and Rehabilitation. 2013;94(11):2248-54.
31. Jee SH, Cabana MD. Indices for continuity of care: a systematic review of the literature. Medical care research and review : MCRR. 2006;63(2):158-88.
32. Bentler SE, Morgan RO, Virnig BA, Wolinsky FD. The Association of Longitudinal and Interpersonal Continuity of Care with Emergency Department Use, Hospitalization, and Mortality among Medicare Beneficiaries. PLoS ONE. 2014;9(12):e115088.
33. Einarsdóttir K, Preen DB, Emery JD, Holman CDAJ. Regular Primary Care Plays a Significant Role in Secondary Prevention of Ischemic Heart Disease in a Western Australian Cohort. Journal of General Internal Medicine. 2011;26(10):1092-7.
34. Einarsdóttir K, Preen DB, Emery JD, Kelman C, Holman CDAJ. Regular Primary Care Lowers Hospitalisation Risk and Mortality in Seniors with Chronic Respiratory Diseases. Journal of General Internal Medicine. 2010;25(8):766-73.
35. Gibson D, Moorin R, Preen D, Emery J, Holman CD. Enhanced Primary Care improves GP service regularity in older patients without impacting on service frequency. Australian Journal of Primary Health. 2012;18(4):295-303.
36. Moorin R. Symposium: Measuring the influence of regularity of GP contact on diabetic potentially preventable hospitalisations. Health Services & Policy Research Conference; Melbourne: Health Services Research Association of Australia & New Zealand; 2015.
37. Youens D, Moorin R. Regularity of General Practitioner contact – analysis of methods for measurement using administrative data. Health Services Research & Policy Conference; Brisbane: Health Services Research Association of Australia & New Zealand; 2017.
38. Youens D, Moorin R. The impact of regular General Practitioner visits on diabetic hospitalisation costs. International Health Economics Association World Congress; Boston: International Health Economics Association 2017.

39. Chung RY, Mercer SW, Yip BHK, Chan SWC, Lai FTT, Wang HHX, et al. The association between types of regular primary care and hospitalization among people with and without multimorbidity: A household survey on 25,780 Chinese. Scientific Reports. 2016;6:29758.
40. Gibson D, Moorin R, Preen D, Emery J, Holman CD. Effects of the Medicare enhanced primary care program on primary care physician contact in the population of older Western Australians with chronic diseases. Australian Health Review. 2011;35:334-40.
41. Caetano PA, Lam JM, Morgan SG. Toward a standard definition and measurement of persistence with drug therapy: Examples from research on statin and antihypertensive utilization. Clinical therapeutics. 2006;28(9):1411-24; discussion 0.
42. Santoleri F, Sorice P, Lasala R, Rizzo RC, Costantini A. Patient adherence and persistence with Imatinib, Nilotinib, Dasatinib in clinical practice. PLoS One. 2013;8(2):e56813.
43. Ling R, Yen DC. Customer Relationship Management: An Analysis Framework and Implementation Strategies. Journal of Computer Information Systems. 2001;41(3):82-97.
44. Hong-kit Yim F, Anderson RE, Swaminathan S. Customer Relationship Management: Its Dimensions and Effect on Customer Outcomes. Journal of Personal Selling & Sales Management. 2004;24(4):263-78.
45. Reinartz WJ, Kumar V. The Impact of Customer Relationship Characteristics on Profitable Lifetime Duration. Journal of Marketing. 2003;67(1):77-99.
46. Lee EW. Data Mining Application in Customer Relationship Management for Hospital Inpatients. Healthcare Informatics Research. 2012;18(3):178-85.
47. MacIntosh E, Rajakulendran N, Khayat Z, Wise A. Transforming health: Shifting from reactive to proactive and predictive care Canada: MaRS; 2016 [Available from: https://www.marsdd.com/news-and-insights/transforming-health-shifting-from-reactive-to-proactive-and-predictive-care/.
48. The Department of Health. Chronic Disease Management (formerly Enhanced Primary Care or EPC) — GP services: The Department of Health; 2014 [Available from: http://www.health.gov.au/internet/main/publishing.nsf/content/mbsprimarycare-chronicdiseasemanagement.
49. United Nations, Department of Economic and Social Affairs, Population Division. World Population Ageing 2017 - Highlights. United Nations, Department of Economic and Social Affairs, Population Division; 2017. Contract No.: (ST/ESA/SER.A/397).
50. WHO. Older people and Primary Health Care: WHO; 2004 [Available from: http://www.who.int/ageing/primary_health_care/en/.
51. AIHW. Older Australia at a glance: AIHW; 2018 [Available from: https://www.aihw.gov.au/reports/older-people/older-australia-at-a-glance/contents/demographics-of-older-australians/australia-s-changing-age-and-gender-profile.
52. Prince MJ, Wu F, Guo Y, Gutierrez Robledo LM, O'Donnell M, Sullivan R, et al. The burden of disease in older people and implications for health policy and practice. The Lancet. 2015;385(9967):549-62.
53. Niccoli T, Partridge L. Ageing as a Risk Factor for Disease. Current Biology. 2012;22(17):R741-R52.
54. Meetoo D. Chronic diseases: the silent global epidemic. British journal of nursing (Mark Allen Publishing). 2008;17(21):1320-5.
55. Wang H, Naghavi M, Allen C, Barber RM, Bhutta ZA, Carter A, et al. Global, regional, and national life expectancy, all-cause mortality, and cause-specific mortality for 249 causes of death, 1980-2015: a systematic analysis for the Global Burden of Disease Study 2015. The Lancet. 2016;388(10053):1459-544.
56. AIHW. Admitted patient care 2016–17: Australian hospital statistics. Canberra: AIHW; 2018. Contract No.: Cat. no. HSE 201.
57. McPake B, Mahal A. Addressing the Needs of an Aging Population in the Health System: The Australian Case. Health Systems & Reform. 2017;3(3):236-47.

58. The Department of Health. Chronic conditions: Chronic conditions are the leading cause of illness, disability and death in Australia: The Department of Health; 2017 [Available from: http://www.health.gov.au/internet/main/publishing.nsf/content/chronic-disease.
59. McRae I, Yen L, Jeon Y-H, Herath PM, Essue B. Multimorbidity is associated with higher out-of-pocket spending: a study of older Australians with multiple chronic conditions. Australian Journal of Primary Health. 2013;19(2):144-9.
60. AIHW. How many Australians have diabetes? Canberra Australian Institute of Health and Welfare; 2017 [Available from: http://www.aihw.gov.au/how-common-is-diabetes/.
61. Lee CM, Colagiuri R, Magliano DJ, Cameron AJ, Shaw J, Zimmet P, et al. The cost of diabetes in adults in Australia. Diabetes Res Clin Pract. 2013;99(3):385-90.
62. Shaw J, Tanamas S. Diabetes: the silent pandemic and its impact on Australia. Canberra: Diabetes Australia; 2012.
63. Ham C. The ten characteristics of the high-performing chronic care system. Health economics, policy, and law. 2010;5(Pt 1):71-90.
64. Dennis SM, Zwar N, Griffiths R, Roland M, Hasan I, Powell Davies G, et al. Chronic disease management in primary care: from evidence to policy. Med J Aust. 2008;188(8 Suppl):S53-6.
65. Coleman K, Austin BT, Brach C, Wagner EH. Evidence On The Chronic Care Model In The New Millennium: Thus far, the evidence on the Chronic Care Model is encouraging, but we need better tools to help practices improve their systems. Health affairs (Project Hope). 2009;28(1):75-85.
66. WHO. Innovative care for Chronic conditions: Building Blocks for Action. Geneva: WHO; 2002. Contract No.: 92 4 159 017 3.
67. Wagner EH, Austin BT, Von Korff M. Organizing care for patients with chronic illness. The Milbank quarterly. 1996;74(4):511-44.
68. Health Research Institute. The Chronic Care Model: Improving chronic illness care 2006 [Available from: http://www.improvingchroniccare.org/index.php?p=the_chronic_caremodel&s=2.
69. Rothman AA, Wagner EH. Chronic Illness Management: What Is the Role of Primary Care? Annals of Internal Medicine. 2003;138(3):256-61.
70. Knight AW, Caesar C, Ford D, Coughlin A, Frick C. Improving primary care in Australia through the Australian Primary Care Collaboratives Program: a quality improvement report. BMJ Quality & Safety. 2012;21(11):948.
71. WHO. Primary health care. Geneva: World Health Organization; 1978.
72. Starfield B. Primary care: Balancing health needs, services, and technology New York: Oxford University Press; 1998.
73. Brekke KR, Nuscheler R, Straume OR. Gatekeeping in health care. Journal of Health Economics. 2007;26(1):149-70.
74. Boerma WG, van der Zee J, Fleming DM. Service profiles of general practitioners in Europe. European GP Task Profile Study. British Journal of General Practice. 1997;47(421):481.
75. Greenfield G, Foley K, Majeed A. Rethinking primary care's gatekeeper role. BMJ. 2016;354:i4803.
76. AMA. General practice in primary care: responding to patient needs. Australia: Australian Medical Association 2008.
77. Kringos DS, Boerma WG, Hutchinson A, van der Zee J, Groenewegen PP. The breadth of primary care: a systematic literature review of its core dimensions. BMC Health Services Research. 2010;10(1):65.
78. Donabedian A. Evaluating the quality of medical care. 1966. The Milbank quarterly. 2005;83(4):691-729.
79. Hogg W, Rowan M, Russell G, Geneau R, Muldoon L. Framework for primary care organizations: the importance of a structural domain. International Journal for Quality in Health Care. 2008;20(5):308-13.

80. Saultz JW, Albedaiwi W. Interpersonal continuity of care and patient satisfaction: a critical review. Annals of family medicine. 2004;2(5):445-51.
81. Van Servellen G, Fongwa M, Mockus D'Errico E. Continuity of care and quality care outcomes for people experiencing chronic conditions: A literature review. Nursing & Health Sciences. 2006;8(3):185-95.
82. Australian Institute of Health and Welfare. A potentially preventable hospitalisation indicator for general practice: consultation paper. The Australian Institute of Health and Welfare. 2018;Cat. no. HSE 214.
83. Frick J, Möckel M, Muller R, Searle J, Somasundaram R, Slagman A. Suitability of current definitions of ambulatory care sensitive conditions for research in emergency department patients: a secondary health data analysis. BMJ open. 2017;7(10):e016109-e.
84. Fleetcroft R, Hardcastle A, Steel N, Price GM, Purdy S, Lipp A, et al. Does practice analysis agree with the ambulatory care sensitive conditions' list of avoidable unplanned admissions?: a cross-sectional study in the East of England. BMJ Open. 2018;8(4).
85. Guthrie B, Saultz JW, Freeman GK, Haggerty JL. Continuity of care matters. BMJ. 2008;337.
86. Shortell SM. Continuity of Medical Care: Conceptualization and Measurement. Medical care. 1976;14(5):377-91.
87. Chen CC, Tseng CH, Cheng SH. Continuity of care, medication adherence, and health care outcomes among patients with newly diagnosed type 2 diabetes: a longitudinal analysis. Medical care. 2013;51(3):231-7.
88. Pollack CE, Hussey PS, Rudin RS, Fox DS, Lai J, Schneider EC. Measuring Care Continuity: A Comparison of Claims-Based Methods. Medical care. 2016;54(5):e30-e4.
89. Pereira Gray DJ, Sidaway-Lee K, White E, Thorne A, Evans PH. Continuity of care with doctors—a matter of life and death? A systematic review of continuity of care and mortality. BMJ Open. 2018;8(6).
90. Breslau N, Reeb KG. Continuity of care in a university-based practice. Journal of medical education. 1975;50(10):965-9.
91. Chan C-L, You H-J, Huang H-T, Ting H-W. Using an integrated COC index and multilevel measurements to verify the care outcome of patients with multiple chronic conditions. BMC Health Services Research. 2012;12(1):405.
92. Leleu H, Minvielle E. Relationship between Longitudinal Continuity of Primary Care and Likelihood of Death: Analysis of National Insurance Data. PLOS ONE. 2013;8(8):e71669.
93. Bice TW, Boxerman SB. A Quantitative Measure of Continuity of Care. Medical care. 1977;15(4):347-9.
94. van Walraven C, Oake N, Jennings A, Forster AJ. The association between continuity of care and outcomes: a systematic and critical review. Journal of evaluation in clinical practice. 2010;16(5):947-56.
95. Hall J. Australian Health Care — The Challenge of Reform in a Fragmented System. New England Journal of Medicine. 2015;373(6):493-7.
96. AIHW. Review and evaluation of Australian information about primary health care: a focus on general practice. AIHW; 2008. Contract No.: ISBN: 978 1 74024 855 6.
97. The Department of Health. General Practice Statistics: Canberra; 2018 [Available from: http://www.health.gov.au/internet/main/publishing.nsf/content/general+practice+statistics-1.
98. Fisher M, Baum F, Kay A, Friel S. Are changes in Australian national primary healthcare policy likely to promote or impede equity of access? A narrative review. Australian Journal of Primary Health. 2017;23(3):209-15.
99. Biggs A. Chronic disease management: the role of private health insurance: Parliament of Australia 2013 [Available from: https://www.aph.gov.au/About_Parliament/Parliamentary_Departments/Parliamentary_Library/pubs/rp/rp1314/ChronDisease.
100. Armstrong B, Gillespie J, Leeder S, Rubin G, Russell L. Challenges in health and health care for Australia. Med J Aust 2007;187(9):485-9.

101. The Department of Health. History of key MBS primary care initiatives 1999-2013: The Department of Health; 2014 [Available from: http://www.health.gov.au/internet/main/publishing.nsf/Content/mbsprimarycare-History.
102. The Department of Health. Enhanced Primary Care Program overview: The Department of Health; 2013 [Available from: http://www.health.gov.au/epc.
103. Wilkinson D, Mott K, Morey S, Beilby J, Price K, Best J, et al. Evaluation of the Enhanced Primary Care (EPC) Medicare Benefits Schedule (MBS) Items and the General Practice Education, Support and Community Linkages Program (GPESCL). Canberra: Commonwealth of Australia; 2003. Contract No.: 0642 82244 1.
104. The Department of Health. Chronic Disease Management - Provider Information: The Department of Health; 2016 [Available from: http://www.health.gov.au/internet/main/publishing.nsf/Content/mbsprimarycare-factsheet-chronicdisease.htm.
105. Medicare Australia. Medicare Australia: Annual Report 2008–2009. Tuggeranong: Commonwealth of Australia; 2008. Contract No.: 0313–1041.
106. Cant RP, Foster MM. Investing in big ideas: utilisation and cost of Medicare Allied Health services in Australia under the Chronic Disease Management initiative in primary care. Australian health review : a publication of the Australian Hospital Association. 2011;35(4):468-74.
107. Jutte DP, Roos LL, Brownell MD. Administrative Record Linkage as a Tool for Public Health Research. Annual Review of Public Health. 2011;32(1):91-108.
108. Population Health Research Network. What is Data Linkage? : Population Health Research Network; 2011 [Available from: https://www.phrn.org.au/about-us/data-linkage/what-is-data-linkage/.
109. Holman CD, Bass AJ, Rosman DL, Smith MB, Semmens JB, Glasson EJ, et al. A decade of data linkage in Western Australia: strategic design, applications and benefits of the WA data linkage system. Australian health review : a publication of the Australian Hospital Association. 2008;32(4):766-77.
110. Brook EL, Rosman DL, Holman CD. Public good through data linkage: measuring research outputs from the Western Australian Data Linkage System. Aust N Z J Public Health. 2008;32(1):19-23.
111. Boyd JH, Ferrante AM, O'Keefe CM, Bass AJ, Randall SM, Semmens JB. Data linkage infrastructure for cross-jurisdictional health-related research in Australia. BMC Health Serv Res. 2012;12:480.
112. Spilsbury K, Rosman D, Alan J, Boyd JH, Ferrante AM, Semmens JB. Cross border hospital use: analysis using data linkage across four Australian states. Med J Aust. 2015;202 (11) 582-6.
113. Lawrence G, Dinh I, Taylor L. The Centre for Health Record Linkage: A New Resource for Health Services Research and Evaluation. Health information management : journal of the Health Information Management Association of Australia. 2008;37(2):60-2.
114. Centre for Health Record Linkage. Master Linkage Key (MLK), : Centre for Health Record Linkage; 2018 [Available from: http://www.cherel.org.au/master-linkage-key.
115. Boyd JH, Randall SM, Ferrante AM, Bauer JK, McInneny K, Brown AP, et al. Accuracy and completeness of patient pathways – the benefits of national data linkage in Australia. BMC Health Services Research. 2015;15(1):312.
116. Newcombe HB, Kennedy JM. Record linkage: making maximum use of the discriminating power of identifying information. Commun ACM. 1962;5(11):563-6.
117. Christen P, Goiser K. Quality and Complexity Measures for Data Linkage and Deduplication. In: Guillet FJ, Hamilton HJ, editors. Quality Measures in Data Mining. Berlin, Heidelberg: Springer Berlin Heidelberg; 2007. p. 127-51.
118. Silveira DP, Artmann E. Accuracy of probabilistic record linkage applied to health databases: systematic review. Revista de saude publica. 2009;43(5):875-82.
119. Mitchell RJ, Cameron CM, McClure RJ, Williamson AM. Data linkage capabilities in Australia: practical issues identified by a Population Health Research Network 'Proof of Concept project'. Australian and New Zealand Journal of Public Health. 2015;39(4):319-25.

120. Sax Institute. SURE- The Secure Unified Research Environment: Sax Institute; 2018 [Available from: https://www.saxinstitute.org.au/our-work/sure/.
121. Roder DM, Fong KM, Brown MP, Zalcberg J, Wainwright CE. Realising opportunities for evidence-based cancer service delivery and research: linking cancer registry and administrative data in Australia. European Journal of Cancer Care. 2014;23(6):721-7.
122. Mazzali C, Paganoni AM, Ieva F, Masella C, Maistrello M, Agostoni O, et al. Methodological issues on the use of administrative data in healthcare research: the case of heart failure hospitalizations in Lombardy region, 2000 to 2012. BMC Health Services Research. 2016;16:234.
123. Gavrielov-Yusim N, Friger M. Use of administrative medical databases in population-based research. Journal of Epidemiology and Community Health. 2014;68(3):283.
124. Brownell MD, Jutte DP. Administrative data linkage as a tool for child maltreatment research. Child Abuse & Neglect. 2013;37(2):120-4.
125. Banks E, Redman S, Jorm L, Armstrong B, Bauman A, Beard J, et al. Cohort profile: the 45 and up study. Int J Epidemiol. 2008;37(5):941-7.
126. Korda RJ, Du W, Day C, Page K, Macdonald PS, Banks E. Variation in readmission and mortality following hospitalisation with a diagnosis of heart failure: prospective cohort study using linked data. BMC Health Services Research. 2017;17:220.
127. Comino EJ, Tran DT, Haas M, Flack J, Jalaludin B, Jorm L, et al. Validating self-report of diabetes use by participants in the 45 and up study: a record linkage study. BMC Health Services Research. 2013;13(1):481.
128. Lujic S, Watson DE, Randall DA, Simpson JM, Jorm LR. Variation in the recording of common health conditions in routine hospital data: study using linked survey and administrative data in New South Wales, Australia. BMJ Open. 2014;4(9).
129. Moorin R, Holman CD. Patient-initiated switching between private and public inpatient hospitalisation in Western Australia 1980 - 2001: an analysis using linked data. Australia and New Zealand health policy. 2005;2:12-.
130. Ha NT, Harris M, Robinson S, Preen D, Moorin R. Stratification strategy for evaluating the influence of diabetes complication severity index on the risk of hospitalization: a record linkage data in Western Australia. J Diabetes Complications. 2017;31(7):1175-80.
131. Youens D, Preen D, Harris M, Moorin R. The importance of historical address information in longitudinal studies using administrative health data. International Journal of Epidemiology. 2017;In press
132. Falster M, Jorm L. A guide to the potentially preventable hospitalisations indicator in Australia. Sydney: Centre for Big Data Research in Health, University of New South Wales in consultation with Australian Commission on Safety and Quality in Health Care and Australian Institute of Health and Welfare; 2017.
133. Jorm LR, Leyland AH, Blyth FM, Elliott RF, Douglas KMA, Redman S, et al. Assessing Preventable Hospitalisation InDicators (APHID): protocol for a data-linkage study using cohort study and administrative data. BMJ Open. 2012;2(6):e002344.
134. Katterl R, Anikeeva O, Butler C, Brown L, Smith B, Bywood P. Potentially avoidable hospitalisations in Australia: Causes for hospitalisations and primary health care interventions. Primary Health Care Research & Information Service. 2012(PHC RIS Policy Issue Review).
135. AIHW. A set of performance indicators across the health and aged care system. Canberra: Australian Institute of Health and Welfare; 2008.
136. Davis WA, Knuiman MW, Hendrie D, Davis TM. Determinants of diabetes-attributable non-blood glucose-lowering medication costs in type 2 diabetes: the Fremantle Diabetes Study. Diabetes Care. 2005;28(2):329-36.
137. McCandless RR. Attributing Inpatient Medicare Costs to Diabetes Among the Texas Elderly. Diabetes Care. 2002;25(11):1958.

138. Levetan CS, Passaro M, Jablonski K, Kass M, Ratner RE. Unrecognized Diabetes Among Hospitalized Patients. Diabetes Care. 1998;21(2):246.
139. Young BA, Lin E, Von Korff M, Simon G, Ciechanowski P, Ludman EJ, et al. Diabetes Complications Severity Index and Risk of Mortality, Hospitalization, and Healthcare Utilization. The American journal of managed care. 2008;14(1):15-23.
140. Hughes AM. Strategic Database Marketing: McGraw-Hill Pub. Co.; 2005.
141. Australian Bureau of Statistics. Census of Population and Housing: Socio-Economic Indexes for Areas Canberra: Australian Bureau of Statistics; 2011.
142. Australian Bureau of Statistics. Census of Population and Housing: Socio-Economic Indexes for Areas. Canberra: Australian Bureau of Statistics; 1981-2006.
143. Holman CD, Preen DB, Baynham NJ, Finn JC, Semmens JB. A multipurpose comorbidity scoring system performed better than the Charlson index. J Clin Epidemiol. 2005;58(10):1006-14.
144. Preen DB, Holman CD, Spilsbury K, Semmens JB, Brameld KJ. Length of comorbidity lookback period affected regression model performance of administrative health data. J Clin Epidemiol. 2006;59(9):940-6.
145. Gannon B, Harris D, Harris M. Threshold effects in nonlinear models with an application to the social capital-retirement health relationship Health Economics. 2014;23(9):1072-83.
146. Cameron AC, Trivedi PK. Count panel data. In: (Ed.) BHB, editor. The Oxford handbook of panel data econometrics: Oxford University Press; 2014.
147. Chamberlain G. Multivariate regression models for panel data. Journal of Econometrics. 1982;18(1):5-46.
148. Mundlak Y. On the Pooling of Time Series and Cross Section Data. Econometrica. 1978;46(1):69-85.
149. Wooldridge JM. Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. Journal of Applied Econometrics. 2005;20(1):39-54.
150. Liao M, Li Y, Kianifard F, Obi E, Arcona S. Cluster analysis and its application to healthcare claims data: a study of end-stage renal disease patients who initiated hemodialysis. BMC Nephrology. 2016;17:25.
151. Wu H-H, Lin S-Y, Liu C-W. Analyzing patients' values by applying cluster analysis and LRFM model in a pediatric dental clinic in Taiwan. TheScientificWorldJournal. 2014;2014:685495-.
152. Rosenbaum PR, Rubin DB. The central role of the propensity score in observational studies for causal effects. Biometrika. 1983;70(1):41-55.
153. Rubin DB. Estimating Causal Effects from Large Data Sets Using Propensity Scores. Annals of Internal Medicine. 1997;127(8_Part_2):757-63.
154. Zakrison TL, Austin PC, McCredie VA. A systematic review of propensity score methods in the acute care surgery literature: avoiding the pitfalls and proposing a set of reporting guidelines. European Journal of Trauma and Emergency Surgery. 2018;44(3):385-95.
155. Sherry W, L. LK, Y. TA, L. HA, Vincent M. Principles for modeling propensity scores in medical research: a systematic literature review. Pharmacoepidemiology and drug safety. 2004;13(12):841-53.
156. Guardabascio B, Ventura M. Estimating the dose-response function through a generalized linear model approach. Stata Journal. 2014;14(1):141-58.
157. Brookhart MA, Schneeweiss S, Rothman KJ, Glynn RJ, Avorn J, Stürmer T. Variable selection for propensity score models. American journal of epidemiology. 2006;163(12):1149-56.
158. Garrido MM, Kelley AS, Paris J, Roza K, Meier DE, Morrison RS, et al. Methods for Constructing and Assessing Propensity Scores. Health Services Research. 2014;49(5):1701-20.

159. Austin PC. Assessing covariate balance when using the generalized propensity score with quantitative or continuous exposures. Statistical Methods in Medical Research. 2018;0(0):0962280218756159.
160. Hirano K, Imbens GW. The Propensity Score with Continuous Treatments. Applied Bayesian Modeling and Causal Inference from Incomplete-Data Perspectives: John Wiley & Sons, Ltd; 2005. p. 73-84.
161. Austin PC. Assessing the performance of the generalized propensity score for estimating the effect of quantitative or continuous exposures on binary outcomes. Statistics in medicine. 2018;37(11):1874-94.
162. World Health Organization. Global report on diabetes. Geneva: World Health Organization; 2016.
163. IHW. How many Australians have diabetes? 2014 [cited 26/8/2016. Available from: http://www.aihw.gov.au/how-common-is-diabetes/.
164. Australian Institute of Health and Welfare. Diabetes expenditure in Australia 2008–09. Canberra: AIHW; 2013.
165. Saydah SH, Fradkin J, Cowie CC. Poor control of risk factors for vascular disease among adults with previously diagnosed diabetes. Jama. 2004;291(3):335-42.
166. Litwak L, Goh S-Y, Hussein Z, Malek R, Prusty V, Khamseh ME. Prevalence of diabetes complications in people with type 2 diabetes mellitus and its association with baseline characteristics in the multinational A1chieve study. Diabetology & Metabolic Syndrome. 2013;5(1):1-10.
167. Chen H-L, Hsiao F-Y. Risk of hospitalization and healthcare cost associated with Diabetes Complication Severity Index in Taiwan's National Health Insurance Research Database. Journal of Diabetes and its Complications. 2014;28(5):612-6.
168. Khalid JM, Raluy-Callado M, Curtis BH, Boye KS, Maguire A, Reaney M. Rates and risk of hospitalisation among patients with type 2 diabetes: retrospective cohort study using the UK General Practice Research Database linked to English Hospital Episode Statistics. International Journal of Clinical Practice. 2014;68(1):40-8.
169. Chang HY, Weiner JP, Richards TM, Bleich SN, Segal JB. Predicting costs with diabetes complications severity index in claims data. The American journal of managed care. 2012;18(4):213-9.
170. Chen H-L, Hsu WW-Y, Hsiao F-Y. Changes in prevalence of diabetic complications and associated healthcare costs during a 10-year follow-up period among a nationwide diabetic cohort. Journal of Diabetes and its Complications. 2015;29(4):523-8.
171. Wu CX, Tan WS, Toh MPHS, Heng BH. Stratifying healthcare costs using the Diabetes Complication Severity Index. Journal of Diabetes and its Complications. 2012;26(2):107-12.
172. Greene WH. Econometric analysis / William H. Greene. 6th (International) ed.. ed. Upper Saddle River, N.J.: Upper Saddle River, N.J. : Pearson/Prentice Hall; 2008.
173. Benchimol EI, Smeeth L, Guttmann A, Harron K, Moher D, Petersen I, et al. The REporting of studies Conducted using Observational Routinely-collected health Data (RECORD) statement. PLoS medicine. 2015;12(10):e1001885.
174. Holman CD, Bass AJ, Rouse IL, Hobbs MS. Population-based linkage of health records in Western Australia: development of a health services research linked database. Aust N Z J Public Health. 1999;23(5):453-9.
175. Australian Electoral Commission. Enrolment Statistics Canberra: Australian Electoral Commission; 2016 [Available from: http://www.aec.gov.au/Enrolling_to_vote/Enrolment_stats/.
176. Australian Electoral Commission. Enrolment - Frequently Asked Questions Canberra: Australian Electoral Commission; 2016 [Available from: http://www.aec.gov.au/faqs/enrolment.htm.
177. Moorin R, Holman CD, Garfield C, Brameld KJ. Health related migration: evidence of reduced "urban-drift". Health & place. 2006;12(2):131-40.

178. Chang HY, Weiner JP, Richards TM, Bleich SN, Segal JB. Validating the adapted Diabetes Complications Severity Index in claims data. The American journal of managed care. 2012;18(11):721-6.
179. Hilbe J. Negative binomial regression / Joseph M. Hilbe. Cambridge: Cambridge : Cambridge University Press; 2007.
180. Gonzalo J, Pitarakis J-Y. Estimation and model selection based inference in single and multiple threshold models. Journal of Econometrics. 2002;110(2):319-52.
181. Hazel-Fernandez L, Li Y, Nero D, Moretz C, Slabaugh L, Meah Y, et al. Relationship of diabetes complications severity to healthcare utilization and costs among Medicare Advantage beneficiaries. The American journal of managed care. 2015;21(1):e62-70.
182. Chen T-T, Chung K-P, Lin IC, Lai M-S. The Unintended Consequence of Diabetes Mellitus Pay-for-Performance (P4P) Program in Taiwan: Are Patients with More Comorbidities or More Severe Conditions Likely to Be Excluded from the P4P Program? Health Services Research. 2011;46(1p1):47-60.
183. Hsiao C. Panel data analysis—advantages and challenges. TEST. 2007;16(1):1-22.
184. Van Loenen T, Faber MJ, Westert GP, Van den Berg MJ. The impact of primary care organization on avoidable hospital admissions for diabetes in 23 countries. Scandinavian Journal of Primary Health Care. 2016;34(1):5-12.
185. Tamayo T, Rosenbauer J, Wild SH, Spijkerman AM, Baan C, Forouhi NG, et al. Diabetes in Europe: an update. Diabetes Res Clin Pract. 2014;103(2):206-17.
186. Centers for Disease Control and Prevention. 2014 National Diabetes Statistics Report: Centers for Disease Control and Prevention; 2014 [Available from: https://www.cdc.gov/diabetes/data/statistics/2014statisticsreport.html.
187. Erny-Albrecht K, Bywood P, Oliver-Baxter J. The role of primary care in primary and secondary prevention of diabetes and related complications: PHCRIS Policy Issue Review. Adelaide Primary Health Care Research & Information Service; 2015.
188. Gibson OR, Segal L, McDermott RA. A systematic review of evidence on the association between hospitalisation for chronic disease related ambulatory care sensitive conditions and primary health care resourcing. BMC Health Serv Res. 2013;13:336.
189. van Loenen T, van den Berg MJ, Westert GP, Faber MJ. Organizational aspects of primary care related to avoidable hospitalization: a systematic review. Family practice. 2014;31(5):502-16.
190. Wolters RJ, Braspenning JCC, Wensing M. Impact of primary care on hospital admission rates for diabetes patients: A systematic review. Diabetes Research and Clinical Practice. 2017;129:182-96.
191. Conry MC, Morgan K, Curry P, McGee H, Harrington J, Ward M, et al. The clustering of health behaviours in Ireland and their relationship with mental health, self-rated health and quality of life. BMC Public Health. 2011;11:692.
192. Clatworthy J, Buick D, Hankins M, Weinman J, Horne R. The use and reporting of cluster analysis in health psychology: a review. British journal of health psychology. 2005;10(Pt 3):329-58.
193. Eisen MB, Spellman PT, Brown PO, Botstein D. Cluster analysis and display of genome-wide expression patterns. Proceedings of the National Academy of Sciences of the United States of America. 1998;95(25):14863-8.
194. Caliński T, Harabasz J. A dendrite method for cluster analysis. Communications in Statistics. 1974;3(1):1-27.
195. Nuti LA, Lawley M, Turkcan A, Tian Z, Zhang L, Chang K, et al. No-shows to primary care appointments: subsequent acute care utilization among diabetic patients. BMC Health Serv Res. 2012;12:304.
196. Bywood P, Katterl R, Lunnay B. Disparities in primary health care utilisation: Who are the disadvantaged groups? How are they disadvantaged? What interventions work? . Adelaide: Primary Health Care Research & Information Service; 2011. Contract No.: ISBN 978-0-9808191-5-1.

197. Davy C, Harfield S, McArthur A, Munn Z, Brown A. Access to primary health care services for Indigenous peoples: A framework synthesis. International Journal for Equity in Health. 2016;15(1):163.
198. Struijs JN, Baan CA, Schellevis FG, Westert GP, van den Bos GA. Comorbidity in patients with diabetes mellitus: impact on medical health care utilization. BMC Health Services Research. 2006;6(1):84.
199. van Oostrom SH, Picavet HSJ, de Bruin SR, Stirbu I, Korevaar JC, Schellevis FG, et al. Multimorbidity of chronic diseases and health care utilization in general practice. BMC Family Practice. 2014;15:61-.
200. Booth GL, Hux JE. Relationship between avoidable hospitalizations for diabetes mellitus and income level. Archives of internal medicine. 2003;163(1):101-6.
201. Grossman M. On the Concept of Health Capital and the Demand for Health. Journal of Political Economy. 1972;80(2):223-55.
202. Tian W-H, Chen C-S, Liu T-C. The demand for preventive care services and its relationship with inpatient services. Health policy (Amsterdam, Netherlands). 2010;94(2):164-74.
203. Calderón-Larrañaga A, Abad-Díez JM, Gimeno-Feliu LA, Marta-Moreno J, González-Rubio F, Clerencia-Sierra M, et al. Global health care use by patients with type-2 diabetes: Does the type of comorbidity matter? European Journal of Internal Medicine. 2015;26(3):203-10.
204. Sanderson C, Dixon J. Conditions for Which Onset or Hospital Admission is Potentially Preventable by Timely and Effective Ambulatory Care. Journal of Health Services Research & Policy. 2000;5(4):222-30.
205. Caminal J, Starfield B, Sanchez E, Casanova C, Morales M. The role of primary care in preventing ambulatory care sensitive conditions. European journal of public health. 2004;14(3):246-51.
206. Department of Health and Ageing. Building a 21st Century Primary Health Care System: Australia's First National Primary Health Care strategy. Commonwealth of Australia. 2010.
207. Jackson C, Shahsahebi M, Wedlake T, DuBard CA. Timeliness of outpatient follow-up: an evidence-based approach for planning after hospital discharge. Annals of family medicine. 2015;13(2):115-22.
208. Department of Health and Ageing. National Hospital Cost Data Collection: Cost report Round 13 (2008–2009) Canberra: Department of Health and Ageing; 2010 [Available from: http://www.health.gov.au/internet/main/publishing.nsf/Content/health-casemix-data-collections-about_NHCDC.
209. Gannon B, Harris D, Harris M, Magnusson L, hollingsworth B, Lnder B, et al. New approaches to estimating the child health-patental income relationship Economics Discussion 2015;15-31.
210. The Royal Australian College of General Practitioners. General practice management of type 2 diabetes 2014-2015. Melbourne: The Royal Australian College of General Practitioners; 2014.
211. American Diabetes Association. Standards of medical care for patients with diabetes mellitus. Diabetes Care. 2003;26 Suppl 1:S33-50.
212. Ha NT, Harris M, Preen D, Robinson S, Moorin R. Identifying patterns of general practitioner service utilisation and their relationship with potentially preventable hospitalisations in people with diabetes: The utility of a cluster analysis approach. Diabetes Research and Clinical Practice. 2018.
213. Zhao Y, Wright J, Guthridge S, Lawton P. The relationship between number of primary health care visits and hospitalisations: evidence from linked clinic and hospital data for remote Indigenous Australians. BMC Health Serv Res. 2013;13:466.
214. Vuik SI, Fontana G, Mayer E, Darzi A. Do hospitalisations for ambulatory care sensitive conditions reflect low access to primary care? An observational cohort study of primary care usage prior to hospitalisation. BMJ Open. 2017;7(8).

215. Falster MO, Jorm LR, Leyland AH. Visualising linked health data to explore health events around preventable hospitalisations in NSW Australia. BMJ Open. 2016;6(9):e012031.
216. Zhao Y, You J, Wright J, Guthridge SL, Lee AH. Health inequity in the Northern Territory, Australia. International Journal for Equity in Health. 2013;12(1):79.
217. Britt H, Miller G, Valenti L, Henderson J, Bayram C, Gordon J. The changing face of Australian general practice across the decades. Australian family physician. 2016;45:628-31.
218. Ridd M, Shaw A, Lewis G, Salisbury C. The patient–doctor relationship: a synthesis of the qualitative literature on patients' perspectives. The British Journal of General Practice. 2009;59(561):e116-e33.
219. Rodriguez HP, Rogers WH, Marshall RE, Safran DG. The Effects of Primary Care Physician Visit Continuity on Patients' Experiences with Care. Journal of General Internal Medicine. 2007;22(6):787-93.
220. Ansari Z, Haider SI, Ansari H, de Gooyer T, Sindall C. Patient characteristics associated with hospitalisations for ambulatory care sensitive conditions in Victoria, Australia. BMC Health Services Research. 2012;12:475-.
221. Ha NT, Harris M, Moorin R, editors. Developing a new metric to capture continuity of primary care: The application of propensity score methods and threshold effects models using linked administrative data International Population Data Linkage conference; 2018; Banff: International Journal of Population Data Science
222. Beadles CA, Voils CI, Crowley MJ, Farley JF, Maciejewski ML. Continuity of medication management and continuity of care: Conceptual and operational considerations. SAGE Open Medicine. 2014;2:2050312114559261.
223. AIHW. Rural, regional and remote health: a guide to remoteness classifications: AIHW; 2004 [Available from: https://www.aihw.gov.au/reports/rural-remote-australians/guide-to-remoteness-classifications/formats.
224. Rosenkranz RR, Duncan MJ, Rosenkranz SK, Kolt GS. Active lifestyles related to excellent self-rated health and quality of life: cross sectional findings from 194,545 participants in The 45 and Up Study. BMC Public Health. 2013;13:1071-.
225. Ron HD, Sherbourne CD, Mazel R. User's Manual for the Medical Outcomes Study (MOS) Core Measures of Health-Related Quality of Life. CA: RAND Corporation. 1995.
226. Jorm LR, Shepherd LC, Rogers KD, Blyth FM. Smoking and use of primary care services: findings from a population-based cohort study linked with administrative claims data. BMC Health Services Research. 2012;12(1):263.
227. Duke Community & Family Medicine. Duke health measures: Duke University Schook of Medicine; 2002 [Available from: https://cfm.duke.edu/research/duke-health-measures.
228. Kluve J, Schneider H, Uhlendorff A, Zhao Z. Evaluating continuous training programmes by using the generalized propensity score. Journal of the Royal Statistical Society: Series A (Statistics in Society). 2012;175(2):587-617.
229. Agency for Clinical Innovation. Building partnerships: a framework for integrating care for older people with complex health needs: Agency for Clinical Innovation; 2014 [Available from: https://www.aci.health.nsw.gov.au/__data/assets/pdf_file/0003/249483/Building_Partnerships_Framework.pdf.
230. Bartlett M, Wang J, Hay L, Pang G. Health service use in the older person with complex health needs. Australian Health Review. 2017:-.
231. Caughey GE, Vitry AI, Ramsay EN, Gilbert AL, Shakib S, Ryan P, et al. Effect of a general practitioner management plan on health outcomes and hospitalisations in older patients with diabetes. Internal medicine journal. 2016.
232. Mora J, Iturralde MD, Prieto L, Domingo C, Gagnon M-P, Martínez-Carazo C, et al. Key aspects related to implementation of risk stratification in health care systems-the ASSEHS study. BMC health services research. 2017;17(1):331-.

233. Comino EJ, Davies GP, Krastev Y, Haas M, Christl B, Furler J, et al. A systematic review of interventions to enhance access to best practice primary health care for chronic disease management, prevention and episodic care. BMC Health Services Research. 2012;12(1):415.
234. Rein DB. A matter of classes: stratifying health care populations to produce better estimates of inpatient costs. Health services research. 2005;40(4):1217-33.
235. Khobzi H, Akhondzadeh-Noughabi E, Minaei-Bidgoli B. A New Application of RFM Clustering for Guild Segmentation to Mine the Pattern of Using Banks' e-Payment Services. Journal of Global Marketing. 2014;27(3):178-90.
236. Thomas SL, Wakerman J, Humphreys JS. Ensuring equity of access to primary health care in rural and remote Australia - what core services should be locally available? International journal for equity in health. 2015;14:111-.
237. Freund T, Campbell SM, Geissler S, Kunz CU, Mahler C, Peters-Klimm F, et al. Strategies for reducing potentially avoidable hospitalizations for ambulatory care-sensitive conditions. Annals of family medicine. 2013;11(4):363-70.
238. Glasziou P, Straus S, Brownlee S, Trevena L, Dans L, Guyatt G, et al. Evidence for underuse of effective medical services around the world. The Lancet. 2017;390(10090):169-77.
239. Australian Government. Improving Primary Health Care for All Australians Australian Government. 2011.
240. Corscadden L, Levesque JF, Lewis V, Breton M, Sutherland K, Weenink JW, et al. Barriers to accessing primary health care: comparing Australian experiences internationally. Aust J Prim Health. 2017;23(3):223-8.
241. Boeckxstaens P, De Graaf P. Primary care and care for older persons: position paper of the European Forum for Primary Care. Qual Prim Care. 2011;19(6):369-89.
242. American Diabetes Association. Standards of Medical Care in Diabetes - 2019 Abridged for Primary Care Providers. Clinical Diabetes. 2019;37(1):11.
243. The Department of Health. Australian National Diabetes Strategy. Commonwealth of Australia. 2015.
244. Australian Government - Department of Health. Medicare Benefits Schedule - Note AN.0.54: Australian Government - Department of Health; 2019 [Available from: http://www9.health.gov.au/mbs/fullDisplay.cfm?type=note&q=AN.0.54&qt=noteID&criteria=2526.
245. The Department of Health. Chronic Disease Management - Provider Information: The Department of Health; 2016 [Available from: https://www1.health.gov.au/internet/main/publishing.nsf/Content/mbsprimarycare-factsheet-chronicdisease.htm.
246. Greisinger AJ, Balkrishnan R, Shenolikar RA, Wehmanen OA, Muhammad S, Champion PK. Diabetes care management participation in a primary care setting and subsequent hospitalization risk. Disease management : DM. 2004;7(4):325-32.
247. Muche-Borowski C, Abiry D, Wagner H-O, Barzel A, Lühmann D, Egidi G, et al. Protection against the overuse and underuse of health care - methodological considerations for establishing prioritization criteria and recommendations in general practice. BMC health services research. 2018;18(1):768-.
248. Choosing Wisely Australia. Tests, treatments, and procedures for healthcare providers and consumers to question: Choosing Wisely Australia; 2018 [Available from: http://www.choosingwisely.org.au/home.
249. Banks E, Joshy G, Weber MF, Liu B, Grenfell R, Egger S, et al. Tobacco smoking and all-cause mortality in a large Australian cohort study: findings from a mature epidemic with current low smoking prevalence. BMC Medicine. 2015;13(1):38.
250. AIHW. The Active Australia Survey: a guide and manual for implementation, analysis and reporting Canberra AIHW; 2003 [Available from: https://www.aihw.gov.au/reports/physical-activity/active-australia-survey/contents/table-of-contents.

Every reasonable effort has been made to acknowledge the owners of copyright material. I would be pleased to hear from any copyright owner who has been omitted or incorrectly acknowledged.