Health determinants in Australian communities: a multilevel investigation of the influence of personal and contextual characteristics

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Statement of Originality

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. I give consent to the final version of my thesis being made available worldwide when deposited in the University’s Digital Repository subject to the provisions of the Copyright Act 1968.
Statement of Authorship

I hereby certify that this thesis is in the form of a series of published papers of which I am a joint author. I have included as part of the thesis a written statement from each co-author, endorsed by the Faculty Assistant Dean (Research Training), attesting to my contribution to the joint publications (see Appendix 0.1).

__________________________________________

Joanne Allen  Date
Dedication

To those of us best understood in context

Ryan Michael McKay

(1984-2013)
Acknowledgements

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# Table of Contents

Synopsis ....................................................................................................................................... 19

References .................................................................................................................................... 26

**Chapter one**: Thesis introduction.......................................................................................... 29

The significance of context for identifying appropriate targets for public health intervention ........................................................................................................ 30

Physical, mental and ‘overall’ indices of health in public health research ................................. 33

Multilevel view of health and its determinants: an interaction between individual and contextual determinants of health ......................................................................................... 38

Health related contextual correlates of population size, density and distance from resources ................................................................................................................................. 48

Health determinants in rural Australia – informing targeted health interventions ............... 60

Current study .......................................................................................................................... 64

Current thesis chapters ........................................................................................................... 66

References .................................................................................................................................... 69

**Chapter two**: Goals and methodologic issues concerning individual participant data analyses from multiple cohort studies ................................................................. 83

Introduction to Chapter two ................................................................................................... 83

Abstract ................................................................................................................................... 91

Background ............................................................................................................................. 93

Discussion .............................................................................................................................. 102

Conclusions ........................................................................................................................... 120

References .................................................................................................................................... 123
Chapter three: Differential associations of personal and social networks with psychological distress across urban and remote communities.................................................................130

Introduction to Chapter three ................................................................. 130

Abstract.................................................................................................................. 137

Background .......................................................................................................... 139

Methods ............................................................................................................... 141

Results ............................................................................................................... 146

Discussion.......................................................................................................... 155

References ......................................................................................................... 163

Chapter four: Do indices of health related quality of life measure the same health related constructs across urban and rural cohorts? .............................................................................. 169

Introduction to Chapter four ............................................................................. 170

Abstract.................................................................................................................. 175

Introduction ......................................................................................................... 177

Methods ............................................................................................................... 180

Results ............................................................................................................... 188

Discussion.......................................................................................................... 201

References ......................................................................................................... 210

Chapter five: Does the association of health related adversity with health related physical and psychological quality of life differ across urban and rural communities.......................... 216

Introduction to Chapter five ............................................................................. 217

Abstract.................................................................................................................. 225

Introduction ......................................................................................................... 227

Methods ............................................................................................................... 230

Results ............................................................................................................... 237
Chapter six: Characterising the health related characteristics of sparsely populated rural areas: identifying the stable personal, social and contextual correlates of physical and mental health for rural men and women ................................................................. 264

Introduction to Chapter six ................................................................................................ 265

Abstract ......................................................................................................................... 273

Background ...................................................................................................................... 274

Data and methods ........................................................................................................... 276

Results ............................................................................................................................... 283

Discussion ......................................................................................................................... 294

References ......................................................................................................................... 301

Chapter seven: Potential causal pathways between personal adversity, social networks and physical and mental health outcomes for rural men and women ................................................................. 308

Introduction to Chapter seven ...................................................................................... 309

Abstract ......................................................................................................................... 314

Introduction ...................................................................................................................... 315

Data and methods ........................................................................................................... 317

Results ............................................................................................................................... 324

Discussion ......................................................................................................................... 333

References ......................................................................................................................... 340

Chapter eight: Discussion and conclusions ..................................................................... 346

Thesis overview: the impact of context on determinants of health across urban to remote areas of Australia .................................................................................................................. 347
The combination of individual participant data across multiple studies may be valuable for addressing new research questions ...................................................................................... 357

The moderating influence of remoteness on health and its determinants ....................... 364

Remoteness and health related contextual effects ................................................................. 376

Determinants of health in rural Australia ............................................................................. 382

Conclusions and recommendations ..................................................................................... 397

References ............................................................................................................................ 400

APPENDICES .......................................................................................................................... I

Appendix 0.1 Statements from co-authors regarding the candidate’s contribution .......... II

Appendix 1.0 Population based studies of urban-rural differences in affective disorders ..... XI

Appendix 2.0 Published manuscript .................................................................................... XXI

Appendix 2.0.1 Ethics approval for eXtending Treatments, Education and Networks for Depression (xTEND) study ......................................................................................................... XXXVI

Appendix 3.0 Published manuscript .................................................................................. XXXIX

Appendix 4.0 Published manuscript ..................................................................................... LI

Appendix 4.1 Supplementary documentation and data supporting published paper presented in Chapter four ......................................................................................................................... LXVII

Appendix 4.2 AQoL-6D items and scoring ............................................................................ LXXXIII

Appendix 5.0 Published manuscript .................................................................................. LXXXVII

Appendix 5.1 supplementary information and analyses supporting paper presented in Chapter five ................................................................................................................................. CIII

Appendix 6.1 Supplementary documentation and data supporting paper presented in Chapter six ................................................................................................................................................... CIX

Appendix 7.1 Supplementary documentation and data supporting paper presented in Chapter seven ................................................................................................................................................... CXXIX
List of Tables

Chapter two

Table 2.1 Reasons for combining experimental or observational research data across cohorts.

Table 2.2 Potential threats to inference when examining data across cohorts.

Table 2.3 Comparability of Australian Rural Mental Health Study (ARMHS) and Hunter Community Study (HCS) measures/samples at baseline and common follow-up.

Chapter three

Table 3.1 Network and Personal support indices administered by the ARMHS and HCS at baseline but common to three year follow-up.

Table 3.2 Analyses of HCS three year follow-up (N = 1716): Logistic regressions examining predictors of high psychological distress, using social support indices equivalent to those from the ARMHS and HCS at baseline.

Table 3.3 Logistic coefficients for predictors of high distress (N = 4219).

Chapter four

Table 4.1 Description of number, origin and criteria for cases included in current analyses.

Table 4.2 Sample characteristics and comparisons by cohort and phase.

Table 4.3 Raw and standardized coefficients from separate CFAs for each AQoL-6D domain (N = 7915).

Table 4.4 Model parameter estimates for two higher-order factors from a factor analysis of AQoL-6D domains (N = 7915).

Table 4.5 Mean (SD) AQoL-6D quality of life impairment domain and factor scores by gender and age.
Table 4.6 Pearson's correlation coefficients between AQoL-6D domains and SF-36 scales.

Table 4.7 Associations of AQoL-6D summary scores with concurrent assessments of quality of life (SF-36) and with independent indices of physical and psychological functioning.

Chapter five

Table 5.1 Descriptive statistics and comparison of HCS (N = 3118) and ARMHS (N = 1246) participants.

Table 5.2 Primary analysis: hierarchical linear regression analysis of the correlates of physical and psychological quality of life impairment (N = 4364).

Table 5.3 Secondary analysis of subjective social capital and health service accessibility by remoteness category from NSW Adult Population Health Surveys (years: 2006-2009).

Table 5.4 Sub-analysis: hierarchical linear regression analysis of the correlates of physical and psychological quality of life impairment (N = 1176).

Chapter six

Table 6.1 Overall participant characteristics and their stability over three survey phases.

Table 6.2 Overall cross-sectional predictors of current physical health and the moderating effects of phase and gender.

Table 6.3 Nested model comparisons for phase and gender moderation in physical (A) and mental (B) health outcome models.

Table 6.4 Overall cross-sectional predictors of current mental health and the moderating effects of phase and gender.

Table 6.5 Comparison of parameter strength across physical and mental health outcome models.
Chapter seven

Table 7.1 Temporal stability and cross-sectional multivariate associations of selected adversity and social factors with physical and mental health (N = 3396).

Table 7.2 Nested model comparisons (comparing the fit of less constrained models against those with greater constraints).

Table 7.3 Path coefficients from cross-lagged panel model (M4).
List of Figures

Chapter one

Figure 1.1 The main determinants of health: Conceptual model of structural, material, social and individual level factors for purposes of health policy and intervention.

Figure 1.2 Conceptual model of contextual factors driving health inequalities.

Figure 1.3 Influences of inequality and administrative forces or ‘the state’ on social capital and some mechanisms through which social capital may influence health.

Figure 1.4 Community remoteness as a factor influencing health relevant contextual characteristics.

Chapter two

Figure 2.1 Bar chart depicting increase in number of journal publications (articles or conference abstracts) including terms referring to pooling raw data, as found by a keyword search between dates 2003-2012 (N = 544).

Figure 2.2 Proportion of the pooled eXtending Treatment, Education and Networks in Depression (xTEND) sample at baseline (T0) and follow-up (T1) by remoteness category and Hunter Community Study (HCS)/Australian Rural Mental Health Study (ARMHS) membership, compared to New South Wales (NSW) population (2008).

Chapter three

Figure 3.0 The associations of social support ($p = .001$) and age ($p = .010$) with high psychological distress were moderated by remoteness.
Figure 3.1  The effect of social support (A) on the prediction of distress outcome as assessed by the HCS and ARMHS equivalent social support indices.

Figure 3.2  The effect of age on the prediction of distress outcomes by remoteness category.

Figure 3.3  The effect of social support on the prediction of distress outcomes by remoteness category.

Chapter four

Figure 4.1  Standardized parameter estimates and squared multiple correlations for the two correlated higher-order factor structure of the six AQoL-6D domains (N = 7915).

Figure 4.2  Profile plot of standardized AQoL-6D domain, factor and total scores by group and for those with poorest quality of life on the SF-36.

Chapter five

Figure 5.0  Moderation of the health impacts of health related adversity by context (Model A). Moderation of health impacts of health adversity and financial adversity by context (Model B).

Figure 5.1  Sub-analysis of the association of social capital and psychological impairment by perceived financial difficulty grouping.

Chapter six

Figure 6.0  Personal and contextual predictors of self-rated physical and mental health in rural Australia.

Figure 6.1  Remoteness categories (colouring) by New South Wales (NSW) area health service regions (black outline) used in defining area-level social capital and health service accessibility characteristics.
Chapter seven

Figure 7.0 Causal associations between variable groups over one and two year time lags.

Figure 7.1 Hypothesised multi-level cross-lagged models of personal adversity, social experiences and health.

Figure 7.2 Significant (solid lines, $p < .01$) and trend level (broken lines, $p < .05$) cross-lagged associations (model M4), standardized coefficients.

Figure 7.3 Causal paths between personal adversity, social networks and physical and mental health observed in the current study.

Chapter eight

Figure 8.0 Local government areas sampled by the ARMHS (green) and Hunter Community Study (Red).
Health is thought to be influenced by individual, community, material and wider societal factors. Knowledge of how these factors interact to influence health may improve our capacity to implement targeted and equitable health policy and interventions. This thesis focuses on the influence of personal psychosocial determinants of health, such as social networks and experiences of adversity, on health and how these associations may be influenced by health related contextual factors, such as socioeconomic status, social capital and service accessibility. This thesis aims to examine whether the psychosocial determinants of health differ with the changing context associated with community remoteness in Australia. It comprises an introductory chapter, six research chapters that are presented as published papers and papers submitted for publication, and a general discussion chapter. Specific chapters address the quantification of the contextual factors thought to vary with community remoteness and their influence on health and its determinants, namely the influence of personal adversity and social networks on health outcomes. At the time of submission, four papers have been accepted for publication in peer reviewed journals and two have been submitted for review. This thesis makes a significant contribution to understanding methods and challenges of combining cohort studies to answer key research questions; and to describing how community remoteness may interact with a range of recognised psychosocial determinants of health.

The Introduction (Chapter one) reviews the literature to present a multidimensional definition of health that includes physical, mental and social well-being. Theoretical and empirical models of the influence of contextual factors on health and its determinants are reviewed and the potential for health determinants to be experienced differently within different contexts discussed. The case of geographic remoteness is used to highlight how broader contextual characteristics such as culture, socioeconomic status and the availability of services may be
influenced by the broader structural and physical characteristics of areas. The potential for these community characteristics to influence the determinants of health is discussed. The importance of this perspective for health in Australia and the need to assess the impacts of context on health and its determinants, to guide the development of targeted health interventions and models of care in these environments, are also discussed. The opportunities to investigate these research questions using existing and ongoing cohort studies are highlighted and the specific research questions addressed in Chapters two through seven are stated.

Chapter two, ‘Goals and methodologic issues concerning individual participant data analyses from multiple cohort studies’, gives an overview of the current body of work by discussing the scope and goals of the project. Specifically, it addresses the current project’s intention to combine data from two existing cohort studies, namely the Hunter Community Study (HCS) and Australian Rural Mental Health Study (ARMHS), to represent persons from a range of urban to remote areas of Australia under the auspices of the eXtending Treatments Education and Networks in Depression (xTEND) study. It also addresses the methodological and analytical challenges associated with drawing upon multiple cohort studies and datasets to address new research questions. Where retrospective harmonization of cohorts is considered, the chapter discusses the benefits associated with conducting a common follow-up phase to increase overlap between cohorts, as was undertaken for the purposes of xTEND. This chapter provides recommendations for other research projects considering undertaking similar tasks. The corresponding research paper has been published in BMC Medical Research Methodology.

Chapter three, ‘Differential associations of personal characteristics and social networks with psychological distress across urban and remote communities’, presents analyses of the association of social support with an established measure of high psychological distress (Kessler 10 psychological distress scale) [1] in the xTEND sample. It addresses how the
association of health and social support may be moderated by community remoteness (operationalized using a standard index of road distance from nearest service centre). To this end, the chapter presents a preliminary calibration of the different social support indices administered by the ARMHS and HCS at baseline, using data from a common follow-up phase. It concludes that the psychological distress associated with low social support may decrease with greater community remoteness (OR 1.22; 99% CI 1.04-1.44). The corresponding research paper has been published in BMC Public Health.

Chapter four, ‘Construct validity and invariance of the Assessment of Quality of Life - 6D (AQoL-6D) across urban and rural community cohorts’, addresses the construct validity and measurement invariance of a health related quality of life instrument (AQoL-6D) [2] administered to the ARMHS and HCS cohorts at baseline and follow-up phases. This chapter addresses the conclusions of Chapter two regarding potential confounds in interpreting analyses of individual participant data across multiple cohorts. The chapter describes circumstances in which combining data across cohorts and phases may be used in conjunction with multiple imputation techniques to estimate data omitted from a given cohort or phase. A two-factor structure of the AQoL-6D (CFA model fit: RMSEA = .07, SRMR = .03; TLI = .96, CFI = .98) which displays measurement invariance across cohorts [configural invariance: RMSEA = .06 (.05, .06), SRMR = .03; TLI = .95, CFI = .97; metric invariance: RMSEA = .05 (.05, .06), SRMR = .03; TLI = .96, CFI = .97, and; covariance/variance invariance: RMSEA = .05 (.05, .06), SRMR = .04; TLI = .96, CFI = .97] and phases [configural invariance: RMSEA = .06 (.05, .06), SRMR= .03; TLI = .95, CFI = .97; metric invariance: RMSEA = .05 (.05, .05), SRMR = .03; TLI = .96, CFI = .97, and; covariance/variance invariance: RMSEA = .05 (.04, .05), SRMR = .04; TLI = .96, CFI = .97] is identified. Recommendations regarding factor scoring and preliminary normative data from the combined samples are provided. The concurrent, convergent and divergent validation of these factor scores in relation to other indices of health related quality of life, physical and
psychological functioning are examined. The chapter concludes that the AQoL-6D has a two factor structure that represents the same latent physical and psychological dimensions of health related quality of life impairment across the ARMHS and HCS samples. The corresponding research paper has been published in Health and Quality of Life Outcomes.

Chapter five, ‘Differential associations of personal adversity with physical and psychological health related quality of life across urban and remote communities’, examines whether the physical and psychological health related quality of life impacts of health related adversity, namely cardiovascular and affective conditions, differ with community remoteness. The chapter addresses conclusions of Chapter two regarding potential confounds in interpreting analyses of individual participant data across multiple cohorts and, to this end, the influence of unmeasured cohort factors (confounds) on model outcomes are examined. The chapter draws upon the conclusions of Chapter four regarding the comparability of the Physical and Psychological domains of the AQoL-6D across the ARMHS and HCS cohorts. The chapter also utilizes data from the New South Wales Adult Population Health Survey to investigate remoteness as a proxy for contextual health service accessibility and social capital. Finally, a sub-analysis using ARMHS data is used to assess whether the impacts of personal adversity (both health and financial) differ when individual ratings of social capital are used as a proxy for area social capital. Remoteness and social capital influence psychological (β = 0.02, p < .001 and β = -0.06, p = .028, respectively), but not physical impairment. The psychological burdens of personal adversity may be ameliorated by greater social capital (financial difficulty: β = -0.07, p = .014; depression: β = -0.08, p = .012, respectively), which displays a non-linear association with community remoteness. Major cities significantly lower social capital than inner regional areas (p < .001) which in turn had lower (p < .001) social capital compared to outer regional areas, remote and very remote areas, which did not significantly differ from each other. The need for better proxies for health related contextual characteristics in rural
areas is discussed. The corresponding research paper has been published in Health and Quality of Life Outcomes.

Chapter six, ‘Personal, social and contextual predictors of self-reported overall physical and mental health for rural men and women’, examines the stable personal and contextual predictors of physical and mental health in the ARMHS sample over three phases of follow-up data collection. This chapter draws upon the conclusions of Chapters three and five regarding the potential for the impact of psychosocial health determinants to vary with contextual factors and the conclusions of Chapter five regarding the limitations of community remoteness as a proxy for these factors. The chapter introduces a method, driven by theory and available data, of characterising the contextual characteristics of social capital and health service accessibility in sparsely populated areas. Multi-level investigations of 1) the personal demographic, health, social, and contextual correlates of self-rated physical and mental health, 2) the stability of these observations over three phases of data collection, and 3) their potential to be moderated by gender, are assessed. The relative strength of model predictors as correlates of physical and mental health outcomes are investigated. Contextual factors displayed hypothesised associations with physical (area socioeconomic indices: $\beta = -0.02$, $p = .233$; health service accessibility: $\beta = 0.04$, $p = .017$; social capital: $\beta = 0.04$, $p = .013$) and mental (area socioeconomic indices: $\beta = 0.04$, $p = .013$; health service accessibility: $\beta = 0.00$, $p = .874$; social capital: $\beta = 0.04$, $p = .010$) health. Social networks and personal adversity present reliable predictors of physical and mental health in rural areas. Components of social networks have different influences on health for men and women residing in rural areas. Findings provide empirical confirmation of the stronger association of affective conditions with psychological impairment compared to physical impairment (-0.19 vs. -0.08, $p < .001$) and of cardiovascular and financial difficulties with physical impairment compared to psychological impairment (CVD: -0.14 vs. -0.04, $p < .001$; FD: -0.14 vs. -0.06, $p < .001$, respectively), as
observed in Chapter four. The chapter concludes that theory driven methods of characterising health-relevant contextual factors may provide viable proxies for health relevant contextual factors in rural areas. The corresponding research paper has been submitted to the Journal of Health and Social Behaviour.

Chapter seven, ‘Causal models of personal adversity, social networks, physical health and mental health over time in rural areas’, builds on conclusions of Chapter six by investigating the reciprocal associations between personal adversity, social networks and physical and mental health over three time points using autoregressive cross lagged panel analyses. The influence of gender on this model is also investigated. Social support and financial adversity display direct impacts on physical and mental health outcomes over time, though the length of time between observations influenced these effects. Mental health influenced physical health over a two-year period (B = .15, p < .001), confirming the physical health burdens presented by poor mental health (as well as the mental health issues themselves) as an important point of health intervention. Social networks displayed potential indirect effects on health through reducing exposure to experiences of personal adversity (social support\textsubscript{T0} predicting financial difficulty \textsubscript{T2}: B = -.22, p = .002; social visibility\textsubscript{T1} predicted adverse life events\textsubscript{T2}: B = .35, p = .005, and; sense of belonging\textsubscript{T1} predicted adverse life events\textsubscript{T2}: B = -.69, p < .001). Causal models suggest the differential association of social visibility on physical health for men and women observed in Chapter six may reflect a negative impact of greater social visibility on physical health for men over time (B = -.27, p = .014). The corresponding research paper has been submitted to the Journal of Health and Social Behaviour.

In conclusion (Chapter eight), this program of research maximised existing resources to address new questions of interest by: drawing on data from two existing cohort studies; engaging in a common follow-up of these cohorts; geocoding existing indices of remoteness and socioeconomic status to survey participants; and constructing novel indices of social
support and health services accessibility from an existing large representative sample. The potential advantages and confounds of these processes have been carefully considered. These efforts have allowed the exploration of the influence of psychosocial determinants of health on indices of both physical health (i.e., physical health related quality of life and self-rated physical health) and psychological health (i.e., psychological distress, psychological health related quality of life and self-rated mental health), as well as the examination of the moderating influence of contextual factors on health determinants. Models suggest social networks and personal adversity influence both physical and mental health outcomes. Some evidence of a moderating effect of contextual characteristics on the association of psychosocial factors with psychological health was observed, however these analyses are potentially limited by the use of remoteness as a proxy for health related contextual characteristics. Associative models suggest theory driven methods of characterising contextual factors may help overcome the difficulties of directly assessing contextual factors in rural areas. Causal models suggest physical health, mental health, social networks and financial adversity each present appropriate points of health intervention for rural populations.
References


**List of citations for papers included in this thesis**


Page | 27
List of additional papers/presentations of relevance to this thesis


Chapter one: Thesis introduction
The significance of context for identifying appropriate targets for public health intervention

Health is a multidimensional state impacted upon by not only the individual’s personal characteristics, but also the wider physical, social and economic environment [1, 2]. The physical, social and economic context in which health is experienced by the individual is thought to have not only direct influences on health, but to moderate the influence of personal characteristics on health. Public health policy and resultant health interventions are significant in determining the volume and nature of health related resources available to individuals. These public health initiatives are informed by a range of evidence-based findings identifying factors which may influence health experiences and outcomes; in the current thesis these factors will be referred to as ‘health determinants’.

Public health theory and literature acknowledge that the physical, social and economic contexts may limit the generalizability of findings across populations [3]. There is increasing acknowledgement that health related aspects of context, such as socioeconomic status, social capital and health related resources have implications for health and health determinants and may influence health inequalities observed between and within countries [2, 4]. The formation and implementation of health initiatives, which are appropriately targeted to populations of interest and their specific needs, is an important step for effective and equitable health care. Understanding the factors that influence health and its determinants is an important step in the creation and implementation of such policies. The current thesis will address health as a multidimensional construct influenced by individual psychosocial factors as well as contextual factors which, when considered in synergy, present potential targets for interventions.
A holistic view of health

“Health is a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity.” – Constitution of the World Health Organisation, 1948 [5]

The definition of health put forward by the World Health Organisation highlights the multidimensional nature of health, that is, as a physical, mental and social experience. Its reference to health as a state of ‘well-being’ in contrast to an ‘absence of disease or infirmity’ acknowledges that positive health states have value and, implicitly, present a goal for personal and public health care. The use of the word ‘complete’ invokes a goal of health that is the same for all, regardless of social or physical circumstance. The dimensions of health raised are more or less understood, although the specific considerations are typically determined by the population or phenomena of interest. Physical well-being may refer to bodily experiences of pain, functioning and longevity. Mental well-being may refer to a range of psychological activity including cognitive functioning, psychological disorder, experiences of distress, and the capacity to carry out and cope with life’s activities and events. Social well-being may refer to the capacity of the individual to engage in their interpersonal roles such as maintaining personal, occupational and community relationships and duties. Social well-being has typically been conceptualised as an important determinant of the physical and mental dimensions of health. While acknowledging the intrinsic importance of social well-being and its interrelation with physical and mental dimensions of health, social well-being will be addressed as a health determinant in the current thesis in recognition of its potential as a point of intervention for physical and mental health outcomes.

Critics highlight that the World Health Organisation’s definition of health does not explicitly acknowledge the capacity to adapt and self-manage functioning in the face of adverse personal and societal circumstances as a characteristic of health and that references to ‘complete’ health may not be useful [6-8]. These omissions are argued to be increasingly
important as chronic health conditions comprise a growing and important part of health care [6]. Alternative definitions sensitive to these issues suggest health should be viewed as physical, mental and social potentials, commensurate with the demands associated with psychosocial and contextual factors such as an individual’s age, responsibilities and culture [9]. This latter view is in line with models of health and its determinants employed in the current thesis. However, while the current thesis acknowledges health as an imperfect state of being experienced by individuals under particular circumstances, it is for these reasons that the ‘aspirational’ perspective put forward by the World Health Organisation is adopted. By highlighting the importance of positive health states, the multidimensional nature of health, and equality in health regardless of circumstance, this definition provides a framework through which research may explore the personal, social, material and contextual determinants of health to address inequalities in health.

The current thesis will address the influence of the context in which a person lives on individual psychosocial determinants of health in the general population. It will begin by commenting on the conceptualisation and measurement of health and well-being in general community samples. It will then draw on theoretical models of the development of health-relevant resources to outline their influence on contextual (socioeconomic, service accessibility and social capital) and individual-level determinants of health. Finally, the discussion highlights rural and remote communities as an example of populations whose health outcomes are considered to be impacted by such contextual factors. The thesis examines the health of persons living in urban, rural and remote areas of Australia, the limitations of current knowledge regarding the impacts of contextual factors on the health of these populations, and how the current research will address these barriers. The thesis concludes by commenting on the limitations and implications of the current methods for informing future research and health related interventions.
Physical, mental and ‘overall’ indices of health in public health research

Mortality remains the primary health outcome endorsed by major epidemiological societies (i.e. International Epidemiological Association, 2013). This reflects, in part, difficulties in quantifying and obtaining information regarding health states. Other objective measures of disease (i.e., rates of infection, presence/absence of specific diagnoses, diagnostic telephone interviews) and quasi-objective econometric measures (i.e., disability adjusted life years, days out of role) have also been used as proxies for health burdens and associated disability. However, the relevance of such measures for the holistic perspectives on population health is limited. The conceptualisation of health as a state of ‘well-being’ calls for an assessment of the subjective experience of health, that is, the individual’s capacity to function in their physical, mental and social domains. The importance of this understanding is particularly evident when considering that the burden associated with a given condition or diagnoses may have different implications for the ‘well-being’ of different individuals.

In contrast, subjective measures of well-being and functioning have been used to assess the impacts of both positive and negative health states on individuals. These self-report indices are not often collected by health institutions, and studies utilizing these health indices are generally based on survey data. Subjective measures of health include tallies of symptoms and symptom frequency, single-item self-reported experiences of health, and indices of subjective disability. These indices have both practical and conceptual strengths and weaknesses which influence their use and utility and these are touched upon below.

Symptom measures. Symptom measures ask respondents to recall the presence/absence/severity/or frequency of symptoms related to a particular health outcome over a specified period of time assumed to be both relevant to the outcome of interest and
representative of the individual’s experiences of symptoms. Symptom measures are often included in health surveys in recognition not only of the health burden posed by the symptoms themselves but also their potential as indicators for serious disorder and need for increased support. However, the capacity of these measures to access ‘well-being’, that is, the impact of symptoms on the individual’s experiences of physical and mental health domains is limited. Reports of the experience of symptoms cannot determine how these symptoms have impacted upon the individual’s experience of health. Further, as measurement relies heavily on participant’s ability to recall specific information regarding the number of frequency of symptoms experienced over a given period of time, these measures are prone to error associated with recall bias, case miss-classification (due to specification of a reference period may not have been representative of the individual’s experiences), and limited information on the cause of the symptoms (which may have been normal or isolated reactions to physical, mental or social events, rather than indicative or underlying disorder).

A strength of these measures is their demonstrated capacity as indicators of meaningful health disorder in the general population, without administration of time and resource consuming diagnostic tools. For example, the Kessler 10 psychological distress scale [10] ask participants to rate the frequency of ten symptoms of psychological distress over the past 4 weeks on a 5-point Likert scale. This measure displays good internal reliability ($\alpha = .93$) and validity as a measure of psychological distress in community samples [11]. Normative data for the Kessler 10 has been collected from a wide range of populations as part of the World Health Organization World Mental Health surveys [12] and other national surveys of health and well-being [13-15] and it has been used in conjunction with the World Health Organization (WHO) Composite International Diagnostic Interview (CIDI) [16] to assess cut-off scores associated with probabilities for meeting ICD-10 criteria for psychological disorder [15].
Thus, symptom measures provide snapshots of experiences of symptoms associated with particular disorders by individuals over a given period of time. These measures are often well validated and have been used to provide brief indices of population health burden without the administration of comprehensive diagnostic measures. However, weaknesses of these measures include the potential for recall bias, case misclassification and provision of information on a specific symptoms, which may not be representative of the individual’s experience of health.

**Single item ratings of perceived health.** Single self-rated physical, mental and ‘overall’ ratings of health are often used as health outcome measures in epidemiological research. As these indices rely on participant responses to a single item, these measures may be particularly susceptible to error due to distraction or misunderstanding. However, such issues may also be abated by the brevity of these items, their clarity, and potential to reduce error associated with participant fatigue. As such these items are often administered to reduce the length of survey administration and preferred in surveys which may include participants whose performance may be negatively affected by poor concentration (e.g., persons who are elderly or unwell). Further, due to the capacity of these items to assess specific dimensions of health in comparable ways (that is, ability to generate standardized questions and response options for the assessment of physical, mental, social and overall health) the measurement properties of these indices may be uniquely comparable across health dimensions. The measurement of multiple health domains using separate but psychometrically comparable ratings scales may be particularly important where health determinants are to be compared across dimensions. Thus, the popularity of self-rated health indices is attributable not only to their ability to assess well-being across a range of health and illness states but also their wide use in the epidemiological literature, brevity, clarity, and favourable psychometric properties.
However, despite their wide use, there are few studies of the reliability of these measures, although their concurrent and predictive validity are well established. For example, single item measures of self-rated health have been shown to perform comparably to multi-item assessments of health such as the SF-36 in the prediction of health outcomes such as mortality [17]. Where studies of measurement reliability have been conducted, single-item ratings of overall health are regarded as having acceptable test re-test reliability in paper survey (immediate re-test, \( \kappa_{w} = 0.70 \) [18, p. 581]; two-week re-test, \( r_{icc} = 0.69 \) [19]; 1 year re-test, \( \kappa_{w} = 0.72 \), [20]) telephone interview survey (15 day re-test, \( \kappa_{w} = 0.86 \), [21]) and face to face interview survey (1 month re-test, \( \kappa_{w} = 0.56 \), [22]) formats. However, given the broad use of these indices, further research into their reliability across different populations and into how models established using these indices would vary with the use of more comprehensive multi-dimensional health outcome measures, are warranted.

**Health related quality of life.** Health related quality of life (HRQoL) measures present a potential step forward in the measurement of well-being. Health related quality of life has typically been conceptualised as the individual’s experience of functionality in physical and mental health domains in light of health burdens [23]. Health related quality of life measures attempt to quantify the burden associated with physical and mental health experiences, rather than simply the presence/absence of symptoms or illness. Thus, in contrast to the previously discussed measures, HRQoL measures explicitly acknowledge that experiences of burden associated with health conditions are influenced by a range of personal, social and contextual resources available to the individual [23, 24]. HRQoL measures are typically comprised of multi-item questionnaires assessing a broad range of health experiences across several areas which may impact upon health. For example, the widely validated and used SF-36 is comprised of thirty-six questions informing has eight scales (physical functioning, role physical, social functioning, mental health, role emotional, vitality, bodily pain and general health) and two
domains (physical and psychological functioning) [25]. Due to their assessment of multiple factors which may impact upon health, HRQoL measures are frequently employed in population health surveys for which general health outcomes and levels of health related burden are of interest but may be overlooked in the assessment of specific health outcomes, as assessed by symptom measures or presence of diagnosed disorder. Further, the assessment of multiple domains provides the researcher with insight into the weaknesses and strengths of respondent’s functioning over a range of areas, which may not be apparent from more general health ratings, such as those provided by single-item self-rated health measures.

A limitation of HRQoL measures is that they typically focus on negative health states with little capacity to describe positive health states. Positive health states may provide more meaningful assessments in the general community, and valuable information regarding factors which may promote positive health states, as opposed to identifying and supporting persons with low functioning. From an analysis perspective, measures assessing positive health states in the community would also provide variables with better distributional properties and progress is being made on this front [26, 27]. An additional limitation is that due to their assessment of a range of functional states HRQoL assessments are relatively long and complex, thus limiting the use of these measures in many general population and health care settings. Further, the broad nature of the questions may make summary scores difficult to interpret, especially given the potential for questions to vary in their meaning between population groups with different health experiences and expectations.

Thus, HRQoL measures have a unique potential to describe individual’s experiences of well-being over a range of health domains. Issues related to the assessment of positive and negative health states as well as interpretability of scores mean that attention to the range of health states of interest and validation of the measure within the population of interest should inform the selection, administration and interpretation of measures.
**Concluding remarks**

In the absence of systematic evidence suggesting a particular measure is superior or more sensitive to health states of interest than another, it is likely that replication of findings against a range of health indices may be the most valid method of confirmation. Further, as physical and mental health represent correlated health domains, consideration of the degree to which predictors of each domain reflect association with the other is warranted and the assessment of both domains is good practice. From both a conceptual and analytic point of view, understanding the commonalities and differences between conclusions of studies using different health outcome measures presents one way in which population health and its determinants may be better understood and interpreted. Finally, it should be noted that the ‘invariance’ of health related measurements across population groups may be important considerations when using these indices to assess health [28]. Thus, where relatively novel or new methods are used, assessment of the invariance of constructs is advised before conclusions are drawn regarding group differences in health or its correlates.

**Multilevel view of health and its determinants: an interaction between individual and contextual determinants of health**

The determinants of health include both the individual’s own characteristics and behaviours, as well as aspects of the broader physical, social and economic environment in which they exist [1, 2]. Dahlgren and Whitehead [2] present a ‘layered’ conceptual framework of the determinants of health to support the formation and implementation of health policy and interventions (Figure 1.1). These layers include aspects of the structural environment (i.e., physical, social and socioeconomic conditions), the material environment (i.e., living and working conditions such as education, employment and sanitation), supportive family and community environments, and the individual’s own behaviours, resources and intrinsic
qualities (i.e., age, gender, genetic factors, which may entail both biological and social features). This model was proposed to support the formation of effective health policy, which may require different approaches depending on ‘layer’ (or layers) at which the factors of interest operate and may be targeted. However, the interaction of these layers in determining health outcomes is also acknowledged [2, 4, 29] as illustrated by the grey arrow heads in Figure 1.1.

![Figure 1.1 The main determinants of health: Conceptual model of structural, material, social and individual level factors for purposes of health policy and intervention. Adapted from Dahlgren and Whitehead [2].](image)

The acknowledgement of the interaction of these layers of health determinants in shaping health outcomes is central to the current thesis. As such, the characteristics of individuals and the social and materials resources which may influence health will be referred to in the current thesis as ‘psychosocial’ health determinants to acknowledge that their impact on health is shaped by the wider physical, social and socioeconomic contexts in which they are experienced. The broader physical, social and economic aspects of the environment in which they live will be referred to as characteristics of the individual’s broader ‘context’. Contextual characteristics such as the availability of services, socioeconomic deprivation [30, 31], and
social capital [32-37] are also recognised as influencing disease and self-rated health outcomes. These contextual health effects may thus be both directly and indirectly related to health outcomes. Within the theoretical model of Dahlgren and Whitehead [2] the indirect impacts of context on health outcomes may represent moderating effects of contextual influences on the individual level psychosocial factors. For example contextual socioeconomic characteristics indicating low levels of health related services may directly decrease the capacity of individuals to maintain health or receive health related information. Alternatively, this contextual lack of services may also influence the capacity of individual’s social connections to improve health, as the potential of these connections to link individual’s to health-related resources is decreased (a moderating effect (a moderating effect of context on the association of social connectivity and health).

Theoretical models of the individual in context

Several theories discuss the foundations of contextual characteristics and how they interact with individual psychosocial characteristics to determine health outcomes [38-41]. Bernard et al. [38] conceptualise context or ‘place’ as a system of health relevant resources and relationships within geographical borders [38, 42]. This model proposes that access to health relevant resources is defined not only by physical proximity of the individual to resources but also the social environment (including cost, social acceptability, facilitation, and demand).

In addition to the relatively well-understood physical health promoting resources such as health services and socioeconomic advantage, Bernard et al.’s model invokes the concept of ‘social capital’ in determining health outcomes. Social capital has been used as an umbrella term to refer to the range of social resources available in the individual’s social context. Social capital describes the social networks within communities which promote trust, reciprocity and social cohesion [39, 43-45] and support the actions of persons within these communities [46,
Social capital has been conceptualised both as a property of individuals, built through interactions within social networks [48], as well as a property of areas or context, such as social norms and beliefs, built through the accumulation of positive and negative interactions within areas [49]. That health-related social networks represent pools of resources that exist at both micro (i.e., individual) and macro (i.e., broader physical and social areas) levels and are reciprocally related is acknowledged. To avoid confusion, and as the current thesis has a particular interest in the implications of context for population health interventions, the term ‘social capital’ will be used to refer the social resources shaped and available within the broader social context unless otherwise stated.

Aspects of social capital may include cognitive components (personal attitudes and capacities that are reinforced by cultural norms, values, and experiences), as well as structural components which include bonding (connections that provide social support and exist between people with similar demographic characteristics), bridging (connections facilitating interactions between dissimilar groups which are important for feelings of trust, reciprocity and civic participation) and linking (top-down connections of those who have power to those who do not) capital [44, 50, 51]. The health influence of social capital has been theoretically [49] and empirically [52] acknowledged. Social capital is thought to impact health through psychosocial pathways that promote individual adaptation to adversity (i.e., building personal capacities for health-related growth and resilience) [53, 54]. Social capital is also thought to influence health through ‘neo-materialist’ pathways, that is, by influencing the health related material and informational resources available to individuals [38, 54, 55].

Figure 1.2 presents a conceptual model of factors influencing health inequalities adopted from Wagstaff [40]. This figure depicts individual health outcomes as nested within a range of contextual factors operating at various distances from the individual; these distances increase from the left to the right and include specific mention of household and community
characteristics, health and other service sectors and government policies and infrastructure. Arrows in this figure travelling from right to left indicate the (non-exhaustive) cascading effects of ‘top-down’ forces upon factors closer to the individual. These effects are well recognised in the distribution of health resources. For example, in his discussion of the health impacts of social capital, Putnam [9, 39] notes that while impacting on the determinants of health, social capital itself is influenced by other aspects of context such as political forces and inequality (Figure 1.3). Arrows travelling left to right in Figure 1.2, indicating the ‘bottom-up’ effects, represent the potential for factors closer to the individual to influence the broader context. These latter effects may be attributable to individuals exerting social change and/or the responsivity of higher level factors to lower level demands, such as identified health burdens.

Figure 1.2 Conceptual model of contextual factors driving health inequalities. Adopted from Wagstaff [40].
Figure 1.3 Influences of inequality and administrative forces or ‘the state’ on social capital and some mechanisms through which social capital may influence health. Adopted from Putnam [39].

*Implications of the individual in context for population research and policy*

In common, these models highlight that the health consequences of individual and contextual health determinants are interrelated. Implications of this are that the factors associated with health in one context may not generalise to another; that is, factors may be stronger or weaker as health determinants under different physical, social or economic environments. Inter-country differences in health and its determinants are perhaps the most widely acknowledged illustrations of this and research findings regarding the appropriate targets for health intervention are recognised as not readily generalizable across countries. Thus, identification of the factors influencing health experiences and outcomes across different, and indeed ‘at risk’, populations is central to the equitable formation and targeting of health interventions and policy [29]. Below, some non-exhaustive examples of well-documented psychosocial determinants of health (namely gender, social networks, and adversity and life events) and how they may be moderated by context are provided to illustrate this potential and to draw attention to some social phenomena that will be discussed throughout this thesis.
**Gender.** The health impacts of an individual’s gender are variously attributed to biological differences and roles (e.g., childbirth, maturation, and hormonal changes), social opportunities (e.g., opportunities for freedom and socioeconomic independence, role fulfilment) and gender roles (e.g., exposure to physical labour, health related behaviours). The importance of the latter factors on health may be understood by comparing health differentials by gender across countries [56] where the social status, norms and opportunities associated with gender vary. These effects reflect differences in the physical, social and economic contexts of these places that have shaped the psychosocial resources and opportunities available to men and women [56, 57].

**Social networks.** Social networks refer to a range of interpersonal interactions and resources available to individuals. ‘Social support’ has been used to refer to potentially supportive interactions and relationships between people who share close personal connections [58]. These interactions have been characterised as providing emotional, informational and instrumental support to an individual’s health [59, 60]: emotional support may be derived from interactions that influence feelings of self-esteem and worth and provide individual opportunities to discuss problems and issues; informational support refers to the potential for relationships to provide individuals with information which effects health; instrumental support refers to the practical support that social networks may provide and may entail material (i.e., financial support) and time (i.e., care for affected persons or sharing child care) resources that may reduce health related burdens. Social interactions in addition to those associated with close socially supportive contacts, are also acknowledged [58]. Similarly, interactions of individual’s within their social networks may also be conduits through which individuals are exposed to social norms, attitudes and beliefs that are relevant to health or health sustaining behaviours such as socialisation and employment.
Both ‘supportive’ and other interactions within social networks may have negative impacts on health if they expose individuals to other health related risks (i.e., if social interaction is overly burdensome or oppressive or communication of social norms and beliefs negatively impacts on health) or are lost (i.e., relationship breakdown). Several commentators acknowledge that the supportive social networks of individuals are embedded within broader social structures such as those characterised by indices of social capital and thus their capacity to influence health is also moderated by these factors [54, 59, 61]. For example, the capacity of social networks to facilitate access to health related resources and information are limited by the availability and acceptability of these resources.

**Adversity and life events.** Experiences of personal adversity, ‘stressful life events’ or trauma encompass a range of adverse experiences which may both tax the individual’s personal resources and have direct consequences for their health. Inventories of stressful experiences typically note a range of life events including moving house, financial difficulties, litigation, relationship breakdown and death of a loved one, though adversity may also be the direct result of health states such as injury and experiences of disease or disorder. Experiences of adversity are thought to impact health by increasing stress and decreasing coping and material resources, such as behavioural, financial and social resources which may otherwise be used to maintain health. Thus the health impacts of adversity are determined by both the individual’s capacity to draw upon personal and institutional support where needed [59, 62] and by the individual’s coping abilities (i.e., effective employment of problem, emotion and/or appraisal focused strategies) [63]. Contexts that have low capacity to support the resolution of or coping with these experiences, and where norms discourage seeking support for the adversity experienced, are likely to influence the health burden associated with the experience of adversity in a given context [29]. For example, in a study of the experiences of persons affected by paraplegia in urban and rural areas of Australia, Allotey et al. [64] identified that a
rural context carried with it several physical (i.e. decreased accessibility to health services and general shopping areas) and social (i.e., increased stigma) factors which were seen as posing particular difficulties to persons living in rural compared to urban environments.

**Operationalization and measurement of contextual characteristics**

Recognition of the health impacts of context has driven the quantification of these factors for research and policy purposes. Health related contextual characteristics such as social capital, health service accessibility and socioeconomic factors have been operationalized using objective (i.e., enrolments in local sports and volunteer organisations [49], volume and distance of services, indices of socioeconomic disadvantage [65], and use and provision of services [66]) and subjective indices (i.e., aggregations of individual’s perceptions of social capital, services and prosperity in an area [42], and home maintenance [67]). However, as summarized in the above discussion, health related contextual characteristics influence, and are influenced by, a range of factors and thus selecting an appropriate proxy for contextual characteristics of areas is difficult. For example, as noted by Bernard et al. [38] and others [29, 68], the accessibility of health related resources is determined not only by the proximity of these resources but also social factors such as their acceptability [38]. As such, objective indices of contextual characteristics are likely to provide an adequate proxy for these characteristics in isolation.

In light of such issues, researchers investigating the health impacts of context have often determined that contextual resources may be better gleaned from the experiences of representative individuals within the context. This has led to the aggregation of perceptions of individuals surveyed within a given geographical area, such as a city block, postal code or state, to quantify contextual characteristics of areas. Objective indices accounting for a wide range of factors, resources and conditions within given geographical areas have also been developed to represent the socioeconomic resources available within defined statistical boundaries. For the
purposes of the current thesis, characterisations of contextual factors within geographical areas will be referred to as ‘area-level’ characteristics, to distinguish them from contextual characteristics, which may or may not be adequately represented using these methods and boundaries.

Specifying the appropriate spatial area over which to aggregate and otherwise quantify observations to capture contextual effects requires sound theory and understanding of the pertinent forces at work [35, 38, 69]. In considering the practicalities of such an exercise, Macintyre et al. [42] highlight that key considerations include the appropriate spatial scale for aggregation, the defined geographical classifications available, and the availability of data points within these classification boundaries. Several studies have chosen to nominate small area levels such as postcode [35-37, 70] or census tracts [34, 71] at which to aggregate data to define ‘neighbourhood’ characteristics. While providing small area definitions of perceptions within an area, it is acknowledged that these statistical areas are otherwise meaningless for characterising the contextual and social experiences of persons within their bounds and may not capture the relevant contextual influences on health [42].

**Conclusions**

Aspects of community and geographic context may influence individual health and impact on known health determinants. Contextual characteristics of areas such as social capital, health service accessibility and socioeconomic disadvantage are shaped by a range of top-down and bottom-up factors. Understanding the nature and impact of contextual characteristics on health and individual-level determinants of health is important for the targeted and equitable distribution of health resources. Both objective and subjective methods used to characterise contextual factors require a) the generation of meaningful indices of these factors, and b) nomination of the geographical units over which they are proposed to generalise and impact. A theoretical understanding of the factors influencing contextual characteristics should inform
these decisions. However, it is important to consider practical issues such as the availability of data and existing statistical boundaries within which data points may be geocoded and aggregated to produce indices of contextual characteristics.

Health related contextual correlates of population size, density and distance from resources

Interest in the influence of ‘urbanization’ on health, and in the health of persons living in ‘rural’ areas, reflect concern regarding influence of contextual factors on health and its determinants as well as health inequalities associated with these population groups. Urban or metropolitan areas are characterised by large dense populations and relatively high levels of services and economic activity. ‘Urbanization’ typically refers to factors associated with increased population size and density, often over time. In contrast, ‘rural’ is a term that has been used to describe a range of geographical areas which exist outside urban centres and which are characterised by relatively smaller and more dispersed populations. To acknowledge that such ‘rural’ areas encompass a range of different environments, the current thesis will use the term ‘remoteness’ to describe characteristics of areas that are associated with decreasing population size and density.

Comparisons of ‘urban’ and ‘rural’ areas are undertaken to understand the health burdens associated with the conditions experienced by persons living in these areas. It is becoming clearer that health impacts of urban and rural areas reflect a range of contextual characteristics that vary between these areas, such as access to services, social norms regarding health behaviours, social capital and socioeconomic status as well as the exacerbating effects of these factors on existing individual-level risk factors [72].

In this section the barriers which have limited investigations into the impacts of contextual factors on health and its determinants in rural areas and propose are noted. It is proposed, as
has been previously [72, 73], that remoteness itself may be used as a proxy for these factors. Limitations discussed include the different contexts of ‘urban’ and ‘rural’ areas across different countries, the advances in the conceptualisation of measurement of ‘rural’ areas, and the lack of assessment of the differential influence of remoteness on determinants of health.

**Difficulties quantifying contextual factors in rural areas**

There are several difficulties in quantifying the contextual factors which may impact health in rural areas. As discussed, health related contextual characteristics such as social capital are often quantified by aggregating the perceptions and experiences of a representative sample of persons within a given area [42]. However, the capacity to generate aggregate indices of contextual characteristics of areas comprised of small, dispersed populations in which few observations may be obtained has been limited. Further, it is likely that the previously noted inadequacies of aggregating contextual characteristics within arbitrary statistical boarders may increase with remoteness [41]. Further, several researchers consider that the relevant spatial scale over which aggregation may meaningfully characterise contextual factors is likely to differ between urban and rural areas [41, 42, 70, 74].

Research using postal-code level aggregation in the Netherlands observed increased social capital to have a greater influence on self-rated health in urban areas compared to rural areas [70]. While this finding may reflect a reduced association of social capital with health in rural communities [70], it may alternatively indicate that postal codes may be less useful for characterising social capital in rural areas. Indeed, other researchers observing null effects of area-level social capital on health outcomes in rural populations have suggested that the inadequacies of using arbitrary statistical boundaries to characterise health relevant resources may increase with remoteness [41].
Indeed, it is contentious whether the health relevant characteristics of rural areas are spread
over larger spatial units, as the relevant resources are spread over greater distances [42, 70] or
smaller spatial units, as townships exist in smaller areas [74]. Differences in social interactions,
networks, expectations, service distribution and burden associated with travel to access these
resources may all contribute to difficulties in defining an appropriate spatial unit to
characterise the health related contextual characteristics in rural areas [75]. To date there has
been little progress made in this debate.

However, it has been proposed that the physical, social and economic qualities of rural areas
are thought to influence the health related conditions experienced by persons who live in
these areas [69, 76, 77]. For example, the small, dispersed population distribution
characteristic of rural areas may shape socio-geographic inequalities such as access to physical
resources, increased risk of injury, and stress due to adverse environmental conditions, as well
as the social norms, beliefs and behaviours [39, 76, 77]. Indeed, increased community
remoteness has been associated with higher ratings of social capital and social support
compared to urban contexts [70]. Thus, understanding the physical, social and economic
contexts are central to understanding the health implications of the rural context [49, 75, 77].
Aggregations of observations based on areas with similar resource and social strains may result
in more meaningful characterisations of contextual factors in rural and remote regions.
However to our knowledge, aggregations based on factors other than residential proximity
have not been explored.

Driven by an acknowledgement of the significance of population size, density and proximity to
urban resources in shaping a range of health related contextual factors (as well as the utility of
easily quantifiable and delineated metrics such as population density for public policy)
community remoteness itself has been proposed as a proxy for health related contextual
factors [72, 73]. Figure 1.4 presents a simple conceptual model of remoteness as a factor
underlying contextual factors, including health service accessibility, social capital and socioeconomic disadvantage. The following sections will discuss issues encountered by researchers who have adopted remoteness itself as a variable of interest and a proxy a range of contextual factors impacting health.

Figure 1.4 Community remoteness as a factor influencing health relevant contextual characteristics.

Limitations of health research assessing the impacts of remoteness on health and its determinants

The literature investigating the health implications of community remoteness face three key issues: i) the differing risks and qualities associated with ‘rural’ settings between countries, ii) the operationalization of remoteness, and iii) a lack of investigations into the impact of remoteness on health determinants. To illustrate these issues, studies investigating the effects of remoteness on mood disorders in community samples (see Appendix 1.1, Table S1) and a recent meta-analysis of the influence of remoteness on mood disorder by Peen et al. [78] are drawn upon. Mood disorders have been selected for this review due to the recurrent concern
regarding psychiatric disorders in remote areas, driven by awareness of the social, socioeconomic and health services accessibility adversities faced by these populations. While the current discussion is limited to mood disorders, the issues illustrated in these studies regarding the assessment and analysis of remoteness in the health literature are generalizable across all health outcomes. Details of other technical aspects of the literature reviewed (including population country of origin, study design, response rate, sample age, sample size, diagnostic tools used and covariates adjusted for and results) are also presented in Appendix 1.1, Table S1.

Peen et al. pooled results of 13 representative community surveys of developed nations that examined urban-rural differences in mood disorders over the past 25 years, concluding that there was a higher urban prevalence of mood disorders compared to rural areas (pooled unadjusted OR 1.39; 95% CI 1.23, 1.58). However recent reviews of the evidence have suggested variously: that prevalence rates of mental illnesses are higher in urban areas compared to rural areas [78]; that there is little evidence of an urban-rural differential in the prevalence of mental health disorders [72]; and that incidence of suicide for men is higher in rural compared to urban areas but do not differ for women [72]. There are several reasons for differences in conclusions between these studies; including differences in populations, response rates and diagnostic indices used (a summary of the related methodological aspects of studies can be found in Appendix 1.1, Table S1). However the current discussion will focus on the reasons associated with the varying conditions and operationalization of remoteness.

**Inter-country differences in ‘urban’ and ‘rural’ contexts**

There is a lack of a standard definition of area remoteness, and indeed what is ‘urban’ and ‘rural’ in the epidemiological literature. This deficiency in part reflects the differing physical, social and structural concerns regarding remoteness in the broader context of a state or country. The potential for environmental and cultural differences to influence differences in
health states between urban and rural areas is recognised. Even within the developed nations, conditions experienced in areas considered ‘rural’ may differ due to a range of factors including social, climatic, historical factors, and material resources.

Peen et al.’s [78] meta-analysis indicated a high level of heterogeneity between individual studies ($I^2 = 65.1\%$), suggesting the effects of urban and rural status on mood disorders in the Western world to be highly variable and incomparable. To examine heterogeneity attributable to differences in culture, Peen et al. compared pooled unadjusted rates of urban-rural mood disorders between American and European studies. This analysis indicated no significant difference in urban-rural rates of mood disorders attributable to ‘culture’. However, studies examining the effect of remoteness on mood disorders across Europe have demonstrated large variation between these countries, suggesting that the assumption that samples within Europe and America represent homogeneous ‘cultures’ associated with rural living are flawed.

Both the Outcome of Depression International Network [ODIN: 79] study covering Finland, Ireland, Norway and the United Kingdom and the European Study of the Epidemiology of Mental Disorders [ESEMeD: 80] demonstrate this variation within Europe by implementing standardised interview protocols and classifications of remoteness across European countries; indeed, region-level influences on urban-rural differences have also been observed within Canada [81]. Such effects suggest that differences in contextual factors associated with remote areas, beyond geographical isolation, influence health outcomes between countries and emphasise the potential impact of physical, social and economic contexts on the health impacts of remoteness.

Due to differences in the nature, definitions, and consequences of ‘remoteness’ between countries, research findings are difficult to generalise outside the setting in which they were conducted. Pertinent policy, cultural, and physical and economic stressors are likely to differ greatly between and possibly within, countries. This suggests that research into the influence
of remoteness on health within the context of the nation, and perhaps region, of interest should be considered. Thus, while drawing on the knowledge and lessons gained from international studies, research attempting to assess the impacts of remoteness, and the ‘risk’ factors associated with health outcomes, should be conducted within the environment of interest.

**Operationalization of remoteness.**

The conceptualisation and operationalization of remoteness is a key issue in interpreting this literature. Few standard definitions of what is ‘urban’ and ‘rural’ exist and studies have rarely defined remoteness in the same way (see Appendix 1.1, Table S1). The lack of a standard definition of what comprises a ‘rural’ community in part reflects the reality that the concept of ‘rural’ is often simplified as a state opposing an ‘urban’ status, both of which may be quantified using several criteria. However, generalised classifications such as ‘urban’ and ‘rural’ must necessarily fall short of characterising the complex area-level variations that are experienced in these areas [72].

Methods of classifying areas as ‘urban’ or ‘rural’ include both subjective and objective characterisations of places. Subjective nominations of an area’s status as ‘urban’ or ‘rural’ have been made by statistical bodies, researchers, and participants themselves (see Appendix 1.1, Table S1). A strength of subjective classifications is that they may account for a range of factors that contribute to the experience of ‘urban’ or ‘rural’ living which may be poorly represented in objective statistical indices. Additionally, these methods provide a relatively easy method of classification that does not require the selection and quantification of objective indices of remoteness or the necessity of obtaining residential information from participants. However, such subjective ratings may be unreliable, as the range of factors accounted for may differ by person and the lack of understanding of factors underlying area nominations limit the application of findings for the formation of public policy. Further, as there are few commonly
understood divisions of area remoteness, the reliability with which areas could be classified beyond a dichotomous classification of ‘urban’ and ‘rural’ status may be highly questionable.

As for other measures of contextual characteristics, objective methods of quantifying area remoteness typically rely on indices of population size and density within specified, often arbitrary, statistical boarders (e.g., postal codes, local government areas etc.). More recent developments take into account factors that may influence the nature of rural towns such as the size of and distance from major and non-major settlements, the proportion of workforce employed in agriculture, and the proportion of workforce commuting to urban areas (see Appendix 1.1, Table S1).

As confirmed by Peen et al. [78], studies of the effects of remoteness often indicate small health inequalities between urban and rural areas. However, recent commentaries have suggested this may partly be due to the over-simplified conceptualisation of the ways in which communities existing along the spectrum of remoteness. Indeed, it has been acknowledged that rural communities are characterised by a range of different contextual norms and stressors than their urban counterparts – factors that are not easily described by distance or population density relative to an urban centre [77, 82-85]. Consequently, dichotomous characterisations of communities as urban or rural may ‘average-out’ differences in health related factors that exist within ‘urban’ and ‘rural’ environs. Each of these categories may encompass areas that are actually diverse in nature, and thus classifying these areas together may obscure important differences.

Some advances have been made to create more fine-grained classifications of community remoteness and several studies using multi-category definitions have demonstrated the presence of differentials at some, but not all levels of remoteness (see Appendix 1.1, Table S1). Such findings suggest more fine-grained definitions of context may have a significant effect on prevalence and associative findings that may be otherwise obscured [i.e. 86, 87], and they are
increasingly being used to inform policy and deliver health services. However, these classifications continue to rely on largely arbitrary cut-offs between remoteness classifications. As existing indices are shown to have limitations in their capacity to characterise rural and remote areas, and as areas themselves change in their characteristics over time, new indices of remoteness are developed and adopted for research and policy related purposes, while others fall out of use (e.g., the Australian Rural, Remote, Metropolitan Areas classification developed in 1994 has largely been replaced by the Accessibility/Remoteness Index of Australia [88]).

In Australia, remoteness classifications have long been used as a basis for health resource allocation by government, such as determining the eligibility of health practitioners for incentives for working in rural locations; thus, the importance of area classification is well recognised. The Accessibility/Remoteness Index of Australia [ARIA+: 88] is a continuous index that is used to classify the remoteness of areas for such purposes. The ARIA+ ranges from 0-15 and the remoteness of a location is calculated based on the size of the nearest service centre (five categories based on population size) and its average estimated road distance from the location. By acknowledging that remoteness is influenced both by distance from as well as the size of populated centres, the ARIA+ provides an index of access to services and resources (i.e., the material and social resources associated with population centres of different sizes). To allow estimation of remoteness values for a range of statistical classifications, the ARIA+ divides the Australian landmass using a 1km² grid overlay and an ARIA+ score is calculated for each grid square. The average ARIA+ value for grid squares within a range of statistical areas (i.e., census areas, postal codes and local government areas) are then calculated to provide an aggregate remoteness value for that statistical classification/location. The ARIA+ is typically divided into five ‘natural break’ categories selected based on groups in the data distribution, minimising variance within groups and maximizing variance between groups. These groupings are known as the Australian Standard Geographic Classification (ASGC) ('Major Cities': ARIA+
values 0.00 to 0.20; ‘Inner Regional’: ARIA+ values > 0.20 <= 2.40; ‘Outer Regional’: ARIA+ values > 2.40 <= 5.92; ‘Remote’: ARIA+ values >5.92 <= 10.53; ‘Very Remote’: ARIA+ values > 10.53]. Though introduced as the basis for health resource allocation by the Australian government in 2009, the significance of these classifications for health and other outcomes remains unknown. The extreme heterogeneity of areas within these categories has been noted as a weakness of the ASGC categorisation [90, 91], suggesting additional criteria for delineating areas and health related stressors within these classifications may be beneficial.

The Census Metropolitan Influenced Zone or ‘MIZ’ is a multi-level classification of areas outside metropolitan areas in Canada [92], which further develops this idea of a classification index, drawing upon multiple contextual factors influencing ‘remoteness’. These classifications are based on population density and distance, but also consider the commuting flow between rural towns and larger centres to provide an index of the ‘influence’ metropolitan areas have on rural communities. These indices can be used to divide areas outside metropolitan areas into four categories with ‘strong’, ‘moderate’, ‘weak’, and ‘no’ influence. The consideration of the ‘metropolitan influence’ on populations, indicates access or isolation of an area from the influence of metropolitan socioeconomic, service and cultural factors, in a way that population distance and population density cannot.

Lack of examination of the impact of context on health determinants

As observed in much of the literature on the impact of contextual factors on health outcomes, recent critiques of the remoteness literature have identified a lack of examination of interactions of remoteness with other risk factors in predicting health outcomes, which may potentially obscure the true health impacts of remoteness [72, 83, 85]. As outlined in our theoretical models of contextual influences on health, the impact of personal factors such as gender or socioeconomic status may vary depending on the culture and resources of areas [72]. While natural policy is largely guided by research derived from observations of urban
populations, identifying how the contextual conditions associated with rural living may influence health and its determinants may allow increasingly targeted and tailored health interventions for these populations.

For example, the capacity of social support to facilitate access to health-related resources is partly shaped by top down structural and administrative forces, as well as the physical and social characteristics of place. Relative to urban areas, the socio-geographic health inequalities associated with rural living, such as poor access to health services, increased risk of occupational injury, and stress due to adverse environmental conditions [72, 93, 94], may limit the capacity of social support to influence health and health relevant behaviours in these environments. Evidence that different aspects of social networks are not uniform predictors of health between urban and rural areas [95, 96], and are more or less significant in predicting health outcomes between countries [95], emphasises the potential contextual influence on associations between psychosocial factors and health outcomes. However, researchers have often not examined the influence of these factors by remoteness [87, 95, 97-99]. Indeed, the significance of psychosocial determinants of health have not often been examined by environmental context [87, 96, 97, 99-101] and little information exists on how the influence of known determinants of health may vary with rural living. This knowledge may be particularly important when considering health interventions as important targets may be overlooked or assumed to operate the same way in both urban and rural settings.

Further, studies have observed the association of gender and health to vary between urban and rural environments, though results vary between studies. In the mood disorder literature, females have displayed an increased risk of depression in urban but not rural areas, with men’s risk displaying no effect of environmental context [79, 87, 95-97]. Others have found no differential effect of gender in urban and rural areas [102, 103], with one study observing the opposite effect, with males showing increased risk of depression in urban but not rural areas,
and no effect of location for females [104]. Amato and Zuo [105] observed three way interactions between rural living, gender and ethnicity, as well as rural living, gender and household composition in determining depression symptomology. African American males displayed higher depression scores in urban than rural areas, while other males had higher depression scores in rural than urban contexts. This interaction of environment and ethnicity was not observed for females. Single men with no children in rural areas were at highest risk of depression, while married women with no children in urban areas had the lowest risk. Similar findings suggesting the influence of individual level psychosocial characteristics with health outcomes will vary with environmental context have been found in relation to individual income and an area’s income inequality [106]. Such findings highlight that the associations between individual characteristics and mental health outcomes may change with community characteristics.

**Conclusion**

There is significant interest in the impacts of health related contextual characteristics that vary with population density. Difficulties in directly characterising contextual factors have contributed to efforts to examine the influence of community remoteness on health outcomes. As remoteness shapes, and is in turn shaped by, a range of physical, social and economic factors, it provides a promising proxy for assessing the influence of contextual factors. There are several limitations in the literature on the impacts of remoteness on health and health determinants. Issues regarding the difference in what is considered ‘rural’, and differences in the contextual effects of ‘rural’ areas between countries, mean that the capacity to generalise findings within this literature across different contexts is limited. Further, the use of largely arbitrary dichotomous classifications of ‘urban’ and ‘rural’ contexts may result in the ‘averaging out’ of effects within heterogeneous rural areas. Consequently, the development and use of more fine-grained classifications of remoteness may have several advantages in
delineating the heterogeneous nature of communities and their health relevant resources, which exist outside urban areas. Multi-category classifications of remoteness reflect an improvement in our understanding and measurement of remoteness; however, they are still limited by the disparate nature of areas categorised together using these indices. While remoteness may have some limitations as a proxy for health related contextual effects, these may be minimised by: i) conducting studies within areas that have common social structure and within which policy decisions may be made regarding resource distribution, such as states or countries; ii) using classifications that provide more fine grained classifications of non-metropolitan areas; and iii) examining the effects of remoteness on the determinants of health. These methods may optimise the capacity to understand the particular impact of remote living within the broader environmental and cultural characteristics of that country and thus better inform understanding of health processes and policy models for that country.

While theoretical models of contextual impacts on health and health determinants suggest that a shift in contextual factors may influence the strength and nature of health determinants, little research has been conducted to assess the impact of remoteness on the determinants of health. Such information may be useful in identifying targets of health intervention specific to rural areas which may assist us in tailoring health intervention models.

**Health determinants in rural Australia – informing targeted health interventions**

Rural Australia has been characterised as having distinct social, environmental and cultural features which may impact on the well-being of persons living in these regions. Indeed both the contextual characteristics associated with rural areas and poor health related outcomes have driven concern regarding the health of the rural population. In Australia’s most populated state of New South Wales (NSW), approximately 84.0% of the landmass is considered rural and
remote. Of the NSW population, 74.0% reside in areas classified as major cities, 19.4% reside in inner regional areas, 6.1% in outer regional areas and just 0.5% in areas considered remote or very remote [107]. Areas outside major cities are broadly characterised by increasingly small, dispersed populations, which include a wide range of environmental conditions, including coastal, agricultural and mining townships. These areas are associated with decreased service accessibility, lower area-level socioeconomic advantage, and exposure to environmental adversity including floods, drought and bushfires. Despite servicing much wider client catchment areas, rural and remote areas have lower per capita provision of generalised and specialist medical professionals [108, 109]. Further, an aging population and increasing outmigration of young persons from rural areas contributes to the decreasing population density in rural areas of NSW [110].

Australian population surveys indicate that rural populations have increased rates of mortality, chronic disease, obesity and health related risk factors, including lower rates of high school completion, higher rates of smoking compared to urban populations [111], as well as increased rates of harmful levels of alcohol use [111] and rates of suicide [112] among men. Despite the potentially stressful conditions associated with rural living, studies have observed no association between rural living and high levels of non-specific psychological distress in either US [113] or Australian [84] populations. However, men in remote areas are more likely to report high levels of psychological distress [109] and increased remoteness has been related to lower levels of satisfaction with life, when controlling for demographic and personality variables [84], suggesting that demographic factors and the operationalization of remoteness are important considerations.

Several studies also note the potentially health related social characteristics of the rural Australian context. Qualitative evidence suggests rural Australia possesses a culture of self-reliance and stoicism [114, 115], which may discourage emotionally expressive and help-
seeking behaviours [114]. While these characteristics have been highlighted as potential barriers to help seeking, rural communities also possess higher levels of potentially beneficial resources, such as individual level ratings of social capital and social support, which may be protective against poor health outcomes [38, 40, 87]. As observed in other rural areas, ratings of social support and individual social capital are higher in rural areas compared to urban areas of Australia [116]. This increase may reflect the influence of smaller populations on the closeness of social networks and increased social visibility [116] as well as a lower reliance on formal infrastructure for support, services and activities.

Few studies to date have attempted to assess the impact of rural environments on the determinants of health. There is growing evidence that the influence of individual level characteristics, such as gender and socioeconomic indices, on mental health outcomes may be moderated or ‘exacerbated’ by the social and physical characteristics of the rural context in Australia [72, 83, 84]. Knowledge regarding the generalizability of findings based on predominantly urban data is needed to understand the influence of contextual factors on health and its determinants in rural areas. Such knowledge may allow us to better target health interventions and resources to factors which may have the greatest benefit for rural populations.

**Issues for investigation into health determinants in rural Australia.**

There are three key issues in assessing and identifying appropriate targets for health intervention in rural areas of Australia. As discussed previously, the operationalization of remoteness and use of largely arbitrary classifications of remoteness in this literature present difficulties for quantifying and understanding the impacts of remoteness on health and health determinants in rural areas of Australia. Advances in this area include the development of standardized indices of remoteness, such as the ARIA+, with multiple cut offs delineating the remoteness of areas (i.e., the ASGC). However, use of largely arbitrary cut offs and
understanding of how these correspond with health relevant contextual characteristics is lacking.

The second barrier to research into the influence of remoteness on health and its determinants in Australia is a lack of comprehensive data across the spectrum of remoteness. Research on the health of rural Australia has focused on populations and regions identified as ‘rural’ [117-119], with few providing more or less urbanized environments with which to compare these results. To add to this deficit, state and national surveys of mental health have limited representation of remote and very remote regions [120-123], leading to limited ability to compare health and well-being in these regions with more urbanized regions of Australia, and the assessment of factors associated with mental health outcomes in these populations. Authors of these publications [i.e. 121] have suggested studies specifically designed to access these populations, such as the Australian Rural Mental Health Study [124], may fill this gap. By assessing a wide range of individual and community level social factors, the first wave of the Australian Rural Mental Health Study has identified differences in psychological distress and well-being across four categories of remoteness and identified experiences of personal adversity and personal social networks as important determinants of health for this population [99].

Recent publications of baseline data from this cohort demonstrate the capacity of this study to detect factors associated with distress and well-being in rural populations and have identified personality, adverse events and social support as key determinants of distress and well-being in these cross-sectional models [99]. However, the capacity of this data to inform whether the impacts of these factors differ from those in urban areas is limited. The third limitation stems from the second and relates to a lack of longitudinal data in rural samples. Longitudinal data is necessary to allow modelling of the causal associations between health and its determinants and is vital for identifying appropriate targets for health interventions for these populations.
In light of the health inequalities associated with remoteness in Australia, research quantifying and providing representation of a spectrum of urban to remote areas of Australia is needed to determine whether the contextual differences associated with rural living impact on the determinants of health in these areas. These findings would inform the value of obtaining better representation of rural and remote areas in surveys of determinants of health and well-being, and also assist in the interpretation of associative and longitudinal data analyses from rural cohorts. Such research will also aid in the development of interventions tailored to meet the needs of persons in rural contexts.

**Current study**

The impacts of community remoteness on health determinants in rural Australia are important, if poorly understood. Several barriers to research in this area exist, regarding: i) the measurement and operationalization of area characteristics and remoteness; ii) a lack of examination of interaction effects; iii) an absence of detailed data representing persons from across the spectrum of urban to remote areas; and iv) a lack of longitudinal data. However, awareness of the potential significance of remoteness for health and its determinants has led to the development of more sophisticated indices of remoteness and the collection of subjective data regarding social capital and health service accessibility in national surveys. Further, cohort studies exist that specifically examine health and well-being in rural and remote populations of Australia.

The current thesis will build on these developments to investigate whether factors associated with community remoteness influence the determinants of health in the state of New South Wales, Australia. These analyses will focus on the differential impacts of key psychosocial determinants of health, namely adverse life events and social networks. The current thesis will also explore whether remoteness is a useful proxy for health related aspects of context. Where
evidence is found that determinants of health differ between urban and rural communities, the causal associations between psychosocial factors and health outcomes in rural communities will be examined.

The xTEND study: a study exploiting existing cohorts, data indices and statistical potential

There are several good reasons that a single, purpose built study sampling from areas across urban and remote areas of Australia would be useful to address these questions. However, limitations in resources such as funding as well as ethical issues regarding taxing small and vulnerable communities, mean that conducting successive studies of the same population are infeasible and unethical. One way in which limitations in data and generalizability have been addressed has been to pool summary or individual participant data points from multiple existing studies to assess whether study groups display heterogeneity in effects.

To obtain representation of persons and contextual factors across the spectrum of urban to remote contexts in NSW, the current thesis will utilise both new and existing data from cohort and population surveys participating in an initiative known as the eXtending Treatments, Education and Networks in Depression (xTEND) study. The xTEND study combined individual participant data from two existing and independent longitudinal cohort studies, namely the Hunter Community Study (HCS) [125] and the Australian Rural Mental Health Study (ARMHS) [124], to represent a spectrum of urban to remote areas of NSW. The HCS collected self-reported psychosocial and physical data, along with clinical assessments, from a sample of persons aged 55 to 85 years who resided in areas surrounding the major urban port of Newcastle, NSW. Newcastle is the largest non-capital city in Australia and houses several hospitals, a university, and is one of the largest coal export terminals in the southern hemisphere. The ARMHS collected self-reported psychosocial and physical data from a sample
of participants aged 18 years and older residing in inner regional, outer regional, remote and very remote local government areas of NSW, oversampling from remote and very remote areas.

In combination these cohorts provided a sample representative of the spectrum of urban to very remote communities, in largely contiguous local government areas, with baseline assessments of a range of social, physical and health. Access to individual participant data that included postal codes presented an opportunity to geocode participant remoteness in a consistent manner across cohorts. Further, as both population studies were designed to allow comparison with existing state and national surveys and, in light of known determinants of health, the studies included several common and potentially comparable measures of health and its determinants. At the point of inception of the xTEND project, both studies had collected baseline data and were due to begin design of 3-5 year follow-up surveys.

**Current research questions**

1. Can cohort data from multiple studies investigating common health determinants and outcomes effectively increase the representation of the combined dataset to inform new research questions?

2. Does community remoteness moderate the impact of psychosocial determinants of health? Specifically, does the association of social support and personal adversity differ across urban to remote regions of New South Wales?

3. Is remoteness an adequate proxy for health related contextual factors?

4. What are the key determinants of health in rural Australia?

**Current thesis chapters**
To increase knowledge regarding appropriate targets for health intervention in rural areas, the current thesis aims to examine the impact of contextual factors on the determinants of health across urban to remote areas of Australia by combining individual participant data from existing cohort studies.

The second chapter of this thesis will consider the potential benefits and threats to inference presented by combining individual participant data from multiple cohort studies to address this research question. It will also provide an overview of practical and statistical methods used to evaluate the reliability of statistical results and interpretation under these circumstances.

The third chapter will examine whether community remoteness influences the impact of key demographic and social support factors on non-specific psychological distress. This chapter utilises a validated measure of high psychological distress as its primary health outcome measure common to both the HCS and ARMHS data sets. Preliminary data from the common follow-up phase of the xTEND project is used to create an index of social support that can be applied to baseline data.

The fourth chapter will address the need to establish a holistic, multidimensional index of health that could be assessed across both the HCS and ARMHS cohorts. This chapter assesses the factor structure, and invariance of the Assessment of Quality of Life (AQoL-6D), across the HCS and ARMHS cohorts. Analyses of the validity and invariance of the best available indices of HRQoL were conducted to ensure optimal comparability of physical and mental health constructs across urban and rural cohorts.

The fifth chapter addresses the potential for community remoteness to influence impacts of health related stress, namely chronic illness, on the physical and mental domains of health related quality of life. This chapter draws on data from the NSW population health survey to examine the adequacy of remoteness as a proxy for health related contextual factors. Finally, it
examines whether the physical and mental correlates of health-related stress – namely, chronic illness and financial difficulty – vary with individual ratings of social capital.

The sixth chapter examines the personal, health, social and contextual factors associated with self-rated physical and mental health in rural NSW. Using a novel theory-driven method of aggregation, secondary data provided by the state health department was used to characterise the contextual health service accessibility and social capital characteristics of rural areas, allowing assessment of their association with health.

The seventh chapter of this thesis builds on the findings of Chapter six, by examining longitudinal causal models of cross-sectional health determinants and their relationships with health outcomes in a rural sample. This information was used to confirm the relationship of health, social networks and personal adversity in rural population and identify appropriate points of intervention.

The eighth and final chapter of this thesis discusses the main findings from this work, including the feasibility of using existing cohort studies to address new questions of interest. It summarises and draws together findings from previous chapters regarding the influence of community remoteness on health determinants, the adequacy of remoteness as a proxy for contextual effects and the utility of health, adversity and social networks as points of health intervention in rural communities.

The candidate contributed substantially to the work presented in each chapter. The specific role of the candidate is described in the introduction to each of these chapters.
References


Chapter two: Goals and methodologic issues concerning individual participant data analyses from multiple cohort studies

This chapter was disseminated in the academic literature as:


Synopsis

This chapter introduces the necessary theoretical, methodological and practical considerations associated with combining participant data from multiple cohort studies and provides examples of how these have been considered and addressed in the xTEND project and current thesis.
Introduction to Chapter two

Communities across the spectrum of urban to remote areas of Australia vary in their physical, social and economic characteristics [1-3]. How the contextual characteristics associated with remoteness influence health and its determinants require further investigation. Several reports have raised concerns regarding the physical and mental health of persons in rural areas and how to support the needs of these populations [4-6]. Evidence-based public health intervention strategies that are tailored to these populations are necessary. There is little to inform us about the applicability of models of health and its determinants developed in urban settings for rural populations.

State and national health surveys are limited in their representation of remote and very remote regions [7-10] and thus have limited capacity to inform investigations into health and well-being across the spectrum of remoteness. Similarly, studies investigating health and its determinants in rural Australia have sampled populations and regions identified as ‘rural’ [11-13], with few providing useful gradations for more or less urbanized environments. As a result, these studies are also limited in their capacity to assess the impacts of community remoteness. Important longitudinal data, allowing modelling of causal associations between health and its determinants in rural environments, are also scarce.

The design and implementation of such geographically representative longitudinal studies are difficult, costly and lengthy processes. Further, due to the small dispersed population mass and associated difficulties in contact and access, remote populations are often under sampled and at risk of being disproportionately taxed by successive surveys. To extend the capacity of existing resources to explore health and its determinants across urban and remote areas, the eXtending Treatments Education and Networks in Depression (xTEND) project aimed to establish a collaboration between two existing longitudinal community cohort studies.
assessing the psychosocial determinants of health: the Australian Rural Mental Health Study [14] sampled persons from across a range of inner regional to very remote areas of New South Wales; and the Hunter Community Study [15] sampled from urban and inner regional areas, overlapping and adjacent to those surveyed by the ARMHS. An illustration of the geographical area sampled within the scope of the xTEND project is provided in Figure 8.0, P. 354.

Combining individual participant data from multiple cohort studies for a common analysis, also known as individual participant data analysis, may have several theoretical, statistical and practical advantages beyond those associated with combining summary statistics from multiple studies as in traditional meta-analyses [16]. However, attention to potential threats to inference, such as the invariance of constructs assessed across different groups, biases introduced by sampling methods, and the existence of sufficient overlap in instruments and constructs of interest, are key considerations in whether to commit the time and resources necessary to conduct individual participant data analyses. Despite the increased interest in these techniques, holistic accounts of the motivations for, potential threats, analysis and practical concerns involved in a project aiming to combine individual participant data from multiple cohorts are lacking.

**Aims and purpose**

The chapter aims to provide an overview of: the xTEND project and how combining data across the ARMHS and HCS cohorts was necessary for achieving these aims; the issues that arose in terms of considered threats to inference; the retrospective harmonization of administered variables; the benefits of conducting a common follow-up phase; and the practical and ethical issues that need to be considered by researchers contemplating such a project. This is the first manuscript of the thesis and has been published in BMC Medical Research Methodology.
**Contribution to primary research question**

This work outlines the motivations and issues associated with combining individual participant data across the ARMHS and HCS to address the questions of how contextual characteristics associated with remoteness influence health and its determinants across urban and remote areas of Australia. The chapter highlights the compatibility between these cohorts in terms of the synchronicity of baseline and follow-up survey phases, the contiguous nature of geographic regions assessed, the similarities and differences to be considered regarding their sampling frame, methods and measures, as well as the opportunities presented by individual participant data analyses to assess assumptions, such as the invariance of measurement across samples for key constructs of interest.

**Candidate’s contribution**

The candidate contributed substantially to the preparation of the current manuscript, drawing on her contributions to several aspects of the xTEND project. Specifically, the candidate: contributed to the initial ethics application for the combination of data from the ARMHS and HCS for the purposes of the xTEND project [protocol #: H-2010-1021, Appendix 2.0.1]; assessed the potential for retrospective (existing baseline and follow-up datasets) and prospective (new measures introduced for the common follow-up phase) harmonization of the ARMHS and HCS datasets for the purposes of the xTEND project; participated in the design of the 2011-2012 common follow-up surveys administered by the ARMHS and HCS; participated in data cleaning for the baseline and follow-up ARMHS and HCS datasets; initiated, designed and assisted in the programming, final appearance and beta testing of an auditable program for applying data harmonization rules for multiple datasets and data collection phases, as well as labelling and merging data; applied consistent scoring algorithms to the combined datasets; participated in discussions regarding the potential threats to inference, governance, ethical and practical
issues faced by the xTEND collaboration; in consultation with a senior statistician, the
candidate devised and applied analysis-specific methods of assessing the comparability and
invariance of key concepts and measures across cohorts, as well as assessing the influence of
non-measured cohort factors on results and subsequent conclusions; and identified additional
questions raised by the combined analyses to be pursued further in the ARMHS dataset.
References


Integrating and extending cohort studies: lessons from the eXtending Treatments, Education and Networks in Depression (xTEND) study

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Abstract

Background

Epidemiologic studies often struggle to adequately represent populations and outcomes of interest. Differences in methodology, data analysis and research questions often mean that reviews and synthesis of the existing literature have significant limitations. The current paper details our experiences in combining individual participant data from two existing cohort studies to address questions about the influence of social factors on health outcomes within a representative sample of urban to remote areas of Australia. The eXtending Treatments, Education and Networks in Depression study involved pooling individual participant data from the Australian Rural Mental Health Study (T0 N = 2639) and the Hunter Community Study (T0 N = 3253) as well as conducting a common three-year follow-up phase (T1 N = 3513). Pooling these data extended the capacity of these studies by: enabling research questions of common interest to be addressed; facilitating the harmonization of baseline measures; permitting investigation of a range of psychosocial, physical and contextual factors over time; and, contributing to the development and implementation of targeted interventions for persons experiencing depression and alcohol issues.

Discussion

The current paper describes the rationale, challenges encountered, and solutions devised by a project aiming to maximise the benefits derived from existing cohort studies. We also highlight opportunities for such individual participant data analyses to assess common assumptions in research synthesis, such as measurement invariance, and opportunities for extending ongoing cohorts by conducting a common follow-up phase.
Summary

Pooling individual participant data can be a worthwhile venture, particularly where adequate representation is beyond the scope of existing research, where the effects of interest are small though important, where events are of relatively low frequency or rarely observed, and where issues are of immediate regional or national interest. Benefits such as these can enhance the utility of existing projects and strengthen requests for further research funding.

Keywords

Cohort studies, Remoteness, Mental health, Individual participant data analysis, Research methods
Background

Cohort studies are invaluable in informing a wide range of research questions and they play a critical part in observational research methods where randomization is impossible due to practical and ethical issues. However, a range of factors such as representativeness, generalizability, the lengthy time frame needed to achieve outcomes, attrition, and associated research costs, mean that projects often cannot address the evolving, or indeed original, research questions of interest.

Pooling data from published studies, national databases, and collaborations between existing cohorts, have been used extensively to address these issues. The potential for pooled data to support the synthesis of existing research is exemplified by the application of meta-analytic techniques, combining summary statistics from existing studies. However, the limitations of synthesizing summary data, and the merits of combining individual participant data across studies, are increasingly acknowledged [1]. These latter methods have been considered the gold-standard in research synthesis [2] and even replace methods based on summary statistics [3]. Furthermore, the increased capacity for online storage and transmission of datasets, together with calls for greater transparency, mean that opportunities for combining datasets for such purposes will only grow in coming years.

Known variously as ‘integrative data analysis’ [4], ‘mega-analysis’ [5], ‘cross-study analysis’ [6], ‘individual participant/patient data analysis’ [7,8] and even ‘individual participant/patient data meta-analysis’ [2,9-13], the combination of raw data from multiple studies into single analysis sets is increasingly undertaken. Figure 2.1 presents the frequency of publications using these terms over the past decade by year, which were identified by a keyword search of the OvidSP database for titles available between 2003-2012. It is evident that the use of these terms, and by proxy, associated analytical methods, has increased in recent years.
Figure 2.1 Bar chart depicting increase in number of journal publications (articles or conference abstracts) including terms referring to pooling raw data, as found by a keyword search between dates 2003-2012 (N = 544). [Database: OvidSP titles listed 2003-2012].

The potential for such research collaborations to maximise the benefits of cohort studies (e.g., identification of causal risk factors, retest effects, assessment of developmental trajectories), while minimising the negatives (e.g., cohort effects, participant fatigue, attrition, cost, length of time) [14] are clearly advantageous. Indeed, maximising the utility of existing resources is a key issue in many areas of research; for example, longitudinal cohort studies often address cross-sectional sub-questions to attract funding to support their ongoing activity (e.g., Dunedin Multidisciplinary Health and Development Study [15]). The potential to extend research through linkage to existing external data concerning the health of individuals and their environment is similarly acknowledged. Collaboration between research groups to address questions of common interest may present a worthwhile conduit for maximising the benefits to be derived from existing cohort studies, to sustain their ongoing activities and to support subsequent comprehensive investigations.
It has been recommended that new cohort studies employ commonly used measures from similar studies [16] and adopt standard protocols for assessment, measurement and statistical analysis [17] to ensure that some key benefits of combining data can be maximised. The combination of data from studies that have been planned to incorporate the potential for synthesis is known as prospective harmonization [18-20]. In contrast, retrospective harmonization refers to the synthesis of research studies that have been planned and conducted without this explicit intention in mind [18-20] and the benefits and weaknesses of these harmonization approaches have been previously discussed [18]. In both approaches consideration of the compatibility of studies in terms of design, as well as specific variables, is paramount. Access to detailed documentation regarding study protocols and outcomes are vital in assessing the capacity to validly combine datasets [18], which requires a high level of cooperation and communication between investigators.

There are several factors to examine when considering pooling individual participant data and the likely benefits of this undertaking. Table 2.1 lists a range of theoretical, statistical and practical rationale for pooling individual participant data, which arose from our own observations, as well as from existing discussion in the literature (e.g., [1,18,20]). While not exhaustive, or necessarily unique to pooled individual participant data analyses, these potential motivating factors are worthy of consideration by researchers considering combination of data across studies. The applicability of some of these arguments relate to the goals of the particular analysis. *Theoretical rationale* for pooling individual participant data relates to the increased capacity of pooled data to address a given research question. *Statistical rationale* largely centre upon increasing sample size (e.g., increasing statistical power and detection of low frequency events). The *practical rationale* emphasize their capacity to maximise the benefits derived from existing resources.
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<th>Potential rationale for combining data</th>
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<td>Increasing observations of infrequent events</td>
<td>✓</td>
</tr>
<tr>
<td>Minimising effects of attrition over time</td>
<td>✓</td>
</tr>
<tr>
<td>Standardizing modelling used in predicting outcomes</td>
<td>.</td>
</tr>
<tr>
<td>Aggregation of data from repeated experiments</td>
<td>.</td>
</tr>
<tr>
<td><strong>Practical</strong></td>
<td></td>
</tr>
<tr>
<td>Maximising existing resources</td>
<td>✓</td>
</tr>
<tr>
<td>Time efficiency/producing information of current public interest</td>
<td>✓</td>
</tr>
<tr>
<td>Cost efficiency</td>
<td>✓</td>
</tr>
<tr>
<td>Preliminary exploration to support funding for more comprehensive research design or inform later phases of research</td>
<td>✓</td>
</tr>
<tr>
<td>Features appealing to funding bodies</td>
<td>✓</td>
</tr>
</tbody>
</table>

Note: Key benefits for the eXtending Treatment, Education and Networks in Depression (xTEND) study are denoted by ✓.
Several methodological aspects regarding the comparability of studies and variables assessed therein should also be given serious consideration. The suggested benefits of pooling individual participant data are made with the caveat that datasets meet *prima facie* conditions for the interpretability of combined data – that studies contain sufficient common information for analyses, and that their populations and methods are reasonably comparable. When pooling data from existing, independently conceived, cohort studies it is important to note that these studies were designed and implemented with a specific focus, which is not necessarily that of the combined analysis. While such threats to inference (i.e., sources of error and bias that prevent the meaningful integration and interpretation of combined data) are relevant to many scientific ventures, they are rarely addressable by traditional methods of research synthesis. Careful consideration of their implications is required for pooled individual participant data analyses [10]. Table 2.2 outlines some important potential threats to inference, which have long been recognised as relevant to inferential studies [21] and clinical research [22]. Recognition of instances where studies or measures are not comparable, or integration is undesirable for other reasons, may minimise the time and effort associated with undertaking pooled individual participant data analyses, as well as suggesting other methods of synthesis that are more appropriate, such as coordinated parallel analyses [17].
Table 2.2 Potential threats to inference when examining data across cohorts.

<table>
<thead>
<tr>
<th>Threats</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contextual</td>
<td>The specific contexts from which samples were derived and recruited may influence results.</td>
</tr>
<tr>
<td>Historical</td>
<td>Events occurring between observations may influence results. May also relate to factors impacting on one cohort but not another at baseline assessments.</td>
</tr>
<tr>
<td>Time synchronicity</td>
<td>Studies are not conducted at a similar point in time, allowing a potential for factors or events associated with the time of administration to influence results. The length of time between follow-up assessments may also differ.</td>
</tr>
<tr>
<td>Geographic region</td>
<td>Similar to contextual factors, but specifically associated with features of geographical region.</td>
</tr>
<tr>
<td>Sampling frame and methods</td>
<td>Sampling frame (who was recruited) and methods could influence results (e.g., survey vs. phone based responses, and methods of following up non-responders).</td>
</tr>
<tr>
<td>Measurement equivalence</td>
<td>Measurement methods or characteristics may differ across cohorts or change differentially (e.g., for assessments to be comparable across samples and timepoints, we may need to examine participant responses and demonstrate that the same latent factors were assessed).</td>
</tr>
</tbody>
</table>
Finally, when pooling individual participant data across cohorts there are several other practical issues to be considered regarding material and personnel resources to undertake the task, the interests of the studies providing data, and ethical issues regarding access to and analysis of datasets. To aid others in their consideration of the benefits and pitfalls of individual participant data analysis, we examine some of the motivations and issues associated with pooling individual participant data, drawing upon our experiences with the eXtending Treatments, Education and Networks in Depression (xTEND) study [23].

The xTEND study

Persons living in remote and very remote areas make up 2.3% of the Australian population [24] and approximately 85.7% of the country is classified as remote or very remote. Residents of these areas may be exposed to distinctive circumstances that impact on their physical and psychological health, including extreme environmental conditions, increased social isolation, and low levels of service accessibility. Of particular concern is evidence of increased suicide rates in rural compared to metropolitan populations, particularly among young men [25]. However, the representation of these populations in state and national surveys of health and well-being is severely limited [26-29]. Differences in the conceptualisation and measurement of remoteness between studies has also posed a significant challenge for the synthesis of literature regarding the influence of remoteness on health [30]. Thus, the generalizability of findings from urban studies about the determinants of well-being and the efficacy of health interventions for remote populations remain unknown.

As detailed elsewhere [23], the xTEND study aims to investigate the personal and social determinants of well-being in Australia and how these may be influenced by contextual factors associated with increased remoteness. The study is funded by several stakeholders, including the National Health and Medical Research Council, beyondblue - the Australian national...
depression initiative, and Hunter Medical Research Institute. To address these research questions access was required to a large, on-going cohort of participants who reflect the general population, reside in geographical areas that encompass urban, rural and remote areas of Australia, and among whom a broad range of physical and mental health attributes could be evaluated. Further, as these questions are of immediate regional and national interest, the timely delivery of research outcomes was considered essential.

Driven by awareness of the limitations of existing research on the health impacts of remoteness, and inspired by cross-national investigations into the influence of social and environmental factors on health outcomes, the xTEND study drew upon data from two existing independent longitudinal cohort studies based in New South Wales (NSW), Australia: the Hunter Community Study (HCS) [31] and the Australian Rural Mental Health Study (ARMHS) [30]. Many of the investigators on these studies were colleagues based in the same regional city and were broadly aware of the methods, scope and aims of each other’s research. The HCS collected self-reported psychosocial and physical data, along with clinical assessments, from a sample of persons aged 55 to 85 years who live in areas surrounding the major urban port of Newcastle, NSW (T_0 N = 3253, 44.5% response rate, collected over two waves in 2004 and 2007; T_1 N = 2252, 67.8% response rate, collected in 2010-2011). The ARMHS collected self-reported psychosocial and physical data from a sample of participants aged 18 years and older, oversampling from remote and very remote local government areas of NSW, to ensure adequate representation of these populations (T_0 N = 2639, 27.3% response rate, collected in 2007-2009; T_1 N = 1261, 47.8% response rate, collected in 2011-2012). Both studies recruited participants living in NSW from the Australian electoral roll and when combined provided a sample representative of the spectrum of metropolitan to remote communities, in largely contiguous local government areas. Baseline assessments in both studies included a range of social, physical and psychological indices. Further, access to participant data presented an
opportunity to geocode participant remoteness in a consistent manner across cohorts. It was agreed that in aggregation these cohorts could provide a cost efficient platform to examine the research questions. At the point of inception of the xTEND project, both studies had collected baseline data and were due to begin design of 3-5 year follow-up surveys; consequently surveys used as part of the common follow-up were administered under the auspices of the parent studies.

The current paper

The current paper outlines some of the advantages and challenges associated with combining individual participant data from multiple independent cohort studies. Drawing on the published literature, we discuss the benefits and pitfalls of individual participant data analysis and illustrate novel issues and applications encountered by the xTEND project. We address the theoretical and practical conditions for combining data as well as methodological considerations in the combination of data from multiple studies. While specific statistical methods used to address calibration of different measures of the same construct across studies have been detailed by others [1,19,32], we discuss general levels and methods of data comparability across studies, including some exploratory methods of calibration. Through our examples, we highlight some of the unique opportunities in extending collaborations by conducting a common follow-up phase. Apart from the obvious increase in assessment overlap, data from a common follow-up also facilitated the development and validation of statistical and psychometric approaches to the manipulation of non-identical measurements from earlier phases of data collection. Finally, we outline other practical issues regarding data access and management unique to individual participant data analysis and how these evolved and were addressed during the course of the xTEND project.
Discussion

A. Rationale for combining cohort data

Motivations for the initiation of the xTEND study, and those which may apply to other studies whose aims relate to the synthesis of existing research, are highlighted in Table 2.1. Analyses conducted for purposes of research synthesis (e.g., meta or mega analyses) derive somewhat different benefits from pooling data. These motivations are more comprehensively outlined elsewhere (e.g., [1,10]) and typically include: unified inclusion criteria; consistent definitions of variables and cut-points; and consistent statistical modelling and assessment of subgroups. Here we will focus on motivations for pooling data in studies addressing new or extended research questions, illustrated by some of the benefits achieved in the xTEND study. The four theoretical benefits identified in Table 2.1 are discussed first, followed by the four distinct statistical reasons for which increased sample size was a motivation for combining cohorts in the xTEND study, and finally we discuss the five practical motivations for the project.

A1. Theoretical rationale

Generalizability. The importance of generalizability of study outcomes has been discussed at length in the literature. For cohort studies, limited representativeness may mean that results cannot be assumed to be true for unsurveyed or underrepresented subsets of the population of interest; this was a key incentive in devising the xTEND study. By pooling individual participant data from the HCS and ARMHS cohorts, the xTEND study accessed data over the spectrum of urban to very remote regions of NSW. Figure 2.2 presents a proportionate breakdown of the pooled xTEND sample by study membership, remoteness category and phase, demonstrating that in combination, these studies have the capacity to represent persons from across the spectrum of geographic remoteness in Australia.
Figure 2.2 Proportion of the pooled eXtending Treatment, Education and Networks in Depression (xTEND) sample at baseline (T0) and follow-up (T1) by remoteness category and Hunter Community Study (HCS)/Australian Rural Mental Health Study (ARMHS) membership, compared to New South Wales (NSW) population (2008).
Interest in known or potential sources of heterogeneity. Sources of heterogeneity refer to factors, either measured or unmeasured, that may influence differences within or between study outcomes. Cross-national studies allowing assessment of the influence of social policy and environment on health outcomes are perhaps the best known examples of such investigations. Curran and Hussong [4] provide a detailed discussion of some key sources and advantages of between-study heterogeneity (i.e., sampling, geographical regions, history, study design and assessment of measurement invariance/comparability). The opportunity to geocode participant remoteness in a consistent manner across the xTEND cohorts allowed us to examine the influence of geographical heterogeneity, not only on mental health outcomes but also its potential as an effect modifier. Other sources of heterogeneity not related to specific research questions (e.g., study inclusion/exclusion criteria) are perhaps better viewed as potential threats to inference, which need to be considered throughout the process of combining, analysing and interpreting combined data, and are discussed in section B.

Methodological considerations.

Questions of interest centre on association/modelling rather than prevalence. The inferences that researchers wish to draw from combined data will often determine whether pooling individual data is a worthwhile undertaking. Samples are often compared with respect to prevalence rates (e.g., rates of diagnoses between the 1997 and 2007 Australian National Survey of Mental Health and Wellbeing [28,33,34]) and in these instances the challenges associated with pooling individual participant data may be superfluous. However, when patterns of association are of interest, such as the mediating effects of geographic remoteness on determinants of mental health outcomes, combining datasets may provide a more systematic and thorough investigation. Although differences in response profiles and rates may make comparisons of unpooleed results untenable, it may still be valid to examine patterns of association across studies if appropriate factors associated with non-response are controlled.
for statistically. Thus, while simple comparisons of published data may be acceptable for questions about rates, prevalence and effect sizes, combining data may be more appropriate where the patterns of association between variables and outcomes are of major interest.

**Identifying directions for future research.** Areas for future research are typically identified based on gaps in current knowledge. However, where the published literature is unclear, pooled individual participant data analyses may assist in the identification of new research questions. Observational studies examining determinants of health outcomes within a longitudinal framework also present an opportunity to identify persons for whom health interventions may be desirable. The xTEND project sought to use baseline data from both cohorts to identify factors associated with alcohol, depression and suicidal ideation across a range of communities, with the aim of tailoring and piloting existing interventions for persons experiencing depression and alcohol issues: Self-Help for Alcohol/other Drug use and Depression (SHADE) [35]; and Partners in Depression project [36]. Responses to the common three year follow-up were used to identify persons who would be most likely to benefit from these interventions (e.g., those with current symptoms). Pooled analyses may also detect effects of interest for further exploration either within the individual cohorts (where constructs which are not assessed in common across cohorts could be additionally considered) or, where cohorts are on-going, by facilitating a common follow-up study.

**A2. Statistical rationale: benefits of increased sample size**

**The effects of interest are small but important.** Contextual effects on health outcomes, such as geographic remoteness, are typically small-moderate in size. However, the importance of even modest contextual effects in population research have become apparent, with increasing acknowledgement that even small shifts in the population distribution can have great impacts on population health outcomes [37,38].
The need to assess more sophisticated statistical models. An inability to examine interactions of geographic remoteness with other risk factors has potentially obscured the true influence of remoteness on health and well-being outcomes [39,40]; thus, our investigation facilitated sophisticated modelling of interactions, for which the parent studies were not originally designed (i.e., such effects may require greater statistical power or representation to detect).

Increasing observations of infrequent events. Low prevalence outcomes are infrequently reported in community cohorts. Hence, larger samples are required to obtain adequate data for the analysis of predictors and consequences of these outcomes. Suicidal attempts and ideation were outcomes of interest which are infrequently observed in community cohort samples. Increased observations of such cases mean that pooling individual participant data across studies provides greater ability in model estimation and increased power to fit more complicated models.

Minimising attrition effects. Cohort studies are vulnerable to the effects of attrition, reducing the available population from which inferences can be made and compromising the capacity to fit models with adequate statistical power and representativeness. While unlikely to address biases introduced by attrition (e.g., healthy persons may remain in cohorts longer), combining cohort data may provide one avenue from which to minimise the loss of power due to attrition. Differences in response rates between the current studies were partly due to differences in age ranges assessed and this difference was less marked in older groups, which were the focus of the xTEND project. While these cohorts were diminished in size at follow-up, in combination they remained representative of the population of interest (i.e., the spectrum of remoteness), enhancing our capacity for model replication and longitudinal inference over an extended period. Selecting appropriate research questions to investigate with pooled individual participant data are important in considering threats to inference (i.e., when considering questions of association, the influence of relative biases in sample recruitment
may be quantified and are likely to be less of a threat to inference relative to studies describing prevalence).

**A3. Practical rationale**

When using existing data, results may be obtained in a time efficient manner compared to beginning a new study. Consequently, answers to research questions can be expedited, particularly where outcomes are of importance to the public, or preliminary results are required to leverage support for a larger study, or common follow-up study, which may be able to more fully address the questions of interest. Such results are relatively cost efficient, and can often be obtained without unnecessary duplication of tasks or additional burden on the target population. In the case of survey based cohort studies, reducing the necessity of identifying additional participants, and sending, receiving and processing survey data for analysis, may mean that the greatest costs associated with survey methods are eliminated. Resources can be refocused on the analyses and dissemination; the cost and technical resource considerations associated with pooling and analysing individual participant data across studies are noted later in this paper. These efficiencies, combined with the potential for pooled analyses to examine the feasibility of funding more comprehensive studies, are features that may be attractive to funding bodies. Additionally, support may be gained for sub-questions that are not the primary focus of the parent or pooled cohorts, but which may support the ongoing activities of the cohort, as was the case for the HCS in the xTEND study. Finally, findings from analyses of combined baseline data influenced decisions about the measures employed in a subsequent follow-up phase coordinated by the xTEND project, as well as informing ways to tailor interventions designed for implementation in these populations (e.g., Partners in Depression and SHADE interventions).
B. Methodological considerations

Methodological considerations in the combination of data across cohorts focus on two general issues. Firstly, factors associated with cohort characteristics and the manner in which data were collected may influence the viability of inferences made using these data, particularly when inferences are derived using multiple cohorts. As mentioned, these potential ‘threats to inference’ are outlined in Table 2.2. Ways in which these factors were considered and examined in the xTEND project are provided, for example, under B1 Features necessary for combining cohort data. Secondly, understanding conceptual and measurement overlap between cohort variables is necessary to enable valid statistical inferences to be drawn from combined cohort data. Acknowledging that few studies are likely to have a large number of directly comparable variables, in discussing B2 Considerations in the analysis of combined data we place particular focus on the degree to which variables overlap, illustrating such issues and how they may be examined and addressed using the xTEND example.

B1. Features necessary for combining cohort data

Contextual. Factors relating to the setting in which the sample was derived, including the physical and political realities, may influence study results. As detailed in our theoretical rationale, geographic remoteness was a contextual factor of key interest in the xTEND project. However, more broadly, such variation between studies could confound inferences drawn if it is not sufficiently quantified and taken into account. The context of participant recruitment may also influence the population attracted to the study (i.e., ARMHS participants agreed to take part in a study of mental health and well-being in rural Australia, while HCS participants were recruited to a study of well-being in older persons, with a particular focus on physical health). It is important to keep such factors in mind when interpreting results (e.g., rates of physical and psychological illness may vary across the parent studies due to differences in
recruitment context and may not necessarily be attributable to the questions of interest). The influence of these characteristics on observed associations could be examined by assessing the moderating effect of cohort. As depicted in Figure 2.2, there was relatively little overlap in geographical representation between the ARMHS and HCS studies (i.e., primarily the ‘Inner Regional’ category). However, this overlap represents an important opportunity to explore potential confounding effects of cohort differences (i.e., examination of differences on the outcome of interest within this category by cohort when known cohort related factors are accounted for).

**Historical.** This potential threat typically involves differences in environmental exposures, which are thought to impact more upon longitudinal designs and intervention research in particular. While our parent cohorts could have been exposed to different historical events, both before and during the assessment period, it is unlikely that differences in exposure would have contributed to where they reside, which was a factor of interest in our analyses. For example, while state and federal elections were experienced by all within this combined cohort, they may have had different effects on urban and rural populations. However, this could be considered a facet of the effect of interest (i.e., geographic remoteness), as could, for example, differences in drought exposure or impact between remote communities and urban communities.

**Time synchronicity.** The majority of baseline data were collected within a six year period, meaning that there was some potential for baseline results to be confounded by factors associated with the time period in which they were conducted (i.e., secular effects). Events occurring during these periods were discussed by investigators, including a flood that impacted on the region in which the HCS was conducted during the second wave of baseline data collection. The common follow-up phase was synchronised, such that surveys were administered within a smaller one year window. Thus, events associated with responding were
similar, and could be used to replicate results observed at baseline, to help assess the potential influence of any temporal threats to inference. An examination of the influence of time from baseline to follow-up will be an important consideration in any longitudinal analyses undertaken for this dataset, which may be controlled for, or which may necessitate the exclusion of the first wave of HCS participants who had a longer time between assessments (up to 6 years).

**Comparable geographic regions.** While the cohorts assessed in the xTEND study were from different geographic regions, they represented roughly contiguous local government areas. This minimised the possibility that the results were influenced by geographical factors other than those coded for in the analyses, such as participant remoteness.

**Sampling frame and methods.** This threat acknowledges that populations sampled, and the methods by which they are recruited and assessed, could result in systematic differences between cohorts, which could confound inferences drawn from analyses of combined data. However, such differences may be addressed to allow inferences to be drawn. Sampling methods were highly similar in the ARMHS and HCS cohorts, with participants selected randomly from the electoral roll, and while the ARMHS and HCS cohorts sampled different age ranges, there was significant overlap in the ages assessed, enabling the statistical modelling of selected age effects, at least among persons aged over 55 years. Comparisons of raw baseline response rates suggested these differed, though examination of documentation revealed samples displayed comparable rates of uncontactable or excluded persons (HCS 26.9% and ARMHS 25.2%).

**Measurement equivalence/invariance.** Studies comparing summary statistics across cohorts or the modifying effects of cohort on associations often assume invariance of the construct being assessed. However, even medical terms may differ in their meaning across cultures (e.g., Dyspnoea, in Dutch vs. US physicians) [41]. Pooled individual participant data presents a
unique opportunity to test these assumptions and explore where aspects of invariance may occur and may aid in understanding the differences in the meaning of concepts between groups and reasons for the presence or absence of between group differences. Such techniques are crucial in several areas, notably when alternate language forms of a measure are used and verification of a common meaning is critical to understanding group differences and differences in association between groups. Although it would be excessive to assess the invariance of all measures across groups, the invariance properties of key concepts of interest should be considered [42]. In the xTEND study, the measurement and structural equivalence of the Assessment of Quality of Life-6D (AQoL-6D) scale [43] was assessed across cohorts and phases using nested multi-group confirmatory factor analyses. Confirming the measurement invariance of this construct allowed us to compare factors affecting quality of life across cohorts and timepoints, and provided an opportunity to contribute to the psychometric literature on this instrument [44].

B2. Considerations in the analysis of combined data

Combining variables for pooled individual participant data analyses is essentially a post-hoc process, which often requires its own design solutions. As differences in focus and methodology across cohorts are often reflected in the questions administered, as an initial step, it is important to identify any differences in study questions and response options and mechanisms (i.e., skip rules or instructions). Clearly, as noted by Bauer and Hussong, “without common measures, [pooled individual participant data analysis] is a non-starter” [16]. The process of pairing common measures for pooled analyses have been discussed elsewhere within categories of ‘stringent’ and ‘flexible’ harmonization [45], ‘complete’, ‘partial-proximate’, ‘partial-tentative’, ‘impossible’ harmonization [46] and ‘statistical’ harmonization [19]. Here we borrow the terminology of Curran and Hussong [4] to outline three broad circumstances under which data may be combined: ‘ideal’ circumstances, where data collected
by cohorts is essentially the same; ‘less than ideal’ circumstances, where data are elicited using highly similar questions; and finally situations where statistical interventions are necessary to compare data across cohorts, noting ways in which such issues have been explored in the xTEND study and elsewhere. Combining datasets for pooled individual participant data analysis will often involve each of these three circumstances. Table 2.3 outlines some of the common variables within the parent studies linked by the xTEND project, and whether the combination of these measures was considered to be ideal (I), less than ideal (LI), requiring statistical intervention (S), and/or where measures of interest were missing from one cohort (M).

**Ideal circumstances.** Where the same information or measures have been collected in comparable circumstances (e.g., same question and response options provided), data may be considered ideal for combination. This is not to say that we can necessarily assume that data may be combined without due care. Indeed, administering the same measures does not ensure that the same latent constructs have been assessed, either between or within constructs (see measurement equivalence). However, these data do lend themselves easily to the assessment of their comparability across studies. In addition to basic demographic indices, the ARMHS and HCS cohorts administered several standard measures of health and well-being (Table 2.3). Further, the opportunity for a common follow-up period substantially increased the number of common items that were assessed. While the Assessment of Quality of Life-6D was administered to both the HCS and ARMHS cohorts at baseline and follow-up, the measurement invariance of this instrument was assessed across groups and timepoints before data were combined or compared, to ensure that comparable latent constructs were assessed in these cohorts [44]; this was particularly important in light of the differing age profiles and research contexts for the parent studies.
Table 2.3 Comparability of Australian Rural Mental Health Study (ARMHS) and Hunter Community Study (HCS) measures/samples at baseline and common follow-up.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Baseline</th>
<th>Follow-up</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demographics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>I</td>
<td>I</td>
</tr>
<tr>
<td>Gender</td>
<td>I</td>
<td>I</td>
</tr>
<tr>
<td>Education</td>
<td>LI</td>
<td>LI</td>
</tr>
<tr>
<td>Marital status</td>
<td>LI</td>
<td>LI</td>
</tr>
<tr>
<td>Retirement status</td>
<td>LI</td>
<td>LI</td>
</tr>
<tr>
<td>Employment status</td>
<td>LI</td>
<td>LI</td>
</tr>
<tr>
<td>Social support/capital</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Personal &amp; network support</td>
<td>S</td>
<td>I</td>
</tr>
<tr>
<td>Sense of place (Environmental distress scale)</td>
<td>M</td>
<td>I</td>
</tr>
<tr>
<td>Family support</td>
<td>M</td>
<td>I</td>
</tr>
<tr>
<td>Psychological distress</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kessler 10 (K-10)</td>
<td>I</td>
<td>I</td>
</tr>
<tr>
<td>Patient Health Questionnaire (PHQ-9) - Depression</td>
<td>M</td>
<td>I</td>
</tr>
<tr>
<td>Depressive symptomatology (CES-D)</td>
<td>M</td>
<td>I</td>
</tr>
<tr>
<td>Suicidal ideation</td>
<td>M</td>
<td>I</td>
</tr>
<tr>
<td>Solastalgia (Environmental distress scale)</td>
<td>I</td>
<td>I</td>
</tr>
<tr>
<td>Self-reported quality of life (AQoL-6D)</td>
<td>I</td>
<td>I</td>
</tr>
<tr>
<td>Personal hopefulness (HOPES-12)</td>
<td>M</td>
<td>I</td>
</tr>
<tr>
<td>Neuroticism (Brief Eysenck scale)</td>
<td>M</td>
<td>I</td>
</tr>
<tr>
<td>Physical illness and wellbeing</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Body Mass Index (BMI)</td>
<td>S</td>
<td>I</td>
</tr>
<tr>
<td>Chronic illness</td>
<td>LI</td>
<td>LI</td>
</tr>
<tr>
<td>Adverse life events</td>
<td>M</td>
<td>I</td>
</tr>
<tr>
<td>Alcohol use</td>
<td>M</td>
<td>I</td>
</tr>
<tr>
<td>Current smoking</td>
<td>LI</td>
<td>LI</td>
</tr>
<tr>
<td>Satisfaction with life</td>
<td>M</td>
<td>I</td>
</tr>
<tr>
<td>Physical and mental wellbeing (SF-36)</td>
<td>M</td>
<td>I</td>
</tr>
<tr>
<td>Contextual effects</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Remoteness and SEIFA (postal code)</td>
<td>I</td>
<td>I</td>
</tr>
<tr>
<td>% rural employment, % land use for agriculture, and % population change (LGA)</td>
<td>I</td>
<td>I</td>
</tr>
<tr>
<td>Social capital and Health service accessibility (regional)</td>
<td>I</td>
<td>I</td>
</tr>
</tbody>
</table>

Note: *I*, Ideal circumstances for data combination; *LI*, Less than ideal circumstances for data combination (e.g., data re-coding required); *S*, Statistical intervention required for data combination; *M*, Missing from one sample or measures not comparable; ^ One subscale was missing from AQoL-6D at ARMHS baseline and imputation was required. # Contextual measures were derived using postal code information, from which indices at the relevant level of aggregation could be geocoded; SEIFA: Socioeconomic Indexes for Areas; LGA: Local government area.
**Less than ideal circumstances.** While ideal circumstances for data combination have been the mainstay of pooled individual participant data analysis, the benefits of ‘less than ideal’ circumstances are increasingly acknowledged for their potential to increase the number of studies included in an analysis [20]. Less than ideal data for combination are those that are elicited as responses to the same or similar questions but with slightly different wording or response options. These situations are often addressed by combining analogous options, to provide a new common variable, which is also known as ‘harmonizing’ data [16]. Although harmonizing data often has good face validity, care needs to be taken to assess the influence of harmonization on the generated variables and their associations with other variables. In the xTEND project, several variables, primarily demographic indices, were harmonized (e.g., educational status, marital status, retirement status, current smoking, self-reported chronic illnesses), which facilitated comparisons of their effects across urban to remote areas of NSW. Examples of harmonization processes have been detailed elsewhere (e.g., [45]).

**Circumstances requiring statistical and design solutions.** Where there is a desire to utilise instruments that are different, though conceptually similar, there may be opportunities to recalibrate these measures to provide comparable assessments of the same construct. Several good texts on equating measurement have been produced in the educational and psychological measurement literature (e.g., [47]). For example, the use of item response theory to create common metrics for assessment across studies is being recognized for its potential to maximise the utility of valuable cohort data in the psychological sciences [32]. Statistical standardization or centring has been cautiously applied to create a common scale for conceptually similar measures (i.e., where the same question is administered across cohorts, but a different number of Likert-style response options are provided) and applications and their limitations are discussed in more detail elsewhere (i.e., [19]). Where there are other known confounders in the administration of an assessment, it may be possible to apply
corrections to address these biases. For example, in the xTEND study, there were potential biases associated with combining self-reported (ARMHS) and clinical (HCS) measures of height and weight across cohorts, which were to be used in calculating body mass index; these biases were substantially overcome by applying correction equations to the self-report data based on previous Australian research [48]. One preliminary method for assessing whether such harmonizing options are viable is to examine the associations that harmonized variables display with related predictors/outcomes in cohort subsamples in which it is believed these variables should display similar effects and determine whether cohort influenced the observed associations (i.e., [49]). Such statistical interventions are typically situation specific and contingent upon the type and amount of data available. Consequently, individual accounts of these processes may serve primarily as inspiration for addressing the particular situation with which researchers are faced.

The vast majority of statistical harmonization strategies in the literature call for at least some overlap in the items administered to assess a given construct. In the xTEND project, while both studies had assessed a range of common constructs, there were a relatively limited number of truly common variables at baseline. To address this, a common follow-up phase was conducted, which improved study overlap, as well as facilitating an examination of non-common baseline measures through triangulation (i.e., assessing phenomena or checking assumptions in multiple ways), by gauging the strength of association and common sensitivity of baseline measures by directly assessing their commonalities at follow-up. The following example is provided to illustrate some of the benefits of such measurement triangulation approaches. While the influence of social support was of particular interest to the xTEND project, it was not assessed using common items across cohorts at baseline. To facilitate the assessment of personal and network aspects of social support across the spectrum of remoteness assessed by the combined ARMHS and HCS cohorts, Allen et al. [50] recalibrated
conceptually similar baseline measures of these constructs using data from a common follow-up administration of these measures in both cohorts. Several features were necessary to conduct this analysis: a common measure of psychological distress at baseline and follow-up; a follow-up period in which all relevant baseline measures were re-administered; an analysis of the baseline constructs or measurement elements commonly assessed by these two cohorts; and an analysis of the corresponding elements within the follow-up data, so that items assessing aspects of social support that were not commonly assessed at baseline could be omitted. Once the common items and concepts were identified, and their comparability assessed at follow-up, item scores could be standardized in the baseline cohorts to provide a common metric. This process of calibration through triangulation allowed us to explore the association of the calibrated social support indices with common psychological indices at baseline.

The common follow-up period provided an additional opportunity to impute baseline data that were not assessed by one cohort. Specifically, the xTEND project provided an opportunity to estimate missing ARMHS mental health subscale items from the AQoL-6D by facilitating access to follow-up data on these items from the ARMHS and to baseline and follow-up data from the HCS (in which the full AQoL-6D was administered) [44]. In essence, this situation is similar to that of planned missingness designs [51,52], wherein random sections of a cohort are asked subsets of questions for purposes of maximising the amount of information derived, while reducing survey length by imputing missing values based on the observed relationships. As the reason for missingness is known and can be coded for, the common follow-up allowed researchers to use imputation procedures to estimate the values of the omitted data, as the structure of the underlying correlation matrix can be derived to provide estimates of the associations between all model variables. These examples illustrate some of the key benefits
of combining cohort data and, in particular, the benefits of conducting a common follow-up phase, where such an opportunity exists.

C. Other considerations

C1. Resource considerations

While we have noted the cost and time efficiencies associated with the combination of data across cohorts, there are other resource issues that also need to be considered. When the combination of data from several studies is contemplated, there is likely to be a disproportionate increase in the logistic and resource considerations. The rigours of individual participant data meta-analysis in particular have been associated with a significant level of time, skill [53] and monetary [54] resources, although these requirements have decreased with modern technology [2]. Several researchers have noted that the task of pooling individual participant data is more expensive and time consuming than traditional meta-analyses [10] and, arguably, that this task is unjustified when the existing literature are adequately reported [55], although this is rarely the case in epidemiological synthesis. The pooling of particular cohorts for purposes other than research synthesis is likely to involve fewer datasets and more intensive collaboration with a smaller group of researchers, although it is unlikely to require less expertise in data management and analysis. Thus, the time, cost and personnel resources available, and the scope of the intended research questions, will be key factors that need to be considered before undertaking an analysis of pooled individual participant data from multiple cohorts. Importantly, the benefits of protocols and systems for systematically combining datasets, pairing variables and applying harmonization strategies have been explored previously [46]. Once early discussions of variables to be paired and harmonized between datasets had begun in the xTEND project, the development of automated tools for the generation of scripts applying discussed variable pairing and harmonization rules was
undertaken so that these rules were applied in a consistent fashion that could be audited. Further, as these studies were ongoing, the capacity of this system to incorporate new and updated datasets as well as new phases of data collection were ensured.

**C2. Maintaining the interests of existing studies**

Pooled individual participant data analyses necessitate the collaboration and cooperation of research groups and opportunities for further collaboration may arise from the correspondence between cohort investigators [2]. However, the involvement of study participants and other stakeholders also needs to be acknowledged including any potential conflict arising from existing governance or ownership agreements. When funding for particular research questions are obtained through an essentially peripheral or independent source, such as in the xTEND study, it may be accepted that these questions can be satisfactorily addressed to varying degrees using the existing data across both cohorts. Nevertheless, when proposing a common follow-up, consideration also needs to be given to the original aims of the individual studies. Consideration of participant burden, associated with the administration of additional measures, consent procedures and the like, should be carefully evaluated. Indeed, even where areas of interest are common, there may need to be negotiation of how the interests of the parent studies will be maintained. Amongst other things, the xTEND project sought to corroborate the calibration of baseline instruments using a common follow-up. To reduce the redundancy across questions and the time burden on participants, a subsample of the ARMHS cohort received a survey containing some instruments used by HCS, which were not of interest to the study as a whole but would allow validation of the baseline data calibration procedures.

Finally, when dealing with two or more independent research groups, an important consideration will be reconciling the aims of these groups with the aims of the whole. In the
case of the xTEND study, the original brief for the project included offering an intervention program (SHADE, Partners in Depression) for persons reporting symptoms of depression and alcohol use during the common follow-up. However, the HCS investigators objected to this component of the proposal, since it may have presented a historical threat to inferences derived from data collected during subsequent phases; that is, they wanted to preserve the naturalistic (non-intervention) elements of the longitudinal study. Thus, this component of the xTEND study was confined to ARMHS participants meeting criteria.

C3. Ethical issues

The ethical issues of combining datasets have rarely been discussed in the literature and as concluded by Cooper et al. “...it remains an open question whether an individual’s agreement to participate in the original study also implies consent to have data included in a secondary analysis. Still, even this issue may be addressed simply by making data sets available to researchers only under the same rules of confidentiality that applied when the data was first collected” [1]. However, this suggestion assumes that confidentiality is the participant’s only prerogative in deciding to participate in a research project. We would further argue that the reasons given for the project are integral to the participant’s decision to provide data and that the focus of the subsequent analyses (and indeed follow up) should not go beyond the general aims of the original projects. Indeed, this will likely hold true for the situation of individual participant data meta-analysis addressed by Cooper et al. [1], where data are combined for the purpose of synthesising studies on a single research question of interest. Thus, these ethical questions have also not arisen in response to traditional meta-analyses, as the questions answered by such studies are isolated to those for which they were originally collected and analysed. Similarly, both the ARMHS and HCS stated that data would be used to assess the determinants of physical and psychological well-being; and we decided that the additional consideration of the influence of remoteness on these determinants was not beyond the scope
of this permission and informed consent. Our project went through an ethical review from the bodies that granted approvals to the original studies. However, it would be advisable when devising consent processes for new cohort studies that researchers include a specific item asking participants to indicate whether they consent to their de-identified data being used for broader purposes than those of the original study.

**Conclusions**

The aim of the current paper was to provide an introduction to the potential benefits, as well as the challenges encountered and methods used, in the pooling of data from epidemiological cohorts, drawing on our experiences with the xTEND study. Many of the issues covered here are not unique to pooling individual participant data but are equally as pertinent, if rarely addressed, for drawing meaningful inferences from any combined data.

With each phase in the xTEND project, we are forced to consider new issues and challenges associated with combining datasets in this way – feedback from reviewers has been both challenging and encouraging. Accounts of the difficulties and solutions arising from other studies undertaking similar analyses have also been helpful (e.g., [32]). The xTEND study presented several methodological challenges within the context of studying how factors associated with mental health outcomes differed across the spectrum of remoteness. Notably, the measures initially administered within the parent studies varied considerably in terms of scope and metric. One of the specific goals of the xTEND project was to assess the influence of social connections on mental health across urban to very remote areas of Australia, by not only increasing the overlap between these studies at 3-year follow-up, but by facilitating baseline comparisons through harmonization and triangulation of important social indices. An additional element of the xTEND project, beyond the analysis of existing data, is that it has also facilitated an active collaboration between two ongoing cohort studies. This has maximised
their future ability to inform the specific research questions of xTEND, along with validating the calibration of baseline measures, allowing analyses of longitudinal trends that would otherwise have been unmanageable.

**Lessons**

In addition to sharing our research experiences and, hopefully, stimulating further discussion, there are several lessons from the current paper that are worth emphasising [with the related section heading (within this thesis chapter) provided]:

- When designing new cohort studies, consideration should be given to future opportunities for extending and synthesising research, by attending to guidelines aimed at facilitating such collaborations (e.g., [17]) [Background].

- Heterogeneity in study design may present a benefit and/or threat to pooling data across cohorts [Discussion A1 and B1];

- In addition to providing a more reliable way of synthesising research than aggregating published statistics, pooling cohort data may be of broader statistical benefit through increased sample size [Discussion A2];

- Combined data may present a time and resource efficient way of obtaining results [Discussion A3];

- Combined cohorts provide a mechanism for continuing existing cohort activities (e.g., facilitating supplementary questions; testing assumptions; initiating common follow-up phases) [Discussion A3];

- It is important to be mindful of the threats to inference associated with combining cohort data [Discussion B1 and Table 2.2];
• Where cohorts differ in their characteristics of interest, it is useful to have some overlap (e.g., in age distributions, geographical remoteness) so that the impact of these factors can be evaluated in analyses [Discussion B1];

• Where common constructs are measured and data pooling is being considered, it may be useful to identify whether these constructs are measured in ‘ideal’ or ‘less than ideal’ circumstances, or in ways that require statistical intervention (e.g., data harmonization, measurement triangulation) [Discussion B2];

• It is important to have some common constructs, measured in comparable ways, and preferably on multiple occasions - which permits cross-validation of findings and patterns of association, as well as an evaluation of the impact of the cohort on measurement (e.g., measurement invariance and stability) [Discussion B2];

• While utilizing existing data may have some efficiencies, the additional material, time and personnel requirements associated with combining data require close consideration [Discussion C1];

• The governance, procedural and scientific integrity of studies are important considerations, particularly where cohorts are on-going [Discussion C2]; and,

• Projects combining individual participant data for the purposes of new research questions should be mindful of the rights of research participants [Discussion C3].
References


Chapter three: Differential associations of personal and social networks with psychological distress across urban and remote communities.

This chapter was disseminated in the academic literature as:


Synopsis

This chapter addresses the administration of different but conceptually similar social support indices administered in existing urban (HCS) and rural (ARMHS) cohorts, to explore whether the association of social support with experiences of high psychological distress differs across a spectrum of urban to remote communities.
Introduction to Chapter three

Rural areas have particular physical, social and economic qualities that may influence the psychosocial determinants of health in these areas. Rural communities are characterised by different cultural norms and stressors than their urban counterparts and community remoteness has been proposed as a proxy for these characteristics [1, 2]. Recent critiques have identified a lack of examination of interactions of remoteness with other risk factors in predicting health outcomes as potentially obscuring the true health impacts of living in rural and remote areas [3, 4]; that is, while community characteristics associated with remoteness may be neutral or even advantageous for some, they may present a significant risk for other portions of the population.

Theoretical models suggest the psychosocial determinants of health are influenced by the context within which they are experienced and formed. Psychosocial health determinants are those personal characteristics and capacities of individuals that have an impact on health outcomes. These capacities and behaviours are in turn influenced by the characteristics of the broader context in which the individual resides.

Social interactions, experiences of adversity and personality factors have emerged as key determinants of psychological distress and well-being in the ARMHS cohort [5]. However, little is known regarding the influence of the remote context on the determinants of health. To date, simplified dichotomisations of ‘urban’ and ‘rural’ areas, and poor representation of persons from across the spectrum of urban to remote communities, have limited investigations into the impact of contextual factors associated with remoteness on health and its determinants. Recent developments of standard indices of remoteness, such as the Accessibility/Remoteness Index of Australia [ARIA+: 6], which describes areas with a continuous value of remoteness based on population size and road distance from other
population centres of different sizes, may improve existing difficulties associated with the use of arbitrary and situation specific definitions of remoteness. Issues regarding the appropriate conceptualisation of remoteness in relation to health related contextual characteristics are further explored in Chapters 5 and 6.

**Aims and purpose**

The following chapter aimed to investigate whether individual level psychosocial determinants of high psychological distress differed with community remoteness in a sample of persons aged 55 years and over residing in communities representative of the spectrum of urban-remote areas of Australia. To this end, the chapter involved the construction and assessment of the measurement properties and comparability of two measures of social support administered to the ARMHS and HCS at baseline in terms of their association with high psychological distress (as assessed by the Kessler 10). Interactions between remoteness and established psychosocial health determinants in the prediction of high psychological distress were used to provide statistical assessment of any moderation of these effects by contextual remoteness. This is the second manuscript of the thesis and has been published in BMC Public Health.

**Contribution to primary research question**

The current chapter examined evidence of a differential association of social networks with psychological distress across urban and remote communities. Included participants reported high psychological distress at a rate comparable to that observed in comparable national samples (9.6%). Interactions between age and remoteness and between social support and remoteness were observed in the prediction of high psychological distress. I conclude that there is some evidence that the association of social support and of age with high psychological distress differed with community remoteness (Figure 3.0); the association of low
social support with psychological distress decreased as remoteness increased, while the association of increased age with psychological distress decreased as remoteness increased.
Figure 3.0. The associations of social support and age with high psychological distress were moderated by remoteness (interactions respectively: $B = 0.20, p = .001$; $\beta = -0.18, p = .010$).

**Candidate’s contribution**

In addition to the ethics, data collection and data processing tasks mentioned previously, the candidate: in consultation with a senior statistician, formulated scale calibration and assessment of whether the social support scales used differed in their association with high psychological distress; undertook all statistical analyses relating to calibration of baseline data, using data from a common follow-up phase; performed retrospective harmonization of social support and demographic indices; investigated appropriate cut-off scores for distress indices; extracted and geocoded an index of contextual remoteness (ARIA+) to combine ARMHS and HCS participant datasets; undertook logistic regression analyses to address the research question; and contributed substantially to the preparation of the current manuscript.
References


Social support and age influence distress outcomes differentially across urban, regional and remote Australia: an exploratory study

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Abstract

Background

The variation of determinants of mental health with remoteness has rarely been directly examined. The current research aims to examine whether the association of psychosocial factors with psychological distress outcomes varies with increasing remoteness.

Methods

Participants were persons aged 55 and over from two community cohorts sampling from across rural and urban New South Wales (N = 4219; mean age = 69.00 years; 46.1% male). Measures of social support from these studies were calibrated to facilitate comparison across the sample. Remoteness was assessed using a continuous measure, the Accessibility/Remoteness Index of Australia. The association between demographic characteristics, social support, remoteness, and their interactions with remoteness in the prediction of high psychological distress (cut-off > 21 on the Kessler 10) were examined using logistic regression.

Results

Not being in a married or defacto relationship (OR 0.69; 99% CI 0.51-0.94), lower education (OR 0.52; 99% CI 0.38-0.71) and decreased social support (OR 0.36; 99% CI 0.31-0.42) significantly predicted psychological distress. There was a significant interaction of age and remoteness (OR 0.84; 99% CI 0.67-1.00), indicating that as remoteness increases, older persons are less likely to be highly distressed, as well as a significant interaction of social support and remoteness (OR 1.22; 99% CI 1.04-1.44), indicating that as remoteness decreases, persons with low levels of social support are more likely to be highly distressed.
Conclusions

Remoteness may moderate the influence of social support and age on psychological distress outcomes.

Keywords

Rural health, Psychological distress, Social support, Aged 55 and over
Background

Rural settings have been characterised as having distinct social, environmental and cultural features which may have a significant impact on the well-being of persons living in these regions. Rural populations report high levels of social capital which may be protective against poor mental health outcomes [1-3]. However, qualitative evidence from Australia suggests rural populations possess a culture of self-reliance and stoicism which may exacerbate social isolation and impede help seeking behaviours [4,5]. In addition to facing substantial geographical barriers to accessing health and mental health services and decreased opportunities for social interaction, rural populations are also at increased risk of occupational injury and stress due to adverse environmental conditions [6]. Further, decreased opportunities in rural areas have led to increased migration of younger generations away from rural communities [7], resulting in increasingly older age profiles in these areas [8]. How these characteristics of remote communities interact to influence psychological distress is not clear.

There is little evidence of an influence of remoteness on psychological distress [9-11]. Recent reviews of the evidence have suggested variously that rates of mental illnesses are higher in urban areas compared to rural areas [12], that there is little evidence of an urban-rural differential in prevalence of mental health disorders [13], and that suicide rates for men are higher in rural compared to urban areas but do not differ for women [13]. Such variations may be attributable to methodological differences between studies, including differing classifications of what is ‘urban’ and what is ‘rural’, as well as variations in the environmental and cultural conditions between countries. While it is unclear whether there is an urban-rural difference in the incidence of mental illness in Australia, there is growing evidence that the influence of individual level demographic and social characteristics on psychological well-being may be moderated or ‘exacerbated’ by the social and physical environment [10,13,14]. Recent
data from the Australian Rural Mental Health Study [9] indicates that individual demographics, recent adverse events and social capital account for a substantial proportion of variability in well-being among a non-metropolitan Australian sample. While such research highlights potential targets for influencing positive mental health outcomes in rural environments, few studies to date have attempted to assess how remoteness may influence the effects of known individual level determinants of health.

Several studies have observed that the association of demographic characteristics, such as gender [2,15-21], marital status [17] and social class [17] with mental health outcomes vary between urban and rural environments. Indeed three-way interactions of remoteness, gender, ethnicity, as well as remoteness, gender and household composition in determining depression symptomology have been observed in a national survey of American households [22]. Studies examining the influence of individual level social factors on depression by remoteness demonstrate a negative association between depression and social support in both urban and rural environments [3,18,21,23,24]. A South Korean cohort observed social support to be strongly associated with depression in those with lifetime rural residence, but not lifetime urban residence [18]. Such studies suggest while social support is an important determinant of well-being, the strength of its protective effect may depend on the social and physical environment in which it is experienced and may be more important for those in rural areas. To determine whether these observations highlight important targets for intervention in Australia, the association between social support and mental health outcomes need to be explored in an Australia sample representative of the spectrum of urban-remote communities.

The current study examined whether individual level characteristics such as demographics and ratings of social support influence psychological distress outcomes differentially across urban-remote regions of Australia in a sample of older persons. Data from the Australian Rural Mental Health Study (ARMHS) [25] and comparable data from a study of urban-inner regional
areas of Newcastle, NSW, known as the Hunter Community Study (HCS) [26] were combined into a single harmonized dataset. Initially, psychosocial measures that were common to these studies are described. Conceptually related baseline measures were calibrated to obtain a common measure of that construct, guided by data from a common follow-up phase conducted by these studies. How these psychosocial characteristics relate to indices of psychological well-being, and how these associations may vary with remoteness was examined. It was hypothesised that there would be an interaction of individual level characteristics such as demographic indices and individuals’ ratings of social support with indices of community remoteness in the prediction of high psychological distress. These findings inform us of risk factors that may be important foci for intervention across urban-remote regions of Australia.

**Methods**

**Sample**

Self-report postal survey data from two population-based cohort studies conducted in New South Wales, Australia were combined to undertake the current study: the Hunter Community study [26]; and the Australian Rural Mental Health Study [25]. Detailed descriptions of sampling, recruitment, and methods employed by these studies can be obtained from their baseline descriptive papers [25,26]. Briefly, the HCS is a study of persons aged 55-85 years residing in Newcastle, New South Wales, and was designed to assess a range of biopsychosocial aspects of aging. The ARMHS is an investigation of persons aged 18 years and older residing in non-metropolitan New South Wales and was designed to assess mental health and well-being in rural and remote regions by over-sampling from remote and very remote populations. Both the HCS and ARMHS randomly selected potential participants from the New South Wales state electoral roll. Introduction and recruitment letters were sent to individuals
by post and non-responding individuals were followed-up with telephone calls. Informed written consent was obtained from all participants. Overall response rates of 44.5% (N = 3253) and 27.3% (N = 2639) for the baseline HCS and ARMHS samples respectively were achieved, with both samples having comparable rates of uncontactable or excluded persons (HCS 26.9% and ARMHS 25.2%). Within the ARMHS sample, among those who were contactable and met study inclusion criteria, participation rates varied by age group (under 55 years: 25.4%; 55-70 years: 32.4%; over 70 years: 20.1%). A comparable pattern emerged within the HCS sample, with responders tending to be slightly younger than non-responders (66.3 vs. 68.6 years) [26]. To maintain comparability with the HCS and address the aims of the current research, only participants aged 55 years and over from the ARMHS cohort (54.3%) were considered for inclusion in the current analysis.

Following ethical approval (University of Newcastle Human Research Ethics Committee, and Hunter New England Area Health Human Research Ethics Committee), baseline survey data from the HCS and ARMHS were combined. For the purposes of the current study, only those participants who provided complete information on key model variables age, gender, social support scale data and psychological distress were included in analyses. Our study is therefore based on a population of N = 4219 adults (HCS N = 3033; ARMHS N = 1186). Within this dataset, preliminary comparisons revealed that the cohorts did not differ in age (F(1, 4218) = .905, p = .341), gender ($\chi^2(1) = 3.56, p = .06$), or the proportion of persons in a married or defacto relationship ($\chi^2(1) = .867, p = .874$). However, a greater proportion of participants in the HCS had completed high school or higher education compared to the ARMHS (77.7 vs. 61.4%; $\chi^2(1) = 109.45, p < .001$), an observation that is consistent with the lower rates of Australian high school completion with increasing remoteness [27].
Measures

Primary outcome variable: Psychological distress

Psychological distress was assessed using the Kessler 10 (K10) [28] in both cohorts. The K10 is a 10-item self-report questionnaire that assesses the frequency of psychological distress over the past four weeks using a 5-point Likert scale. Scores range from 10 to 50, with higher scores denoting greater psychological distress. The K10 has been used extensively as part of the World Health Organization World Mental Health surveys [29], has been shown to be sensitive to non-specific psychiatric distress [28,30], and normative data for Australian populations have been developed [30,31]. A cut-off score of > 21 was used to indicate high psychological distress in the current study. Data from the 2007 National Survey of Mental Health and Wellbeing suggests that this cut-off is associated with a 63% likelihood of meeting 12 month ICD-10 criteria for any affective, anxiety or substance use disorder in an Australian community sample (compared to 15% of persons scoring < 21), with 9.5% of respondents rated in this category [31]. Data from the 2003 New South Wales Population Health Survey found 8.3% of participants aged 50 years and over scored above this cut-off [32].

Independent variables

Demographic characteristics. Self-reported demographic information, including age, gender, education and marital status, were assessed in both cohorts.

Social support. The HCS and ARMHS collected conceptually related baseline social support measures assessing participant’s network and personal support relationships. Network support was assessed using the Berkman Social Network Index [33] in the ARMHS cohort and using the Network sub-scale of the abbreviated Duke Social Support Index [34] in the HCS cohort. These scales are comprised of similar items assessing the number of friends and relatives who may be available to the individual to provide social support, the frequency of contact with these
individuals, and participant’s involvement in organised social groups. Personal support relationships were assessed using the Availability of Attachment subscale of the Interview Schedule for Social Support [35] in the ARMHS cohort and using the Satisfaction subscale of the abbreviated Duke Social Support Index [34] in the HCS cohort. Both the HCS and ARMHS assessments of close personal social supports assess participant’s access to close personal relationships with persons who could provide emotional support. The HCS assessment additionally assessed participant’s feelings of belonging and involvement with friends and family.

Under the auspices of the Extending Treatments, Education and Networks in Depression project (xTEND) [36], a common three year follow-up phase was conducted, which included administration of a range of baseline measures from both cohorts. Preliminary follow-up data from the HCS, representing the first N = 2031 surveys returned at three year follow-up, was used to calibrate baseline indices of social support so that the influence of social support on psychological distress could be assessed across studies at baseline. These preliminary analyses are reported at the beginning of the results.

**Remoteness.** The Accessibility/Remoteness Index of Australia (ARIA+) [37] was used to provide a postal-area level index of participant remoteness for both cohorts. The ARIA+ is a continuous index score ranging from 0-15 (higher scores indicating greater remoteness) that is calculated based on the size of the nearest service centre and its average estimated road distance from the location. In the current study, three categories of remoteness (Urban: ARIA + 0-0.02; Regional: ARIA + 0.03-5.92, and; Remote: ARIA+ >5.92) were used to graphically explore how the association of other independent variables with psychological distress differed by remoteness.
Data analysis

Analyses were conducted using SPSS 19 and graphs were produced using Microsoft Excel 2010. Chi squared tests were used for between group comparisons of categorical variables and one-way ANOVAs were used for continuous variables. Binary logistic regression was used to identify significant predictors of high distress, with effect sizes reported as adjusted odds ratios (AORs) and associated 99% confidence intervals. Results of the social support calibration procedure utilizing common three year follow-up data are initially reported. To assess whether predictors of high distress differed by participant remoteness in the combined baseline sample, product terms [remoteness (continuous) by age, gender, marital status, education and social support] were produced using standardized values. Variables were entered into the model in two steps: a six variable model examining the influence of age, gender, marital status, education, remoteness, and social support on high distress; and an eleven variable model that included the interaction terms. Male gender (1) was the reference category in contrast to female gender (0); married/defacto relationship (1) was the reference category in contrast to not being in a married/defacto relationship (0), and completion of 12 or more years of education (1) was the reference category in contrast to completion of less than 12 years of education (0). To explore significant interaction effects between independent variables (A) and remoteness (R), associations between independent variables and the probability of high psychological distress were plotted by remoteness category using the equation \( P(\text{distress}) = \frac{1}{1 + e^{-(\text{intercept} + \beta A + \beta R + \beta A R)}} \). An \( \alpha < .01 \) was used as a partial control for the number of statistical tests and trends \( p < .05 \) are reported.
Results

Preliminary analyses: Social support scale calibration using data from the HCS three year follow-up

Of the 2031 participants in the HCS preliminary three year follow-up dataset, 96.7% provided K10 scores and were included in the social support scale calibration analyses. These participants had a mean age of 69.67 (SD = 7.26) years, 48.2% were male, 73.5% were married or in a defacto relationship, 79.5% had completed 12 or more years of education, and they had an overall mean psychological distress score of 13.71 (SD = 4.83). Almost 8% of participants reported a high level of psychological distress. Highly distressed participants were less likely to be married (63.2 vs. 74.4%; $\chi^2(1) = 9.07, p = .004$) and were less likely to have 12+ years of education (71.5 vs. 80.2%; $\chi^2(1) = 6.47, p = .015$) than participants experiencing low-moderate levels of distress.

Network support

Network support items administered to the HCS and ARMHS cohorts at baseline and jointly administered to the HCS three year follow-up are presented in Table 3.1. Total scores for network support items were calculated to give equal weight to similar questions within each scale: HCS Network total = ZSum(items 1 to 4); ARMHS Network total = ZSum(items 1-3) + (mean(item 4)*4). These standardized total scores displayed a significant positive correlation in the HCS follow-up dataset, $r(1819) = .61, p < .001$, providing evidence that they assess reasonably comparable aspects of network support.
Table 3.1 Network and Personal support indices administered by the ARMHS and HCS at baseline but common to three year follow-up.

<table>
<thead>
<tr>
<th>Baseline ARMHS Measures</th>
<th>Baseline HCS measures</th>
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<tr>
<td><strong>Network support</strong></td>
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<tr>
<td>1. How many close friends do you have? (People that you feel at ease with, can talk to about private matters, and can call on for help) [scored 0-4]</td>
<td>None</td>
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<td>1 or 2</td>
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<td></td>
<td>6 to 9</td>
</tr>
<tr>
<td></td>
<td>10 +</td>
</tr>
<tr>
<td>2. How many relatives do you have that you feel close to? [scored 0-4]</td>
<td>None</td>
</tr>
<tr>
<td></td>
<td>1 or 2</td>
</tr>
<tr>
<td></td>
<td>3 to 5</td>
</tr>
<tr>
<td></td>
<td>6 to 9</td>
</tr>
<tr>
<td></td>
<td>10 +</td>
</tr>
<tr>
<td>3. How many of these friends and relatives do you see at least once a month? [scored 0-4]</td>
<td>None</td>
</tr>
<tr>
<td></td>
<td>1 or 2</td>
</tr>
<tr>
<td></td>
<td>3 to 5</td>
</tr>
<tr>
<td></td>
<td>6 to 9</td>
</tr>
<tr>
<td></td>
<td>10 +</td>
</tr>
<tr>
<td>4. Do you belong to any of these kinds of social groups? a) a social or recreational group; b) a labour union, commercial group, professional organisation; c) a church group; d) a group concerned with children (e.g., boy scouts, patents and friends etc); e) a charity concerned with community betterment, charity, or service; f) any other group. [scored 0-6]</td>
<td>+1 for each group</td>
</tr>
<tr>
<td></td>
<td>4. (Other than at work) About how often did you go to meetings of social clubs, religious meetings, or other groups that you belong to in the past week? [scored 1-3]</td>
</tr>
<tr>
<td></td>
<td>6 to 9</td>
</tr>
<tr>
<td></td>
<td>10 +</td>
</tr>
<tr>
<td></td>
<td>3 to 5</td>
</tr>
</tbody>
</table>

ARMHS: Australian Rural Mental Health Study; HCS: Hunter Community Study.
## Table 3.1 (continued) Network and Personal support indices administered by the ARMHS and HCS at baseline but common to three year follow-up.

<table>
<thead>
<tr>
<th>Baseline ARMHS Measures</th>
<th>Baseline HCS measures</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Personal support</strong></td>
<td></td>
</tr>
<tr>
<td>5. If something unpleasant or irritating happens and you get upset or angry about it, do you have someone you can go to who isn’t involved and tell them just how you feel? [scored 0-1]</td>
<td>No</td>
</tr>
<tr>
<td>6. Is there anyone who lives in or near the district you now live in who knows you very well as a person? (this includes friends as well as family members) [scored 0-1]</td>
<td>No</td>
</tr>
<tr>
<td>7. Is there any particular person you feel you can lean on? [scored 0-1]</td>
<td>No</td>
</tr>
<tr>
<td>8. Do you feel there is one particular person who feels very close to you? [scored 0-1]</td>
<td>No</td>
</tr>
<tr>
<td>9. When you are happy, is there any particular person you can share it with, someone whom you feel sure will feel happy simply because you are? [scored 0-1]</td>
<td>No</td>
</tr>
<tr>
<td>10. At present, do you have someone you can share your most private feelings with (confide in)? [scored 0-1]</td>
<td>No</td>
</tr>
<tr>
<td>5. Does it seem that your family and friends (that is, people who are important to you) understand you? [scored 1-3]</td>
<td>Hardly ever</td>
</tr>
<tr>
<td>6. Do you feel useful to your family and friends (that is, people who are important to you)? [scored 1-3]</td>
<td>Hardly ever</td>
</tr>
<tr>
<td>7. Do you know what is going on with your family and friends? [scored 1-3]</td>
<td>Hardly ever</td>
</tr>
<tr>
<td>8. When you are talking with your family and friends, do you feel you are being listened to? [scored 1-3]</td>
<td>Hardly ever</td>
</tr>
<tr>
<td>9. Do you feel you have a definite role (place) in your family and among your friends? [scored 1-3]</td>
<td>Hardly ever</td>
</tr>
<tr>
<td>10. Can you talk about your deepest problems with at least some of your family and friends? [scored 1-3]</td>
<td>Hardly ever</td>
</tr>
<tr>
<td>11. How satisfied are you with the kinds of relationships you have with your family and friends? [scored 1-3]</td>
<td>Very dissatisfied</td>
</tr>
</tbody>
</table>

ARMHS: Australian Rural Mental Health Study; HCS: Hunter Community Study.
Personal support

Personal support items administered to the HCS and ARMHS cohorts at baseline and jointly administered to the HCS three year follow-up are presented in Table 3.1. Due to the broader scope of the personal support items administered by the HCS at baseline, a stepwise regression of HCS personal support items onto the ARMHS personal support total score was conducted using the HCS follow-up data to identify baseline HCS personal support scale items assessing similar concepts to those tapped by the baseline ARMHS personal support scale. This analysis identified five items from the HCS personal support scale that were positively predictive of ARMHS personal support total score: item 10 (β = .39, p < .001; R² = .15); item 5 (β = .17, p < .001, R² = .17); item 9 (β = .10, p < .001, R² = .18); item 11 (β = .06, p = .007, R² = .18); and item 6 (β = .06, p = .028, R² = .19). These results were used to construct the personal support scores: HCS Personal total = ZSum(items 5, 6, 9, 10, 11); and ARMHS Personal total = ZSum(items 1-6). The correlation between these standardized totals displayed a moderate positive correlation in the HCS follow-up dataset, r(1813) = .41, p < .001, providing evidence that they assess reasonably comparable aspects of personal support.

Composite index of social support

Two composite indices of social support were constructed by taking the average of the standardized network and personal support scores as assessed by the HCS and ARMHS at baseline (e.g., ARMHS social support index = mean(ARMHS Network total, ARMHS Personal total)). The correlation between these composite indices was moderate in the HCS follow-up dataset, r(1718) = .65, p < .001, indicating 41% shared variance. A binary logistic regression examining the influence of age, gender, marital status, education, remoteness and social support on reporting of high distress was conducted using the HCS and ARMHS social support
indices separately in the HCS follow-up dataset using participants who had completed all
model variables and both indices of social support (N = 1716; see Table 3.2).

Table 3.2 Analyses of HCS three year follow-up (N = 1716): Logistic regressions examining
predictors of high psychological distress, using social support indices equivalent to those
from the ARMHS and HCS at baseline.

<table>
<thead>
<tr>
<th></th>
<th>B</th>
<th>SE</th>
<th>p</th>
<th>AOR</th>
<th>99% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ARMHS equivalent index</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.00</td>
<td>0.01</td>
<td>1.00</td>
<td>0.96</td>
<td>0.96-1.03</td>
</tr>
<tr>
<td>Male</td>
<td>0.31</td>
<td>0.20</td>
<td>1.37</td>
<td>0.83</td>
<td>0.64-2.26</td>
</tr>
<tr>
<td>Married/defacto</td>
<td>-0.41</td>
<td>0.21</td>
<td>0.67</td>
<td>0.39</td>
<td>0.39-1.14</td>
</tr>
<tr>
<td>12+ yrs education</td>
<td>-0.45</td>
<td>0.22</td>
<td>0.04</td>
<td>0.64</td>
<td>0.36-1.12</td>
</tr>
<tr>
<td>Social support</td>
<td>-0.52</td>
<td>0.10</td>
<td>**</td>
<td>0.59</td>
<td>0.46-0.77</td>
</tr>
<tr>
<td>(Z)Remoteness</td>
<td>0.03</td>
<td>0.09</td>
<td>1.03</td>
<td>0.81</td>
<td>0.81-1.30</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.83</td>
<td>0.99</td>
<td></td>
<td>0.16</td>
<td></td>
</tr>
<tr>
<td><strong>HCS equivalent index</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>-0.01</td>
<td>0.01</td>
<td>0.99</td>
<td>0.96</td>
<td>0.96-1.03</td>
</tr>
<tr>
<td>Male</td>
<td>0.18</td>
<td>0.20</td>
<td>1.20</td>
<td>0.71</td>
<td>0.71-1.02</td>
</tr>
<tr>
<td>Married/defacto</td>
<td>-0.39</td>
<td>0.22</td>
<td>0.68</td>
<td>0.39</td>
<td>0.39-1.18</td>
</tr>
<tr>
<td>12+ yrs education</td>
<td>-0.26</td>
<td>0.23</td>
<td>0.77</td>
<td>0.43</td>
<td>0.43-1.40</td>
</tr>
<tr>
<td>Social support</td>
<td>-0.95</td>
<td>0.10</td>
<td>**</td>
<td>0.39</td>
<td>0.30-0.50</td>
</tr>
<tr>
<td>(Z)Remoteness</td>
<td>0.02</td>
<td>0.10</td>
<td>1.02</td>
<td>0.78</td>
<td>0.78-1.32</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.95</td>
<td>1.01</td>
<td>0.14</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* p < .01, ** p < .001

The association with high psychological distress was similar for the HCS [AOR = .39, p < .001
(99% CI .30-.50), R² = .15] and ARMHS [AOR = .59, p < .001 (99% CI .46-.77), R² = .05] social
support indices. Overlapping 99% CIs between the HCS and ARMHS social support indices
suggests the association between social support and psychological distress did not differ
between the two indices. The association of each index with the likelihood of distress was
plotted for social support values ranging from -1.5 to 1 SD from the mean (see Figure 3.1).
Figure 3.1 The effect of social support (A) on the prediction of distress outcome as assessed by the HCS and ARMHS equivalent social support indices. 99% CIs for each index are represented by grey areas with upper and lower limits determined using the equation:

$$P(\text{distress}) = \frac{1}{1 + e^{-(\text{intercept} + \beta_A A + \text{SE} \beta_A \times Z)}}$$

**Primary analyses: Influence of remoteness on predictors of baseline psychological distress**

Baseline participants who provided information on all model variables (N = 4219; 89.5%) were included in analyses. These participants had a mean age of 69.00 (SD = 7.61) years, 46.1% were male, and 74.6% were married or in a defacto relationship; age and gender distributions were comparable to those for NSW [38] though persons in married or defacto relationships were somewhat over represented [65.9% of persons aged over 55 in NSW: [39]. Three-quarters (73.3%) had completed 12 or more years of education, and participants had a mean composite social support index of 0.01 (SD = 0.82) and a mean remoteness score of 1.14 (SD = 2.39). By remoteness category, 66.0% (N = 2786) of participants lived in urban areas, 27.5% (N = 1159)
in regional areas and 6.5% (N = 274) in remote areas. Participants had a mean psychological distress score of 14.41 (SD = 5.30) and 9.6% of participants reported a high level of psychological distress. Highly distressed participants were less likely to be married (62.5 vs. 73.9%; $\chi^2(1) = 23.49, p < .001$), were less likely to have 12 or more years of education (62.3 vs. 74.5%; $\chi^2(1) = 26.09, p < .001$) and they had lower levels of social support (M = -0.76, SD = 1.05 vs. M = 0.09, SD = 0.75; $F(1, 4217) = 425.01, p < .001$) than participants experiencing low-moderate levels of distress, but did not differ in age, gender or remoteness.

A hierarchical logistic regression assessing predictors of high distress and whether these varied with remoteness was conducted (see Table 3.3). Results suggest that the six variable model including age, gender, marital status, education, social support and remoteness was a better fit than the constant only model ($\chi^2(6) = 364.06, p < .001$). The 11 variable model assessing whether predictors of distress varied with remoteness also significantly improved the model (step $\chi^2(5) = 17.46, p = .004$) with significant interactions of remoteness by social support ($p = .002$) and of remoteness by age ($p = .014$) observed in the prediction of high distress. No other interactions were significant. The final model accounted for 18.4% of the variance in high psychological distress ($\chi^2(11) = 381.52, p < .001$). When holding other variables constant, this model suggests that: being in a married or defacto relationship decreased the odds of high distress by 31%; having 12 or more years of education decreased the odds of high distress by 48%; and each one standardised unit increment in social support decreased the odds of high distress by 64%. The interaction of age and remoteness indicates that as remoteness increases, older persons are less likely to be highly distressed. The interaction of social support and remoteness indicates that as remoteness increases, persons with low levels of social support are less likely to be highly distressed.
Table 3.3 Logistic coefficients for predictors of high distress (N = 4219).

<table>
<thead>
<tr>
<th>Step</th>
<th>Entered</th>
<th>B</th>
<th>SE</th>
<th>p</th>
<th>AOR</th>
<th>99% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(Z)Age</td>
<td>-0.05</td>
<td>0.06</td>
<td>0.95</td>
<td>0.82</td>
<td>0.82-1.11</td>
</tr>
<tr>
<td></td>
<td>Female</td>
<td>-0.13</td>
<td>0.11</td>
<td>0.88</td>
<td>0.65</td>
<td>0.65-1.18</td>
</tr>
<tr>
<td></td>
<td>Married/defacto</td>
<td>-0.37</td>
<td>0.12</td>
<td>*</td>
<td>0.69</td>
<td>0.51-0.94</td>
</tr>
<tr>
<td></td>
<td>12+ yrs education</td>
<td>-0.66</td>
<td>0.12</td>
<td>**</td>
<td>0.52</td>
<td>0.38-0.71</td>
</tr>
<tr>
<td></td>
<td>Social support</td>
<td>-1.01</td>
<td>0.06</td>
<td>**</td>
<td>0.36</td>
<td>0.31-0.42</td>
</tr>
<tr>
<td></td>
<td>(Z)Remoteness</td>
<td>-0.08</td>
<td>0.06</td>
<td></td>
<td>0.92</td>
<td>0.79-1.08</td>
</tr>
<tr>
<td></td>
<td>Constant</td>
<td>-1.77</td>
<td>0.13</td>
<td>**</td>
<td>0.17</td>
<td>.</td>
</tr>
<tr>
<td>2</td>
<td>(Z)Age x (Z)Remoteness</td>
<td>-0.18</td>
<td>0.01</td>
<td>*</td>
<td>0.84</td>
<td>0.67-1.00</td>
</tr>
<tr>
<td></td>
<td>Gender x (Z)Remoteness</td>
<td>0.13</td>
<td>0.12</td>
<td></td>
<td>1.14</td>
<td>0.84-1.54</td>
</tr>
<tr>
<td></td>
<td>Marital status x (Z)Remoteness</td>
<td>-0.08</td>
<td>0.13</td>
<td></td>
<td>0.92</td>
<td>0.67-1.27</td>
</tr>
<tr>
<td></td>
<td>Education x (Z)Remoteness</td>
<td>0.25</td>
<td>0.13</td>
<td></td>
<td>1.28</td>
<td>0.92-1.78</td>
</tr>
<tr>
<td></td>
<td>Social support x (Z)Remoteness</td>
<td>0.20</td>
<td>0.06</td>
<td>*</td>
<td>1.22</td>
<td>1.04-1.44</td>
</tr>
<tr>
<td></td>
<td>Constant</td>
<td>-1.77</td>
<td>0.13</td>
<td>**</td>
<td>0.17</td>
<td>.</td>
</tr>
</tbody>
</table>

* p < .01, ** p < .001

To explore the interaction of age and remoteness in the prediction of high psychological distress, Figure 3.2 was constructed to plot the association between age and high distress for each remoteness category using coefficients from Table 3.3. The median ARIA + value was used in these analyses to quantify each level of remoteness: Urban = 0.00 (Z = -.50); Regional = 1.96 (Z = 0.29) and; Remote = 7.72 (Z = 2.60). Age values were plotted from -1 to 1 SD around the mean score. Figure 3.2 indicates that there was little influence of age on distress in urban areas and the greatest influence in remote areas, with regional areas displaying an intermediate association.
Figure 3.2 The effect of age on the prediction of distress outcomes by remoteness category.

To explore the interaction of social support and remoteness in the prediction of high psychological distress, Figure 3.3 was constructed to plot the association between social support and high distress for each remoteness category using coefficients from Table 3.3. As in Figure 3.2, median ARIA + values were used to quantify the level of remoteness. Social support values were plotted from -1.5 to 1 SD around the mean score. Figure 3.3 indicates there is a negative influence of low social support on distress outcomes in urban and regional areas, however this association was weaker in remote areas.
Discussion

The current study examined whether individual level characteristics influence psychological distress outcomes differentially across urban to remote regions of Australia in a community sample of persons aged 55 and over. We hypothesised that the association of individual level characteristics with high psychological distress would be moderated by indices of area remoteness. Results provide support for our hypothesis and suggest that remoteness may have a moderating effect on the association of both social support and age with high psychological distress. Persons with low levels of social support were less likely to be highly distressed as remoteness increased; an effect particularly evident in remote, compared to urban and regional, participants. Further, older persons were less likely to be highly distressed as remoteness increased, with urban participants showing little change in psychological distress with increasing age. This study is the first to examine how determinants of psychological distress vary across urban to very remote regions of Australia.
The current results confirm often observed findings that increased likelihood of high psychological distress is associated with lower levels of education and with not being in a married or defacto relationship. Results also indicate that when controlling for age, education, marital status, social support and remoteness, there was no influence of gender on high distress in either the combined urban-remote baseline sample or the three year follow-up data from the urban-regional HCS. Recent Australian population data found women to have higher K10 scores across all age groups compared to men [31], though these effects are not always observed [40]. Additionally, a Canadian population study noted that when using a criterion cut-off for major depression, differences in the rate of major depression between men and women decreased with increasing age [41]. Given the older age of the current sample such an effect may have contributed to current results. While it is unclear why some studies of psychological distress do not show gender effects, we also observed no differential effect of gender by remoteness, suggesting that community remoteness was not a factor in the lack of gender effect, as previously proposed [40].

Interpretations of the lack of main effects of age and remoteness and the main effect of social support on the likelihood of high psychological distress are more difficult in the presence of their significant interactions. However, while the lack of association between high psychological distress and remoteness confirms observations in American [11] and Australian [10] community samples, the current research suggests that it may moderate the effects of other potential demographic and social risk factors. Previous literature has observed a positive relationship between age and psychological distress, however it is likely that the restricted age range of the current sample may explain the lack of association observed here. Indeed research suggests there is a spike in psychological distress in the adult life for persons aged in their 50s [40] and, as our study was a cohort of persons 55 and over, this restriction may explain the absence of a positive association of age and distress. The exploration of the
observed interaction of age and remoteness suggested that increased age was associated with a decreased likelihood of distress in our regional and remote participants, although this had little or no impact on distress in urban areas. These results suggest that there may be some benefits associated with aging in non-metropolitan communities; however, this may also represent an urban-drift phenomenon wherein persons experiencing high levels of distress move to urban or regional areas in their older age. Indeed a Western Australian study of migration patterns of remote, regional, and urban populations found that persons in remote areas were more likely to move to urban areas following onset of disease relative to background rates of urban migration in the healthy population [42]. While the mechanisms underlying the current observation that older persons were less likely to be highly distressed as remoteness increased are unclear, the current research highlights the importance of examining contextual variations, such as remoteness, when assessing the influence of demographic factors such as age on psychological outcomes.

The current study confirmed findings that decreased levels of social support were associated with an increased likelihood of psychological distress. Exploration of the significant interaction of social support and remoteness demonstrates that the direction of this association was consistent across urban, regional and remote areas, though the strength varied. Stress and coping theories addressing the protective effects of social support on psychological well-being suggest that these effects may be due to ‘stress buffering’ processes wherein social support decreases the stress associated with challenging or stressful situations by increasing the individual’s coping resources thus moderating the impact of stressful life events on mental health outcomes [43]. Such theories have received limited support as literature examining an association between life stressors and levels of social support have rarely observed this buffering effect (see [44] for review). More recent ‘social cognitive’ theories such as Relational Regulation Theory [45] have proposed that the protective influence of social support may
actually reflect a general heightening of well-being and self-esteem resulting from social interactions and support and that the level of support needed to maintain this well-being benefit varies depending on the individual’s desire for social interaction (i.e., as shaped by social norms and individual’s personality characteristics etc.). Both researchers and theorists [2,3,46,47] have proposed that high levels of social support and social capital in rural samples underlie observations of lower rates of psychiatric morbidity compared to urban samples, however this proposal has rarely been formally tested. The current findings indeed suggest that the characteristics of the place in which we live may moderate the protective effect of social support on psychological well-being. However, they indicate that low levels of social support have a greater effect on well-being in urban and regional centres than in remote areas and, as discussed below, there are a number of scenarios which may contribute to this finding.

Firstly, this result may reflect a real difference in the association between social support and psychological distress that is borne of the values and environmental context associated with remote, in contrast to urban or regional, living. The isolation and associated social norms that come with living in remote communities may mean that the self-esteem of persons living in these environments may be less influenced by their level of social support. Alternatively, there may be more salient stressors that underlie psychological well-being in these communities (i.e., drought, access to resources, physical well-being), the effects of which are not moderated by social support.

Secondly, Relational Regulation Theory [45] suggests that different persons need different levels of social support to maintain well-being. As such, results may reflect a self-selection process wherein individuals who have a lesser reliance on social support for maintenance of their psychological well-being will move to or remain in remote areas, whereas individuals who require high levels of social support for maintenance of well-being will move to regional or urban areas where there is a greater opportunity to have these needs met.
Thirdly, researchers assessing the potentially negative consequences of ‘social support’ have noted that too much social interaction and participation may be detrimental to well-being when these interactions exceed the coping resources of the individual. In a community sample of persons aged 50 years and over, Beard et al. [48] observed that everyday contact with family and friends was related to increased depressive symptoms over time, potentially reflecting increased involvement of social networks with persons who have greater need, or increased social demand on individuals which may be beyond their coping resources. It is feasible that increased levels of social interaction in remote areas may be associated with additional burdens (i.e., stress associated with leaving farm or work commitments, longer distances to travel etc.) which may not be as keenly felt in regional or urban environments and thus the protective effect of social interactions is reduced in remote populations.

Finally, these results may indicate that social relationships described here, such as access to close confiding relationships and group participation do not describe the types of social support that are important for the maintenance of well-being in remote communities. There is some evidence that the influence of all facets of social support on psychological well-being are not uniform between urban and rural environments [18,21], perhaps reflecting the increased salience of some aspects of social support in determining psychological well-being in these environments. Such findings may indicate that the influence of different aspects of a person’s social sphere may differently influence, or be influenced by, psychological well-being depending on the environmental and social context in which that individual lives. Recent research from a South Australian study conducted as part of a broader survey by the South Australia Department of Health [24] examined a range of social capital indices, with confirmatory factor analyses producing factors representing three aspects of social capital: cognitive (‘Trust’ in the wider community; belief in the ‘Reciprocity’ of helping, and; perceived community ‘Cohesion’ in terms of character and values); bonding (the availability of ‘Help’
from close connections if needed); and bridging (‘Networks’ participation in community groups, and; individual’s participation in ‘Civic activities’ such as marches, voting, and local action groups). Structural equation models of demographic and social capital influences on mental health urban and non-urban populations revealed that ‘Trust’, ‘Help’ and ‘Cohesion’ were associated with good mental health in both the urban and rural models, while ‘Networks’ were only associated with mental health in the urban model, perhaps suggesting social networks are either less important for mental health in rural areas, or are less prone to the effects of mental health. Current evidence highlights the necessity of examining the relative influence of different aspects of social capital on psychological well-being outcomes in different environments.

**Strengths and limitations**

A strength of the current research is its capacity to compare determinants of psychological distress across a broad spectrum of urban-remote populations, which was achieved by combining studies sampling urban and non-urban environments. By uniting cohorts in this way, the Extending Treatments, Education and Networks in Depression project (xTEND) [36] is not only able to examine these baseline associations but to ensure overlap in measures for their respective three year follow-up surveys. There are a growing range of approaches for integrating and comparing data across different cohorts (e.g., [49,50]). The current study used a process of calibrating different though conceptually similar measures of social support to provide comparable assessment of their association with psychological distress outcomes across both cohorts. The availability of a common follow-up phase allowed us to employ methods to directly compare the association of these measures of social support both with each other and a common measure of psychological distress to create a single index of social support. However, while we have combined data from studies designed for different purposes, and with differing response rates, they were conducted within similar time frames, drew
samples from electoral rolls using a similar methodology and had comparable socio-demographic profiles. Nevertheless, questions remain as to whether the differences in measures used influenced our current findings. In the HCS three year follow-up dataset, the correlation between the social support measures was only moderate. However, the overlapping confidence intervals for the adjusted odds ratios of our composite measures of social support in the prediction of high distress suggest that the association between social support and high distress did not differ between the two indices. These findings will need to be verified using common measures of social support (when three year follow up data are available for both the HCS and ARMHS cohorts), as well as replicated in other samples using common measures of social support both to confirm current findings and ensure generalizability to other areas of Australia. Researchers interested in examining effects of remoteness should consider collaborations with similar cohorts to improve their representativeness.

A limitation of the current research is that younger people were not represented and so current findings may not be generalizable to this section of the population. Further, traditional measures of social support, as used in the current research, do not take into account modern forms of socialisation such as instant video, chat and text messaging and social networking services, nor do they consider the importance of persons outside the community for sustaining mental health. With the increasing accessibility and use of these services, it is likely that these modes of social communication will become increasingly important for the maintenance of psychological well-being, perhaps particularly in isolated communities. Future research is needed to develop tools to assess the use of and support derived from these sources.

Finally, future research should consider the influence of previous environmental exposure on relationships between remoteness and psychological well-being. Kim et al [18] found that the influence of remoteness on the association between social support and depression outcomes
was moderated by the individual’s migration history. While the ARMHS collected information on how many years the individuals had lived in their current district, no information on previous area of residence or residential history was collected from HCS participants. As such, the current research is unable to determine what effect, if any, previous environmental exposure had on the current associations. Future research is needed to examine what effects such migration patterns have on the current findings.

Conclusions

This research extends our work investigating determinants of mental health [9] across the spectrum of urban to very remote communities of Australia by combining existing cohort datasets. Current findings confirm certain demographic and social factors as protective against high levels of psychological distress in a sample drawn from across the spectrum of urban-rural environs of NSW, Australia. Individual’s marital and educational status both contributed to prediction of high psychological distress. The current research suggests that increasing age may be negatively associated with high distress in regional and remote areas. Furthermore, social support may have a greater influence on psychological distress in urban and regional areas compared to remote areas. This latter finding suggests that initiatives aimed at improving mental health outcomes in urban and regional areas should aim to improve supportive relationships at the personal level. Initiatives in remote communities may be better targeted at improving other aspects of social well-being, such as community level social capital. Future research is needed to examine the psychosocial factors important for the maintenance of well-being in remote communities. These results suggest that the nature of the community in which one lives may moderate the protective effect of individual risk factors. Future research will examine features of the social (person, family and community factors) and environmental (availability and nature of services, climate events) factors that may be associated with mental health outcomes.
References


Chapter four: Do indices of health related quality of life measure the same health related constructs across urban and rural cohorts?

This chapter was disseminated in the academic literature as:


Synopsis

This chapter examines the structure of an assessment of health related quality of life (AQoL-6D), whether this assessment represents the same underlying constructs in the HCS and ARMHS, and the external validity of its factor structure. This chapter confirms the capacity for this outcome to be meaningfully compared across these cohorts and over time.
Introduction to Chapter four

‘Health Related Quality of Life’ (HRQoL) refers to the impacts of health on a person’s capacity to carry out activities of daily life and is used to assess the experience of health. The Assessment of Quality of Life 6D (AQoL-6D) is a self-report measure of HRQoL that was designed to assess both negative and positive health states so as to increase its utility for measuring health in general community samples [1]. Further, the AQoL-6D aimed to assess a range of health related experiences and capacities, including physical and psychological aspects of health experience. Due to these properties, the AQoL-6D was selected as a key outcome measure by both the ARMHS and HCS community cohort studies. However, the construct validity of the AQoL-6D, including the appropriate factor structure and scoring of this relatively new measure, have yet to be examined outside its construction sample. Further, the concurrent, convergent and divergent validity properties of the measure have yet to be assessed, which are important for the interpretation of this measure and its values.

As the xTEND project aimed to assess factors associated with health outcomes, the harmonization of AQoL-6D data across these cohorts presented an important step for this project. In addition to the construct validity issues mentioned above, as discussed in Chapter two, the importance of confirming that the underlying constructs assessed by the AQoL-6D had equivalent meaning across the ARMHS and HCS cohorts was paramount to establishing the interpretability of future analyses utilising this outcome measure [2]. This chapter also utilizes the social support index developed in Chapter three in its assessment of the external validity of the AQoL-6D factors. As some items assessing the mental health dimension of the AQoL-6D were omitted from the ARMHS baseline data collection due to perceived redundancy with the administration of highly similar items from the Kessler 10 psychological distress scale the potential to impute this data was explored. As the reason for missing was known (Time and
Cohort) and could be included for in imputation models, missing data imputation was conducted using a Full Information Maximum Likelihood estimation procedure employing a Markov chain Monte Carlo algorithm and the stability of the resulting estimations examined (see Appendix 4.1 for details).

**Aims and purpose**

The purpose of this chapter was to establish the appropriate factor structure for a HRQoL measure administered to both ARMHS and HCS cohorts at baseline and follow-up phases. Additionally, the chapter aimed to establish whether the latent constructs assessed by this measure were invariant across the ARMHS and HCS samples and thus could be meaningfully compared across these groups in subsequent analyses. Finally, the chapter aimed to establish the external validity of the identified constructs by assessing their concurrent and convergent validity in relation to established indices of health and HRQoL as well as objective clinical measures of health. This is the third manuscript of the thesis and has been published in Health and Quality of Life Outcomes.

**Contribution to primary research question**

This study provided validation of a two factor structure of the AQoL-6D, representing Physical and Psychological domains of HRQoL impairment. This factor structure displayed invariance across the ARMHS and HCS cohort groups, as well as across the baseline and 3-5 year follow-up phases of assessment. The physical and psychological domain scores produce indices displaying approximate normal distributions in the general community, supporting their assessment of both positive and negative health states. Subscale and domain scores displayed moderate-strong associations with a concurrent assessment of HRQoL (SF-36) as well as other health related indices. The AQoL-6D presents an interpretable outcome measure of physical
and psychological quality of life impairment that can be utilized in individual participant data analyses of the combined ARMHS and HCS cohorts for the purposes of the xTEND project.

**Candidate’s contribution**

In addition to the ethics, data collection and data processing tasks mentioned previously, and contributing substantially to the preparation of the current manuscript, the candidate investigated, formulated and undertook statistical analyses relating to: the multiple imputation of missing baseline mental health subscale data from the ARMHS survey; exploratory factor analyses investigating the structure of the AQoL-6D; multi-group confirmatory factor analyses to confirm the structure of the AQoL-6D across the ARMHS and HCS cohorts and over time; generation of normative data tables stratified by age and gender; the assessment of the concurrent, convergent and divergent validity of the physical and psychological HRQoL subscales.
References


Performance and usage of the Assessment of Quality of Life - 6D scale (AQoL-6D) in two longitudinal cohort studies: summary score recommendations and profiles

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Abstract

Background

The Assessment of Quality of Life - 6D scale (AQoL-6D) is a self-report instrument designed to provide a sensitive multidimensional evaluation of health related quality of life. The current paper assesses the construct, concurrent and convergent validity of the AQoL-6D in a combined longitudinal population sample drawn from across urban, regional and remote areas of Australia.

Methods

The AQoL-6D was administered within the Hunter Community Study and the Australian Rural Mental Health Study over time (mean years lag = 3.90, SD = 1.30). Observations with sufficient data were used to confirm the construct validity of the AQoL-6D domains and higher-order structure using confirmatory factor analyses (CFA, N = 7915). The stability of this structure across cohorts and over time was assessed using multi-group CFA. Additionally, the concurrent validity (against the SF-36) and convergent validity of AQoL-6D domains and factors were assessed.

Results

The construct validity of the AQoL-6D domains was considered satisfactory. Two higher-order factors, representing the physical and psychological components of quality of life were identified (CFA model fit: RMSEA = .07, SRMR = .03; TLI = .96, CFI = .98). These factors displayed group and temporal invariance, as well as concurrent and convergent validity against a range of measures. Recommendations for the derivation of summary scores are provided, together with a provisional set of norms.
Conclusions

The AQoL-6D is a useful tool for assessing quality of life impairment in epidemiological cohort studies, both cross-sectionally and over time. It displays appropriate levels of construct, concurrent and convergent validity. Conceptualisation of higher-order factors as representing the physical and psychological aspects of quality of life impairment may increase the sensitivity and appeal of the AQoL-6D, particularly for studies examining predictors of and changes in social and psychological outcomes.
Introduction

With many countries facing the health care challenges associated with an ageing population, factors associated with quality of life (QoL) and its maintenance are of immediate interest and concern. Quality of life has typically been conceptualised as the perception of physical and psychological well-being or functioning, although some formulations have also included environmental and social assets [1]. Self-report instruments measuring QoL have generally acknowledged this multidimensional structure, characterising life quality by means of various domains assessed using single or multiple items; the scope of any particular QoL measure is typically determined by a trade-off between the brevity and sensitivity required.

The Assessment of Quality of Life (AQoL) family of measures share an overarching conceptualisation of QoL in terms of handicap, or the impact of a reported health state on personal functioning and satisfaction within the person's social context [2]. To date the AQoL family comprises four multidimensional self-report survey instruments, each assessing somewhat differing domains of QoL. While scale construction often involves the compilation of a pool of items from which emergent factors are identified, the AQoL measures employ a conceptual approach to scale construction, with the aim of increasing the breadth of and sensitivity to a specified range of health features and states. In this approach, the target domains of QoL to be assessed are identified and relevant items are developed in consultation with panels of stakeholders, including researchers, clinicians and other health care professionals. Items are then refined within domains to identify items best characterising the health states of interest.

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1 For the purposes of this paper, the terms 'items', 'domains' and 'factors' will be used in a consistent manner. 'Items' refer to the individual question(s) to which participants respond, 'domains' refer to the first-order factors these items characterise, and 'factors' refer to the second-order factors to which these domains relate (i.e., items can be combined to form domains, and domains can be combined to form factors).
The Assessment of Quality of Life – 6D scale (AQoL-6D) is a relatively new addition to the AQoL family (previously labelled as the AQoL-II) and was developed in part to improve the content validity of QoL measures [3] and thus their sensitivity to a range of factors influencing life quality. In addition, the AQoL-6D aimed to create a measure appropriate for population health assessment, with increased sensitivity to wellness states compared to previous versions. The AQoL-6D is a 20 item assessment of six domains of QoL, characterised as ‘independent living’, ‘relationships’, ‘mental health’, ‘coping’, ‘pain’ and ‘senses’ and takes only a few minutes to complete. While the authors of the scale note that items assess both physical and psycho-social areas of QoL, these six domains may be combined to form a single global QoL factor.

In the process of constructing the AQoL-6D, additional items were developed for the AQoL item bank to increase coverage of QoL concepts both between and within domains [3]. Best performing items in terms of factor coherence and psychometric performance were determined from a construction sample, in which the overall factor structure was then confirmed [2-4]. As intended, the final 20 items formed a model with 3–4 items loading on each of the six domain scores, which in turn loaded onto a global QoL factor [2-4]. The AQoL-6D has been reported to discriminate between older persons at differential risks for falls [5], and to be associated with body mass index in adolescents, identifying the coping domain as particularly decreased in obese teens [6]. While these results suggest the AQoL-6D is a usable and sensitive instrument for a range of age groups, to date, there has been no published confirmation of the factor structure of the AQoL-6D outside of its original construction sample.

In light of its design for use in population health surveys and representation of physical and psycho-social aspects of QoL, the AQoL-6D was administered at the baseline and follow-up phases of two independently conceived but concurrent longitudinal community cohort studies conducted in New South Wales, Australia: 1) the Australian Rural Mental Health Study (ARMHS) [7], a project examining regional to very remote communities, which conducted
baseline surveys in 2007–2009 and follow-up surveys from 2011–2012; and 2) the Hunter Community Study (HCS) [8], a project examining urban and inner regional communities around the Hunter Region, which conducted baseline surveys in 2004–2007 and follow-up surveys from 2010–2011. Under the auspices of the Extending Treatments, Education and Networks in Depression (xTEND) project [9], these cohorts have been combined with an aim to investigate issues of common interest and to maximise the utility of existing community surveys and national datasets. However, the comparability of the quality of life constructs assessed by the AQoL-6D across these cohorts, which encompass different age ranges and environmental contexts, is as yet unknown. Furthermore, concerns regarding ‘response shift bias’ are a potential problem in longitudinal studies of QoL [10], that is, when the conceptualization of an experience or state of being changes over time or with health states, resulting in confounding. Thus, confirming the structure and validity of the AQoL-6D scale across groups and timepoints is of importance not only for confirming its factor structure, but to facilitate meaningful and interpretable comparisons using this measure.

Using this large, aggregate longitudinal sample compiled for the purposes of the xTEND study, the current paper aims to: 1) review the performance of the AQoL-6D items and assess the internal validity and stability of the six associated domains; 2) confirm the overall factor structure of the AQoL-6D and its stability over time and across cohorts; 3) assess the concurrent validity of the AQoL-6D against an established measure of quality of life (the SF-36); and 4) assess the convergent validity of AQoL-6D factors by examining their association with indices of personal functioning (e.g., mental health functioning, psychological distress, satisfaction with life, physical functioning, body mass index, spirometry, pedometry and mobility).
Methods

Participants

Self-report postal survey data from two population based cohort studies were combined to undertake the current study: the Hunter Community study (HCS) [8]; and the Australian Rural Mental Health Study (ARMHS) [7]. Detailed descriptions of recruitment, sample characteristics and methods employed can be obtained from their respective baseline descriptive papers. Briefly, the HCS is a study of persons aged 55–85 years residing in Newcastle, Australia, which was designed to assess a range of bio-psychosocial aspects of ageing. The ARMHS project includes persons aged 18 years and older residing in non-metropolitan areas, which was designed to assess mental health and well-being in rural and remote regions by over-sampling from remote and very remote populations. Both the HCS and ARMHS randomly selected potential participants from the state electoral roll. Introduction and recruitment letters were sent to individuals by post and non-responding individuals were followed-up by telephone calls. Overall, baseline response rates of 44.5% and 27.3% for the HCS (N = 3318) and ARMHS (N = 2639) respectively were achieved, with both samples having comparable rates of un-contactable or excluded persons (HCS: 26.9% and ARMHS: 25.2%). To reduce participant burden, survey items were administered over two baseline postal surveys in both cohorts: among respondents, 81.4% from the ARMHS and 97.4% from the HCS returned both surveys and were included in the current analyses. Between 2010 and 2012, 59.0% of baseline participants responded to a follow-up survey. Following ethical approval (Human Research Ethics Committees from the University of Newcastle and Hunter New England Area Health) individual participant survey data from the HCS and ARMHS were combined.

Table 4.1 displays information regarding numbers of cohort participants observed at baseline and follow-up phases, as well as the rationale for the selection of cases used in the current
analyses. Of the combined N = 8896 baseline and follow up cases, 89.1% responded to all administered AQoL-6D items. Due to an administrative error, influenced by the perceived redundancy within the mental health items included in the survey, the mental health domain of the AQoL-6D (comprising 4 items) was not assessed in the ARMHS cohort at baseline. To address this issue, a subsample comprised of participants who had no more than 25% missing data on imputation model variables was used in the imputation of missing mental health domain items. This level of missing data has been demonstrated to produce minimal bias when using full information maximum likelihood estimation [11]. Following this procedure, the capacity of the multiple and single imputation sets of the mental health subscale to maintain the associative properties of the observed values (follow-up ARMHS, baseline and follow-up HCS) was examined. It was determined that a single imputation of mental health scale items for baseline ARMHS participants provided adequate representation of the missing values and these values were merged with the original dataset. A detailed account of the imputation and related analyses are provided in Appendix 4.1, which includes information regarding item response rates and floor/ceiling effects (see Table S2). Participants with complete AQoL-6D data in the resulting overall set were used to assess the scale characteristics, structure, invariance and validity of the AQoL-6D (N = 7915).
Table 4.1 Description of number, origin and criteria for cases included in current analyses.

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th></th>
<th>Follow up</th>
<th></th>
<th>Cohort N (group invariance)</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ARMHS</td>
<td>HCS</td>
<td>ARMHS</td>
<td>HCS</td>
<td>ARMHS</td>
<td>HCS</td>
</tr>
<tr>
<td>Returned both surveys</td>
<td>2149</td>
<td>3234</td>
<td>1261$^*$</td>
<td>2252$^*$</td>
<td>2127</td>
<td>3168</td>
</tr>
<tr>
<td>Included in imputation procedure</td>
<td>2127</td>
<td>3168</td>
<td>1234</td>
<td>2171</td>
<td>8700</td>
<td>9000</td>
</tr>
<tr>
<td>(&lt;25% missing data on imputation model variables)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Complete AQoL data$^\dagger$</td>
<td>1987</td>
<td>2884</td>
<td>1111</td>
<td>1933</td>
<td>3098</td>
<td>4817</td>
</tr>
<tr>
<td>(cases used for all reported analyses)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Phase N (cases included in analyses of temporal invariance)</td>
<td>4871</td>
<td>3044</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$^*$ Only one survey booklet was administered at follow-up, these values refer to N participants returning a follow-up survey. $^\dagger$ Imputed values for the four mental health subscale items were merged into the original (un-imputed) set for ARMHS baseline participants.
**Measures**

**Quality of life**

The Assessment of Quality of Life – 6D scale (AQoL-6D) is a 20-item self-report measure of QoL and general functioning [3]. Response options for each item include 4–6 levels, with higher scores indicating quality of life impairment. The 20 items of the AQoL-6D represent six domains, characterised as independent living (4 items), relationships (3 items), mental health (4 items), coping (3 items), pain (3 items) and senses (3 items). Items and response options are available online (http://www.aqol.com.au/) and reproduced in Appendix 4.2. The AQoL-6D was administered to the ARMHS and HCS cohorts at both baseline and follow-up phases.

Concurrent measurement of health related quality of life was conducted using the SF-36v1 (Australian version) [12], which was administered to HCS participants at both baseline and follow-up phases. The SF-36 is a well validated assessment of physical and mental health outcomes and has eight scales (physical functioning, role physical, social functioning, mental health, role emotional, vitality, bodily pain and general health) [13]. Scale scores were calculated according to the SF-36 manual [14], with items within scales recoded where necessary, summed and transformed to provide a scale score (range 0–100), with higher scores indicating greater health within that domain. The physical functioning and mental health scales of the SF-36 have been identified as ‘pure’ measures of their underlying constructs (physical and mental health respectively), with variability in each scale largely attributable to variation in its target health state [13]; for the current paper, these scales were used as concurrent indices, against which the AQoL-6D factors could be evaluated.
Other psychological functioning indicators

**Psychological distress.** The Kessler 10 (K10) [15] was used to assess current psychological distress and was administered to the ARMHS and HCS cohorts at both baseline and follow-up phases. The K10 is a 10-item self-report questionnaire that assesses the frequency of psychological distress over the past four weeks using a 5-point Likert scale: ‘none of the time’, ‘a little of the time’, ‘some of the time’, ‘most of the time’, ‘all of the time’. K10 scores range from 10 to 50, with higher scores denoting greater psychological distress. This measure displays good internal reliability (α = .93) and validity as a measure of psychological distress in community samples [16]. K10 items are also highly similar to AQoL-6D mental health subscale items, asking participants to rate the frequency with which they recently experienced anxious/negative affective states.

**Life satisfaction.** The Satisfaction With Life (SWL) scale was used to assess life satisfaction and was administered to the ARMHS cohort at baseline and to both the ARMHS and HCS cohorts at follow-up. The SWL [17] is a five-item scale measuring global life satisfaction, with participants rating each statement on a 7-point Likert scale (‘strongly disagree’ to ‘strongly agree’). A total global life satisfaction score is derived by summing all five items, with higher scores indicating greater life satisfaction (range = 5–35). The SWL is a widely used and well validated measure of life satisfaction [18] that displays good internal reliability (α = .87) [17].

Other physical functioning indicators

**Body mass index (BMI).** At baseline, height and weight measurements were undertaken as part of a battery of clinical measures recorded by staff in the HCS, while the ARMHS obtained these measurements through self-reported survey responses. To address the significant potential for bias in the self-reporting of height and weight measurements, correction equations based on 2007–2008 Australian national survey data [16] were applied to self-
reported height and weight indices for ARMHS participants before BMI was calculated. BMI was calculated as weight in kilograms divided by height in metres squared (kg/m²). BMI profiles by age for the sample are comparable to Australian population estimates compiled by the Australian Bureau of Statistics (see supplementary information provided in Additional file 1 for further details regarding the transformation and BMI profiles of the current sample).

Several other pertinent measures of physical functioning were collected in the HCS at baseline: 

**Pedometry** – a pedometer worn for 7 consecutive days during waking hours to record step count, from which mean daily steps was calculated; **Timed up and go (TUG)** - a measure of functional mobility that is operationalized as the time (in seconds) that a person takes to rise from a chair, walk three metres, turn around, walk back to the chair and sit down [19]; and **forced expiratory volume (FEV)** in 1 second - assessed (in litres) using electronic spirometers, together with Spida 5 software [20,21].

**Data analysis**

Analyses were conducted using IBM SPSS Statistics for Windows v20.0 [22] and AMOS v20.0 [23]. Chi square tests were used for between group comparisons of categorical variables and one-way ANOVA for continuous variables. Unless otherwise stated, p < .01 was used as the threshold for all tests of statistical significance as a partial control for the number of statistical comparisons and the large number of observations.

**Factor analyses**

Maximum likelihood estimations were used for all confirmatory factor analyses (CFA). Correlation matrices used to produce all models reported here are provided in the supplementary documentation (Appendix 4.1, Tables S6). To assess the internal consistency of AQoL-6D domains, one factor congeneric models of each domain were constructed and the association of indicators with the domain, item variance explained by the domain (squared
multiple correlation: SMC), and the reliability of scale items were inspected. Item reliabilities were assessed using both Cronbach’s alpha (\(\alpha\)), which uses item correlations to assess a common construct, and Coefficient H [24], which uses model parameters to determine the reliability with which items assess a latent construct. As the majority of domains were just-identified [25] (reflecting the small number of items per domain), no fit statistics were calculated for these models.

To confirm that the six domains assessed a common underlying QoL construct, a one factor model of these domains was initially evaluated using CFA. Bagozzi et al.’s [26] method of determining discriminant validity, which utilizes nested models to assess whether scales are best represented by one or two higher-order factors, was used to assess the fit of competing models. The fit of a two factor solution, where the factor covariance was freely estimated (two correlated factors), was compared with a model where the correlation was constrained to be 1.00 (a single factor) and a chi-squared difference test conducted. To confirm whether the AQoL-6D factor structure was equivalent across the ARMHS and HCS samples and over time, multi-group confirmatory factor analyses (MGCFA) were conducted. Nested models were used to assess increasingly restrictive models of invariance across groups and time, to confirm that AQoL-6D factors displayed configural (indicators load on the same latent factor), metric (indicators contribute consistently to the latent factor), and variance/covariance invariance (the latent factor represents the same range of values and displays consistent relationships) across groups/ time. Such multi-group methods present a widely accepted and powerful approach for testing measurement invariance [27]. Where models displayed group and temporal invariance, model parameters are reported for the overall sample. Model fit was assessed by inspecting absolute [standardised root mean square residual (SRMR) and root mean square error of approximation (RMSEA)] and incremental fit statistics [Tucker-Lewis Index (TLI), Comparative Fit Index (CFI)], as well as parameter estimates. Acceptable fit is
indicated by RMSEA close to or less than .06, SRMR < .06 and incremental fit indices > .95 [28]. Where model fit was unacceptable, modification indices were inspected and considered in conjunction with the theoretical underpinnings of factors to improve model fit.

**Psychometric analyses**

Construction of aggregate AQoL-6D domain and factor scores for the sample are described and the stability of scores over-time assessed using the intra-class correlation coefficient (absolute) [29]. One-way ANOVAs were conducted to assess the influence of age and gender on factor and total scores and post-hoc age category comparisons using orthogonal polynomials were used to assess patterns of differences between age categories. The concurrent validity of AQoL-6D domain and factor scores was assessed against SF-36 domain scores. The magnitude of the associations between quality of life domains were examined using canonical correlations and Pearson's correlation coefficient. Where multiple observations of an individual over time were available, analyses weighted and unweighted for the number of observations were conducted; correlation matrices for these analyses did not differ (maximum coefficient difference of r = .02) and unweighted analyses are reported in the manuscript. Factor score stability over time was contrasted with those of the SF-36 physical and mental health scales. The sensitivity of the SF-36 total score to impairment on each AQoL-6D domain was examined by standardizing AQoL-6D scores and plotting a score profile for those participants ranking in the lowest 25th percentile on the SF-36. We also build upon observations regarding the convergent validity of the AQoL-6D by examining the multiple correlation of AQoL-6D factor scores with sets of physical and psychological functioning indices ($R^2$ with set) to assess the proportion of variance shared with these conceptually related constructs.
Results

Sample characteristics

Baseline and follow-up characteristics of the sample are presented in Table 4.2. Of the N = 2740 participants who provided AQoL-6D data at both timepoints, there was an average lag of 3.90 years (SD = 1.30) between baseline and follow-up surveys. Cohorts differed significantly in demographic and bio-psychosocial indices and cohort differences were largely consistent at both timepoints. Compared to baseline, follow-up participants were older, more likely to be married/de facto (ARMHS), had a higher level of education, were more likely to be retired (HCS), had lower psychological distress, and lower life satisfaction (ARMHS).
Table 4.2 Sample characteristics and comparisons by cohort and phase.

<table>
<thead>
<tr>
<th></th>
<th>Baseline - Cohort Comparisons</th>
<th></th>
<th>Follow up - Cohort Comparisons</th>
<th></th>
<th>Phase Comparisons</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HCS</td>
<td>ARMHS</td>
<td>Overall</td>
<td>p</td>
<td>HCS</td>
</tr>
<tr>
<td>Sample N</td>
<td>2884</td>
<td>1987</td>
<td>4871</td>
<td></td>
<td>1933</td>
</tr>
<tr>
<td>Socio demographic characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (SD)</td>
<td>65.83 (7.59)</td>
<td>55.91 (4.03)</td>
<td>61.77 (11.76) **</td>
<td></td>
<td>69.19 (7.13)</td>
</tr>
<tr>
<td>Female %</td>
<td>51.9</td>
<td>60.3</td>
<td>55.3</td>
<td>**</td>
<td>51.2</td>
</tr>
<tr>
<td>Married/defacto %</td>
<td>75.3</td>
<td>71.2</td>
<td>73.6</td>
<td>**</td>
<td>75.4</td>
</tr>
<tr>
<td>High school complete %</td>
<td>77.8</td>
<td>71.3</td>
<td>75.2</td>
<td>**</td>
<td>81.3</td>
</tr>
<tr>
<td>Retired %</td>
<td>61.8</td>
<td>36.1</td>
<td>37.8</td>
<td>**</td>
<td>76.9</td>
</tr>
<tr>
<td>Indices of personal functioning (mean, SD)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Psychological distress (K10)</td>
<td>14.41 (5.31)</td>
<td>14.62 (5.16)</td>
<td>14.5 (5.25) ns</td>
<td></td>
<td>13.67 (4.85)</td>
</tr>
<tr>
<td>Life satisfaction (SWL)</td>
<td>.</td>
<td>25.82 (6.44)</td>
<td>.</td>
<td></td>
<td>25.51 (6.08)</td>
</tr>
<tr>
<td>Body Mass Index</td>
<td>28.70 (4.85)</td>
<td>28.07 (5.45)</td>
<td>28.43 (5.12) **</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mental Health (SF-36)</td>
<td>79.72 (15.73)</td>
<td>.</td>
<td>.</td>
<td></td>
<td>79.84 (15.53)</td>
</tr>
<tr>
<td>Physical Functioning (SF-36)</td>
<td>73.31 (24.15)</td>
<td>.</td>
<td>.</td>
<td></td>
<td>74.07 (24.14)</td>
</tr>
<tr>
<td>FEV (litres)</td>
<td>2.43 (0.70)</td>
<td>.</td>
<td>.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TUG (seconds)</td>
<td>9.33 (2.71)</td>
<td>.</td>
<td>.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Steps per day (1000’s)</td>
<td>6.87 (3.18)</td>
<td>.</td>
<td>.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. * p < .01; ** p < .001; physical and psychological health indices did not deviate remarkably from available age relevant norms for these measures: K10 [30]; SWL [18]; BMI [31]; SF-36 [32]; forced expiratory volume (FEV) [33]; and timed up and go (TUG) [34, 35]; while HCS step counts are similar to those of older persons in Switzerland, though greater than those in Colorado [36].
**Internal validity and structure**

**Items and domains**

As detailed in Table 4.3, one factor congeneric modelling indicated that the AQoL-6D domains display positive associations with all of their component items and explained a considerable amount of item variance (SMC). Internal consistency of most domains was acceptable (Cronbach’s α range .73-.86), with the possible exception of the relationships (α = .63) and senses (α = .50) domains. The relationships domain had acceptable consistency in reference to Coefficient H (H = .76), which does not assume all items are equally good indicators of the latent construct, however, the consistency of the senses domain was still low (H= .61). Latent domains were generally a good fit to items, with the majority displaying high item reliabilities (SMC > .50), though relationships (aq5), senses (aq18 and aq20), and coping (aq12) domains contained some items with unacceptable reliability (SMC < .30).
Table 4.3 Raw and standardized coefficients from separate CFAs for each AQoL-6D domain (N = 7915).

<table>
<thead>
<tr>
<th>Domain</th>
<th>Item</th>
<th>B</th>
<th>SE</th>
<th>β</th>
<th>SMC</th>
<th>Error variance</th>
<th>Domain α</th>
<th>Domain H</th>
</tr>
</thead>
<tbody>
<tr>
<td>Independ. living</td>
<td>aq1 Household tasks</td>
<td>1.00</td>
<td>0.75</td>
<td>0.56</td>
<td>&lt;--</td>
<td>0.30</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Independ. living</td>
<td>aq2 Getting around</td>
<td>1.34</td>
<td>0.02</td>
<td>0.88</td>
<td>0.77</td>
<td>&lt;-</td>
<td>0.21</td>
<td>0.86</td>
</tr>
<tr>
<td>Independ. living</td>
<td>aq3 Walking</td>
<td>1.16</td>
<td>0.02</td>
<td>0.75</td>
<td>0.57</td>
<td>&lt;-</td>
<td>0.39</td>
<td></td>
</tr>
<tr>
<td>Independ. living</td>
<td>aq4 Self-care</td>
<td>0.71</td>
<td>0.01</td>
<td>0.73</td>
<td>0.54</td>
<td>&lt;-</td>
<td>0.17</td>
<td></td>
</tr>
<tr>
<td>Relationships</td>
<td>aq5 Intimate</td>
<td>1.00</td>
<td>0.32</td>
<td>0.10</td>
<td>&lt;--</td>
<td>0.52</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Relationships</td>
<td>aq6 Health &amp; family</td>
<td>1.53</td>
<td>0.07</td>
<td>0.81</td>
<td>0.66</td>
<td>&lt;-</td>
<td>0.07</td>
<td>0.63</td>
</tr>
<tr>
<td>Relationships</td>
<td>aq7 Health &amp; community</td>
<td>1.90</td>
<td>0.08</td>
<td>0.74</td>
<td>0.54</td>
<td>&lt;-</td>
<td>0.17</td>
<td></td>
</tr>
<tr>
<td>Mental health</td>
<td>aq8 Despair</td>
<td>1.00</td>
<td>0.74</td>
<td>0.55</td>
<td>&lt;--</td>
<td>0.25</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mental health</td>
<td>aq9 Worry</td>
<td>1.11</td>
<td>0.02</td>
<td>0.75</td>
<td>0.56</td>
<td>&lt;-</td>
<td>0.29</td>
<td>0.79</td>
</tr>
<tr>
<td>Mental health</td>
<td>aq10 Sadness</td>
<td>0.94</td>
<td>0.02</td>
<td>0.72</td>
<td>0.52</td>
<td>&lt;-</td>
<td>0.25</td>
<td>0.80</td>
</tr>
<tr>
<td>Mental health</td>
<td>aq11 Agitation</td>
<td>0.63</td>
<td>0.01</td>
<td>0.59</td>
<td>0.34</td>
<td>&lt;-</td>
<td>0.24</td>
<td></td>
</tr>
<tr>
<td>Coping</td>
<td>aq12 Energy</td>
<td>1.00</td>
<td>0.52</td>
<td>0.27</td>
<td>&lt;--</td>
<td>0.44</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coping</td>
<td>aq13 Control</td>
<td>1.35</td>
<td>0.04</td>
<td>0.79</td>
<td>0.63</td>
<td>&lt;-</td>
<td>0.18</td>
<td>0.73</td>
</tr>
<tr>
<td>Coping</td>
<td>aq14 Coping</td>
<td>1.07</td>
<td>0.03</td>
<td>0.76</td>
<td>0.58</td>
<td>&lt;-</td>
<td>0.13</td>
<td></td>
</tr>
<tr>
<td>Pain</td>
<td>aq15 Pain frequency</td>
<td>1.00</td>
<td>0.78</td>
<td>0.60</td>
<td>&lt;--</td>
<td>0.39</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pain</td>
<td>aq16 Pain severity</td>
<td>0.59</td>
<td>0.01</td>
<td>0.77</td>
<td>0.59</td>
<td>&lt;-</td>
<td>0.14</td>
<td>0.84</td>
</tr>
<tr>
<td>Pain</td>
<td>aq17 Pain impact</td>
<td>1.06</td>
<td>0.02</td>
<td>0.85</td>
<td>0.72</td>
<td>&lt;-</td>
<td>0.26</td>
<td></td>
</tr>
<tr>
<td>Senses</td>
<td>aq18 Vision</td>
<td>1.00</td>
<td>0.35</td>
<td>0.12</td>
<td>&lt;--</td>
<td>0.37</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Senses</td>
<td>aq19 Hearing</td>
<td>2.58</td>
<td>0.19</td>
<td>0.73</td>
<td>0.54</td>
<td>&lt;-</td>
<td>0.29</td>
<td>0.50</td>
</tr>
<tr>
<td>Senses</td>
<td>aq20 Communication</td>
<td>0.84</td>
<td>0.04</td>
<td>0.45</td>
<td>0.20</td>
<td>&lt;-</td>
<td>0.15</td>
<td></td>
</tr>
</tbody>
</table>

Note: CFA = confirmatory factor analysis; SMC = squared multiple correlation; Domain α = Cronbach’s alpha coefficient for items within the domain; Domain H = H coefficient for items within the domain.

**Overall factor structure**

Domain scores were initially calculated as the mean of the standardized factor weighted item scores, to both account for differing item reliabilities and reduce the inconsistency due to differing numbers of items and response options across domains. Standardized weights applied to item scores in the calculation of domain scores are presented in the supplementary documentation (Appendix 4.1, Table S5). CFA indicated a one-factor model of QoL displayed a
positive association with all domains ($\beta = .33-.81$) and explained a reasonable amount of the variance in domain scores (SMC = .11-.65). However, model fit was poor [RMSEA= .20 (.19, .20), SRMR= .08; TLI = .70, CFI = .82], suggesting that the domain scores tapped somewhat dissimilar underlying constructs. Modification indices indicated that allowing the relationship between the mental health and coping domain errors to vary would reduce the discrepancy between the observed and optimal covariance matrixes by $\chi^2 = 2122.37$. This suggested that a two factor solution with mental health and coping representing a separate factor, perhaps assessing the psychological, as opposed to the physical, aspects of QoL, may improve the model. Model fit for the two factor solution was good [RMSEA = .07 (.07, .08), SRMR = .03; TLI = .96, CFI = .98]. A chi-square difference test indicated that the single factor solution significantly worsened the model compared with the two factor solution ($\chi^2(1) = 2429.40, p < .001$), indicating that the two constructs are reasonably different.

Multi-group CFAs were conducted to assess whether this two factor solution was consistent across groups (ARMHS vs. HCS) and timepoints (baseline vs. follow-up). Results provided evidence that the two factor solution displayed configural [RMSEA = .06 (.05, .06), SRMR = .03; TLI = .95, CFI = .97], metric [RMSEA = .05 (.05, .06), SRMR = .03; TLI = .96, CFI = .97], and covariance/variance [RMSEA = .05 (.05, .06), SRMR = .04; TLI = .96, CFI = .97] invariance in both cohorts, suggesting this model was viable in both samples. Likewise, assessment of temporal invariance provided evidence that scales displayed configural [RMSEA = .06 (.05, .06), SRMR= .03; TLI = .95, CFI = .97], metric [RMSEA = .05 (.05, .05), SRMR = .03; TLI = .96, CFI = .97], and covariance/variance [RMSEA = .05 (.04, .05), SRMR = .04; TLI = .96, CFI = .97] invariance over time, suggesting this model was viable at both baseline and follow-up timepoints. Parameters for the two factor model are presented in Table 4.4 and its structure depicted in Figure 4.1.
Table 4.4 Model parameter estimates for two higher-order factors from a factor analysis of AQoL-6D domains (N = 7915).

<table>
<thead>
<tr>
<th>Factor</th>
<th>Domain</th>
<th>B</th>
<th>SE</th>
<th>β</th>
<th>SMC</th>
<th>Error variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical</td>
<td>INDEPENDENT LIVING</td>
<td>0.61</td>
<td>0.01</td>
<td>0.85</td>
<td>0.72</td>
<td>0.14</td>
</tr>
<tr>
<td>Physical</td>
<td>RELATIONSHIPS</td>
<td>0.35</td>
<td>0.01</td>
<td>0.78</td>
<td>0.61</td>
<td>0.08</td>
</tr>
<tr>
<td>Psychological</td>
<td>MENTAL HEALTH</td>
<td>0.44</td>
<td>0.01</td>
<td>0.75</td>
<td>0.56</td>
<td>0.15</td>
</tr>
<tr>
<td>Psychological</td>
<td>COPING</td>
<td>0.46</td>
<td>0.01</td>
<td>0.85</td>
<td>0.73</td>
<td>0.08</td>
</tr>
<tr>
<td>Physical</td>
<td>PAIN</td>
<td>0.47</td>
<td>0.01</td>
<td>0.66</td>
<td>0.43</td>
<td>0.29</td>
</tr>
<tr>
<td>Physical</td>
<td>SENSES</td>
<td>0.17</td>
<td>0.01</td>
<td>0.33</td>
<td>0.11</td>
<td>0.23</td>
</tr>
<tr>
<td>Physical</td>
<td>Psychological</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.59</td>
</tr>
</tbody>
</table>

Note: SMC = squared multiple correlation.

Figure 4.1 Standardized parameter estimates and squared multiple correlations for the two correlated higher-order factor structure of the six AQoL-6D domains (N = 7915).
**Calculation of domain and factor scores**

**Domains: factor weighted scores vs. item weighted scores vs. utility scores**

Correlations between standardized factor weighted domain scores and those derived by calculating the mean unit weighted domain score (i.e., giving equal weight to each item) were highly correlated for all scales [independent living \( r = .993 \); relationships \( r = .883 \); mental health \( r = .998 \); coping \( r = .962 \); pain: \( r = .996 \); senses \( r = .954 \)]. The comparatively lower correlation for the relationships domain is due to the smaller standardized factor weighting of item aq5 \( (w = .055) \), which addresses general satisfaction with relationships, as opposed to items aq6 \( (w = .634) \) and aq7 \( (w = .311) \), which address the impact of an individual’s health on their ability to fulfil relationship roles (see Appendix 4.1, Table S5). Utility weighted domain scores \([37]\) also correlated highly with mean unit weighted domain scores (range \( r = -.918 \) to \( r = -.983 \)). Therefore, for parsimony, mean unit weighted domain scores were used for subsequent analysis and reporting (i.e., giving equal weight to items in calculating domain scores, and equal weight to domains in calculating factor scores).

**Factor scores**

AQoL-6D physical and psychological factors were calculated as the mean of their component unit weighted domain scores; both displayed a correlation of \( r = .99 \), \( p < .001 \) with their counterparts calculated as the mean of factor weighted domain scores. Internal consistency estimates, based on the set of items associated with each factor were, respectively, \( \alpha = .86 \) and \( \alpha = .84 \) for the physical and psychological factors. Physical and psychological factor scores displayed a correlation of \( r = .56 \), \( p < .001 \), which was highly consistent with the association observed in the two factor CFA model (see Figure 4.1). A total score, the mean of the physical and psychological factors, was also calculated. The internal consistency for the full set of AQoL-6D items contributing to the total score was \( \alpha = .89 \). As expected (given their mathematical
relationships), correlations between factors and the total score were high: physical $r = .87$, $p < .001$; psychological $r = .90$, $p < .001$).

Table 4.5 presents means and standard deviations for the domain and factor scores by gender and age, and provides a provisional set of norms for the proposed AQoL-6D scoring scheme. There was a significant but small effect of gender on both physical ($F(1, 7915) = 34.21$, $p < .001$) and psychological ($F(1, 7914) = 51.34$, $p < .001$) factor scores, with men reporting greater impairment on physical and women reporting greater impairment on psychological factors. There was no influence of gender on the total score ($F(1, 7914) = 1.35$, $p = .246$). There was no significant influence of age category on psychological functioning ($F(4, 7901) = 3.06$, $p = .016$) but a significant effect of age category on physical functioning ($F(4, 7901) = 138.21$, $p < .001$) and the total score ($F(4, 7901) = 33.082$, $p < .001$). Post-hoc age category comparisons revealed significant linear components of trend for both the physical functioning ($F(1, 7897) = 551.13$, $p < .001$) and total scores ($F(1, 7897) = 132.82$, $p < .001$), indicating a progressive increase in impairment with increased age. No higher order (i.e., non-linear) effects were observed for any of these scores.
<table>
<thead>
<tr>
<th>Group</th>
<th>Age (years)</th>
<th>N</th>
<th>Independent living</th>
<th>Relationships</th>
<th>Mental health</th>
<th>Coping</th>
<th>Pain</th>
<th>Senses</th>
<th>Psychological Factor</th>
<th>Physical Factor</th>
<th>TOTAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>18-34</td>
<td>53</td>
<td>1.42 (0.64)</td>
<td>1.31 (0.36)</td>
<td>1.92 (0.62)</td>
<td>1.81 (0.67)</td>
<td>1.55 (0.74)</td>
<td>1.40 (0.42)</td>
<td>1.87 (0.59)</td>
<td>1.42 (0.40)</td>
<td>1.64 (0.44)</td>
</tr>
<tr>
<td></td>
<td>35-44</td>
<td>110</td>
<td>1.41 (0.50)</td>
<td>1.29 (0.42)</td>
<td>1.95 (0.59)</td>
<td>2.01 (0.59)</td>
<td>1.68 (0.62)</td>
<td>1.75 (0.46)</td>
<td>1.98 (0.54)</td>
<td>1.53 (0.40)</td>
<td>1.75 (0.43)</td>
</tr>
<tr>
<td></td>
<td>45-54</td>
<td>265</td>
<td>1.45 (0.52)</td>
<td>1.36 (0.46)</td>
<td>1.85 (0.64)</td>
<td>1.99 (0.60)</td>
<td>1.73 (0.67)</td>
<td>1.87 (0.47)</td>
<td>1.92 (0.57)</td>
<td>1.60 (0.38)</td>
<td>1.76 (0.42)</td>
</tr>
<tr>
<td></td>
<td>55-64</td>
<td>1343</td>
<td>1.63 (0.64)</td>
<td>1.38 (0.44)</td>
<td>1.90 (0.59)</td>
<td>2.00 (0.57)</td>
<td>1.84 (0.73)</td>
<td>2.01 (0.44)</td>
<td>1.95 (0.53)</td>
<td>1.72 (0.43)</td>
<td>1.83 (0.43)</td>
</tr>
<tr>
<td></td>
<td>65+</td>
<td>1772</td>
<td>1.93 (0.74)</td>
<td>1.48 (0.52)</td>
<td>1.83 (0.54)</td>
<td>2.01 (0.53)</td>
<td>1.86 (0.74)</td>
<td>2.07 (0.45)</td>
<td>1.92 (0.49)</td>
<td>1.84 (0.47)</td>
<td>1.88 (0.43)</td>
</tr>
<tr>
<td>Female</td>
<td>Total</td>
<td>3543</td>
<td>1.76 (0.70)</td>
<td>1.43 (0.48)</td>
<td>1.86 (0.57)</td>
<td>2.00 (0.56)</td>
<td>1.83 (0.73)</td>
<td>2.01 (0.46)</td>
<td>1.93 (0.51)</td>
<td>1.76 (0.45)</td>
<td>1.85 (0.43)</td>
</tr>
<tr>
<td></td>
<td>18-34</td>
<td>149</td>
<td>1.34 (0.41)</td>
<td>1.25 (0.34)</td>
<td>1.93 (0.57)</td>
<td>1.98 (0.61)</td>
<td>1.34 (0.54)</td>
<td>1.41 (0.37)</td>
<td>1.95 (0.54)</td>
<td>1.33 (0.30)</td>
<td>1.64 (0.37)</td>
</tr>
<tr>
<td></td>
<td>35-44</td>
<td>275</td>
<td>1.37 (0.49)</td>
<td>1.32 (0.40)</td>
<td>1.99 (0.63)</td>
<td>2.12 (0.59)</td>
<td>1.50 (0.63)</td>
<td>1.56 (0.42)</td>
<td>2.06 (0.56)</td>
<td>1.44 (0.36)</td>
<td>1.75 (0.42)</td>
</tr>
<tr>
<td></td>
<td>45-54</td>
<td>414</td>
<td>1.46 (0.51)</td>
<td>1.33 (0.40)</td>
<td>1.91 (0.54)</td>
<td>2.06 (0.52)</td>
<td>1.73 (0.67)</td>
<td>1.82 (0.38)</td>
<td>1.99 (0.48)</td>
<td>1.58 (0.36)</td>
<td>1.79 (0.38)</td>
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<tr>
<td></td>
<td>55-64</td>
<td>1648</td>
<td>1.62 (0.61)</td>
<td>1.38 (0.40)</td>
<td>1.99 (0.57)</td>
<td>2.07 (0.52)</td>
<td>1.87 (0.74)</td>
<td>1.83 (0.39)</td>
<td>2.03 (0.49)</td>
<td>1.67 (0.41)</td>
<td>1.85 (0.40)</td>
</tr>
<tr>
<td></td>
<td>65+</td>
<td>1873</td>
<td>1.96 (0.77)</td>
<td>1.48 (0.47)</td>
<td>1.94 (0.56)</td>
<td>2.07 (0.53)</td>
<td>1.93 (0.76)</td>
<td>1.89 (0.42)</td>
<td>2.01 (0.49)</td>
<td>1.81 (0.47)</td>
<td>1.91 (0.42)</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>4359</td>
<td>1.73 (0.70)</td>
<td>1.41 (0.44)</td>
<td>1.96 (0.57)</td>
<td>2.07 (0.53)</td>
<td>1.84 (0.74)</td>
<td>1.82 (0.42)</td>
<td>2.02 (0.49)</td>
<td>1.70 (0.44)</td>
<td>1.86 (0.41)</td>
</tr>
</tbody>
</table>
Table 4.5 continued. Mean (SD) AQoL-6D quality of life impairment domain and factor scores by gender and age.

<table>
<thead>
<tr>
<th>Group</th>
<th>Age (years)</th>
<th>N</th>
<th>Independent living</th>
<th>Relationships</th>
<th>Mental health</th>
<th>Coping</th>
<th>Pain</th>
<th>Senses</th>
<th>Psychological Factor</th>
<th>Physical Factor</th>
<th>TOTAL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Overall</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>18-34</td>
<td>202</td>
<td>1.36 (0.48)</td>
<td>1.27 (0.35)</td>
<td>1.93 (0.58)</td>
<td>1.94 (0.63)</td>
<td>1.39 (0.6)</td>
<td>1.41 (0.38)</td>
<td>1.93 (0.56)</td>
<td>1.36 (0.33)</td>
<td>1.64 (0.39)</td>
</tr>
<tr>
<td></td>
<td>35-44</td>
<td>385</td>
<td>1.38 (0.49)</td>
<td>1.31 (0.40)</td>
<td>1.98 (0.62)</td>
<td>2.09 (0.59)</td>
<td>1.55 (0.63)</td>
<td>1.61 (0.44)</td>
<td>2.04 (0.56)</td>
<td>1.47 (0.37)</td>
<td>1.75 (0.42)</td>
</tr>
<tr>
<td></td>
<td>45-54</td>
<td>679</td>
<td>1.46 (0.52)</td>
<td>1.34 (0.42)</td>
<td>1.89 (0.58)</td>
<td>2.03 (0.55)</td>
<td>1.73 (0.67)</td>
<td>1.84 (0.41)</td>
<td>1.96 (0.52)</td>
<td>1.59 (0.37)</td>
<td>1.78 (0.39)</td>
</tr>
<tr>
<td></td>
<td>55-64</td>
<td>2991</td>
<td>1.63 (0.63)</td>
<td>1.38 (0.42)</td>
<td>1.95 (0.58)</td>
<td>2.04 (0.54)</td>
<td>1.85 (0.73)</td>
<td>1.91 (0.42)</td>
<td>1.99 (0.51)</td>
<td>1.69 (0.42)</td>
<td>1.84 (0.41)</td>
</tr>
<tr>
<td></td>
<td>65+</td>
<td>3645</td>
<td>1.94 (0.75)</td>
<td>1.48 (0.49)</td>
<td>1.89 (0.55)</td>
<td>2.04 (0.53)</td>
<td>1.89 (0.75)</td>
<td>1.98 (0.45)</td>
<td>1.97 (0.49)</td>
<td>1.82 (0.47)</td>
<td>1.90 (0.43)</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>7915</td>
<td>1.74 (0.70)</td>
<td>1.42 (0.46)</td>
<td>1.92 (0.57)</td>
<td>2.04 (0.54)</td>
<td>1.84 (0.73)</td>
<td>1.91 (0.45)</td>
<td>1.98 (0.50)</td>
<td>1.73 (0.45)</td>
<td>1.85 (0.42)</td>
</tr>
</tbody>
</table>

Temporal stability ($r_{icc}$) 2740 0.70 0.57 0.55 0.63 0.67 0.62 0.65 0.75 0.73

Note: Age category for N = 5 women and N = 8 men from HCS were unknown; $r_{icc}$ = intra-class correlation coefficient (absolute); all p < .001; for all measures, higher scores indicate a poorer quality of life.
**Concurrent validity**

Associations between AQoL-6D domains and SF-36 scales are reported in Table 4.6. All domain scores displayed significant negative associations, indicating that increased impairment on AQoL-6D domains was associated with poorer quality of life on the SF-36 scales. Conceptually related scales were more highly related than those that were not conceptually related, supporting the convergent validity of the AQoL-6D domains. The canonical correlation (six AQoL-6D domains vs. eight SF-36 scales) revealed a high level of shared variance ($R_c = .884$ or 78% shared) between these sets, suggesting that the two sets measure highly similar aspects of life quality.

Table 4.6 Pearson’s correlation coefficients between AQoL-6D domains and SF-36 scales.

<table>
<thead>
<tr>
<th>SF-36 Scales</th>
<th>N</th>
<th>AQoL-6D Domains</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Independent living</td>
</tr>
<tr>
<td>Physical functioning</td>
<td>4748</td>
<td>-0.77</td>
</tr>
<tr>
<td>Role physical</td>
<td>4701</td>
<td>-0.59</td>
</tr>
<tr>
<td>Social functioning</td>
<td>4795</td>
<td>-0.52</td>
</tr>
<tr>
<td>Mental health</td>
<td>4758</td>
<td>-0.32</td>
</tr>
<tr>
<td>Role emotional</td>
<td>4692</td>
<td>-0.38</td>
</tr>
<tr>
<td>Vitality</td>
<td>4762</td>
<td>-0.56</td>
</tr>
<tr>
<td>Bodily pain</td>
<td>4783</td>
<td>-0.57</td>
</tr>
<tr>
<td>General health</td>
<td>4693</td>
<td>-0.60</td>
</tr>
</tbody>
</table>

Note: All $p < .001$; correlations of 0.60 or higher are highlighted in bold font.

The stability of domain and factor scores over time are presented as intra-class correlation coefficients at the bottom of Table 4.5. All domain and factor scores displayed moderate stability over time ($r_{cc}$ range .55-.75). Temporal stability of the AQoL-6D psychological factor was lower than that of the physical factor, a pattern that is consistent with that observed for the SF-36 mental health and physical functioning scales (see Table 4.7).
Table 4.7 Associations of AQoL-6D summary scores with concurrent assessments of quality of life (SF-36) and with independent indices of physical and psychological functioning.

<table>
<thead>
<tr>
<th>AQoL-6D Summary Scores</th>
<th>Physical factor</th>
<th>Psychological factor</th>
<th>Total score</th>
<th>Temporal stability</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>r</td>
<td>$R^2$ with set</td>
<td>r</td>
</tr>
<tr>
<td><strong>Physical indices</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Physical functioning SF-36</td>
<td>4748</td>
<td>-0.73</td>
<td>-0.40</td>
<td>-0.63</td>
</tr>
<tr>
<td>Body mass index</td>
<td>4433</td>
<td>0.24</td>
<td>0.10</td>
<td>0.19</td>
</tr>
<tr>
<td>Timed up and go</td>
<td>2554</td>
<td>0.44</td>
<td>0.19</td>
<td>0.35</td>
</tr>
<tr>
<td>Pedometry</td>
<td>2217</td>
<td>-0.30</td>
<td>-0.10</td>
<td>-0.22</td>
</tr>
<tr>
<td>Forced expiratory volume</td>
<td>2312</td>
<td>-0.16</td>
<td>-0.09</td>
<td>-0.14</td>
</tr>
<tr>
<td><strong>Psychological indices</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mental health SF-36</td>
<td>4758</td>
<td>-0.43</td>
<td>-0.74</td>
<td>-0.66</td>
</tr>
<tr>
<td>Psychological distress</td>
<td>7831</td>
<td>0.44</td>
<td>0.71</td>
<td>0.66</td>
</tr>
<tr>
<td>Life satisfaction</td>
<td>4899</td>
<td>-0.34</td>
<td>-0.55</td>
<td>-0.52</td>
</tr>
</tbody>
</table>

Note: All $p < .001$; pedometry = mean steps per day; $r_{ICC} = $ intra-class correlation (absolute); $R^2$ with set based on HCS baseline participants only: physical indices $N = 1973$, and psychological indices $N = 1808$. 
Figure 4.2 presents a profile plot of standardized AQoL-6D domain and factor scores for each cohort by phase. Compared to the HCS, ARMHS participants displayed lower impairment across all domains. The sub-group scoring below the 25th percentile on the SF-36 (i.e., lower than 63.50 on a mean total of the SF-36 scales) generally reported greater impairment (approximately 1 standard deviation above the mean) on all subscales of the AQoL-6D. However, impairment experienced in this subgroup on the AQoL-6D senses domain dropped to around half a standard deviation above the mean.

**Convergent validity**

Results for the correlation and multiple correlation of factor and total scores with other indices of physical and psychological functioning are presented in Table 4.7. Greater impairment on AQoL-6D summary scores was associated with poorer functioning on all psychological and
physical indices. The psychological factor displayed higher correlations with concurrent psychological indices, while the physical factor displayed higher correlations with the concurrent physical indices. Similarly, the psychological factor displayed a greater proportion of shared variance with psychological than physical functioning indices, while the physical factor displayed a greater proportion of shared variance with physical than psychological functioning indices.

**Discussion**

The AQoL-6D was designed to be sensitive to a range of health domains and an increased spectrum of wellness/illness states, and to be suitable for administration in community cohorts. The current analyses build upon the recent work of Richardson et al. [3] reporting on the processes of ensuring the content validity of the AQoL-6D. Utilising individual participant data drawn from two large longitudinal community cohorts, the current study confirms that the instrument was acceptable to participants even when administered within an extensive survey battery, with 89% completing all administered AQoL-6D items. In line with previous work [3], questions regarding close and intimate relationships had the poorest response rate (3% missing). Current results largely confirm the internal consistency of AQoL-6D domains, providing evidence that the items within domains assess a single underlying construct. Comparison of nested CFA models suggested AQoL-6D domains are best represented by two correlated higher-order factors representing the physical and psychological aspects of life quality impairment. This model produced good fit across demographically diverse cohorts, as well as over time. Observations that increased age is associated with poorer physical quality of life, with little or no effect of age on psychological quality of life, are consistent with other Australian population surveys utilizing QoL instruments with multidimensional scoring [38-41].
**Domain structure and validity**

Characterising the handicap associated with a representative range of experiences of impairment was an explicit goal in the development of the AQoL-6D. One-factor congeneric models and indices of internal consistency suggest the items provided a cohesive representation of their underlying domains, though the internal consistency of the relationships ($\alpha = .63$) and senses ($\alpha = .50$) domains was relatively poor. Items within the relationships domain address somewhat different aspects of social interactions (including general satisfaction with relationships, and the impact of an individual's health on their ability to fulfil relationship roles). The senses domain was designed to assess the impairment associated with sensory dysfunction (visual, hearing and communication) and, while dysfunctions do not necessarily co-occur, they do pose similar barriers to social functioning and thus life quality. The reduction in consistency within these scales thus represents a trade-off between domain cohesion and sensitivity.

Analyses also support the concurrent validity of AQoL-6D domain scores against SF-36 scale scores. Domain scores constructed from mean item scores were highly consistent with those of the SF-36, with the two sets of scores having 78% shared variance. Scores for common constructs consistently demonstrated strong associations: independent living was highly associated with SF-36 physical functioning and most weakly associated with SF-36 mental health, with the opposite effect observed for AQoL-6D mental health; pain and SF-36 bodily pain were highly related, with weak associations observed with SF-36 mental health and role emotional scales; and coping displayed its strongest association with SF-36 vitality and weakest with bodily pain scale. Two AQoL-6D domains did not display such convergence with other SF-36 scales: relationships was moderately associated with all SF-36 scales, likely reflecting the component item’s predominant representation of the impact of physical functioning on relationships, rather than general social well-being or the impact of psychological functioning.
on relationships; and senses was weakly associated with all SF-36 scales, suggesting the absence of an analogous assessment of sensory impairment in the SF-36. This inference was also supported by our plot of standardized AQoL-6D domain scores for those with poorest quality of life on the SF-36 (see Figure 4.2). This plot demonstrated that while the remaining five AQoL-6D subscales for this group were at least one standard deviation above the mean, scores on the sensory domain were only half a standard deviation above the mean, reflecting an insensitivity of the SF-36 to experiences of sensory impairment as assessed by the AQoL-6D.

**Factor structure and validity**

Current results show two correlated but divergent factors, here characterized as physical (independent living, relationships, pain and senses) and psychological (mental health and coping) factors, provide a better explanation of the model variance than a single global QoL factor in our community sample. The moderate correlation between scores on the physical and psychological factors (r = .59) demonstrates that they are not completely independent. Several global and disease specific scales assessing QoL support the existence, association and utility of these divergent factors (i.e., the SF-36 [13]). There are several possible reasons that current results regarding the fit of a single factor model for the AQoL-6D differed from those observed in its construction sample. During its construction, the final 20 AQoL-6D items were administered within a survey of 112 items to a sample of community members (N = 316), hospital outpatients (N = 206) and inpatients (N = 96). The completion of a large number of similar items may have reduced each participant’s capacity to discriminate between health states due to fatigue or contributed to the emergence of a particular response pattern. Further, approximately half of this relatively small sample was drawn from hospital services. Comorbidity of poor physical and psychological quality of life may be greater in such samples than in the general community, resulting in greater differentiation of aspects of life quality in community compared to hospital based samples. Research contrasting model fit for
community and hospital samples may be necessary to determine the most appropriate factor structure for representing quality of life in such populations.

The availability of multiple groups and timepoints in which to confirm the AQoL-6D factor structure is a strength of the current work. While not often tested or acknowledged, when the same variable is compared across groups or timepoints it is assumed that the measure is interpretable as the same construct across observations. The current study formally addressed these assumptions using multi-group confirmatory factor analyses. These analyses place increasingly stringent constraints upon the likeness of the model across groups, to assess whether the theoretical model fitted the observed data in both groups. The current analyses assessed whether: (1) the domains were associated with the same latent factor (configural invariance); (2) the domains were associated with the latent factor with the same strength and direction (metric invariance); and (3) the latent factors represented the same range of values and were related to each other with the same strength (variance/co-variance invariance). The first two of these represent assessments of measurement invariance. The latter is a test of structural invariance (i.e., comparable value ranges and relationships across groups and times); while included largely for theoretical reasons, this analysis confirmed that the AQoL-6D factors provide consistent representations of overall life quality. Thus, the two factor model displayed a psychometrically and theoretically meaningful representation of life quality across two community groups which differ on a range of demographic, bio-psychosocial and contextual indices. The two-factor model was replicated over time, suggesting the two factor solution is also suitable for assessing performance over time. This demonstration of invariance facilitates confident interpretation and, for the xTEND project, encourages us to undertake future examinations of the cross-sectional and longitudinal drivers of QoL (e.g., the impacts of chronic illness, social factors such as retirement, and community remoteness).
The AQoL-6D factor scores displayed convergent validity in their associations with a range of other indices of physical and psychological functioning. Temporal stability of domains and factors over a three year follow-up period was consistent with the patterns observed for the SF-36. Physical factor scores were more strongly associated with measures of physical functioning, as assessed by the SF-36, BMI, mobility, pedometry and spirometry, and explained 50.2% of variability in this set of indices but only 24.6% in the psychological indices. Similarly, psychological factor scores were associated predominantly with psychological indices of mental health, psychological distress, and life satisfaction, and explained 60.6% of variability in this set of indices but only 13.2% in the physical indices. Such evidence provides support for the differential sensitivity of these factors to associated physical and psychological states.

Our analyses also confirmed that the proposed AQoL-6D total score displayed comparable associations with the SF-36 physical and mental health scales (see Table 4.7), suggesting that an aggregate based on either measure would tend to have similar properties. As with any other composite score, such an aggregation would also tend to underestimate associations with factors that were differentially linked to the underlying components; in the current study, for example, the physical and psychological aspects of quality of life were differentially associated with gender and age, associations that would be obscured if only total scores were used. On the other hand, such a summary score could be of interest to researchers wishing to obtain a global rating of QoL, from which to broadly characterise their sample and/or to track changes over time; based on the current analyses, for example, gender differences could be largely ignored if the AQoL-6D total score was the primary focus. In short, the research value of composite scores depends on the context and the questions of interest (cf., two factors based on psychometric scoring vs. a single utility index).
Practical issues

As noted previously, utility weights have been developed for the AQoL-6D. Utility weighting is commonly used in an effort to increase the interpretability of quality of life scores as a trade-off between quantity and quality of life, by accounting for preferences for health states; however, caution is advised in their interpretation and population specific weights accounting for preferences for health states are required. While utility measures have been popular in the health-related decision making literature, there has been relatively low interest in health utilities in relation to mental health treatment decision making. In econometric QoL studies, the motivation for choosing a particular QoL measure may be to provide an index by which health related burden or cost can be estimated (e.g., quality adjusted life years or cost-utility measures); in which case, the multidimensional nature of QoL may not be important or useful, and a single index may be desirable [42]. However, if the motivation for instrument selection is to assess the determinants of well-being and their outcomes, as is often the case in the social sciences, acknowledging the multidimensional nature of QoL is of considerable importance and may have several psychometric benefits. For example, by acknowledging the divergent qualities of these factors, we may be able to produce QoL scores with greater external validity and sensitivity to a broader range of determinants and outcomes. Investigation of the burdens and determinants of physical and mental health outcomes present a situation in which QoL and its correlates are of greater interest. Using the simple scoring routine described in the current paper (and reproduced in Appendix 4.2), a set of preliminary age and gender normative scores were derived. While they could be improved through increased representation of persons under 55 years of age, particularly in urban areas, to our knowledge, these provisional norms provide the largest and most representative collection of AQoL-6D community data to date.
The current paper may also help inform researchers in the selection of instruments for administration in the general community. We present evidence that the AQoL-6D domains and factor scores depicted here display construct validity and are interpretable over a range of community contexts. Additionally, while the AQoL-6D displays a high level of commonality with a concurrent assessment of quality of life, the SF-36, there are several points of difference between these instruments, including: a smaller number of items (20 vs. 36) assessed in the AQoL-6D; the differing aspects of relationships measured; and the absence of an explicit assessment of the impact of sensory impairment on life quality in the SF-36 scale. The sensory domain could be particularly important in assessing health related life quality in older groups and for persons living in non-urban areas, where often fewer facilities are provided or adapted to assist persons experiencing sensory (e.g., visual impairment) or physical disability. Researchers planning to assess quality of life experienced in the community should consider the relative value of these measures for addressing their research questions.

**Limitations**

A potential limitation of the current study lays in the imputation of missing baseline mental health item data. However, in this instance, the apparent cause of data missingness is known (the items were inadvertently omitted from the baseline ARMHS survey). This situation is similar to that of planned missingness designs [43,44], wherein random sections of a cohort are asked subsets of questions for purposes of maximising the amount of information derived while reducing survey length. Moreover, in the current study, the imputed data performed as expected with respect to item and domain profiles, comparisons across cohorts and phases, and relationships with other scales.

A second potential limitation relates to the exclusion of participants without complete data. As the purpose of this paper was to describe the structure, group and temporal invariance of the AQoL-6D across two large cohorts, and a relatively low proportion of participants had
incomplete data (11%), it was judged that observations with complete data were adequate to characterise the variability observed across cohorts and phases.

A third limitation relates to current results regarding the concurrent and convergent validity of the AQoL-6D. These results are largely based on associations from an older sample of persons from urban-inner regional areas (i.e., the Hunter Community Study); for example, the reported associations of the SF-36 and physiological measurements with the AQoL-6D may differ from findings based on younger age groups.

Finally, there is ongoing debate regarding the appropriate statistics for reporting in CFA. While the majority of sources recommend that multiple fit indices should be considered in assessing model fit, some argue that the vulnerabilities of the χ2 statistic to large sample sizes may distract from reasonable model fit [45]. Others suggest that it is wrong to suggest that the nonperfect absolute model fit indicated by the χ2 statistic is necessarily trivial, and should provide a basis for investigating model misspecification [46]. The purpose of the current analyses was to identify a coherent structure under which an existing brief instrument characterised by coherent domain scores could be meaningfully aggregated; consequently, we have not reported the associated χ2 statistics, instead assessing the variance explained by the factor scores. In short, the parsimony and interpretability of the model was our primary goal – to model practical methods of characterising, scoring and interpreting the aggregate descriptive system of the AQoL-6D – in our case, for the ongoing purposes of the xTEND project, but we are happy to share and recommend this approach to the calculation of AQoL-6D summary scores.

Conclusions

To our knowledge, this is the first study to assess the factor structure of the AQoL-6D outside its construction sample. We were able to confirm the internal validity of the six domains
assessed by the AQoL-6D. These scores displayed a moderate level of temporal stability over the four year follow-up period, with physical factors displaying greater stability than psychological factors. Current findings suggest a two factor model, characterised here as physical and psychological quality of life impairment, provides the best fit for the data when the AQoL-6D is administered as described in the general community. This model fits equally as well over two diverse cohorts and over the four year follow-up period. The concurrent validity of domain and factor scores were upheld in light of their strong associations and shared variance with an established concurrent measure of health related quality of life. Evidence for the convergent validity of factors was demonstrated through a higher proportion of shared variance with corresponding domains of physical and psychological indices of personal functioning. The xTEND study demonstrates the value of pooling individual participant data from comparable longitudinal cohorts, particularly for the purposes of scale validation, where issues of factor invariance across groups and time are otherwise of concern, but untestable.
References


Chapter five: Does the association of health related adversity with health related physical and psychological quality of life differ across urban and rural communities

This chapter was disseminated in the academic literature as:


[Appendix, 5.0]

Synopsis

This chapter assesses whether the quality of life impacts of health related personal adversity differ by remoteness and its associated characteristics. It draws on a large representative secondary data source to examine whether objective indices of remoteness based on road distance from service centres adequately characterise the health relevant contextual characteristics thought to vary with remoteness.
**Introduction to Chapter five**

Personal experiences of adversity have emerged as a key group of psychosocial health determinants [1, 2]. The availability and acceptability of formal and informal support systems and services to assist persons experiencing adversity are likely to play an important role in determining the health impact of these experiences [3, 4]. While the vulnerability of rural populations to experiences of adversity, particularly financial adversity, has long been a focus of concern and public policy, health related personal adversity in the form of chronic disease is a particular concern in aging [5] and rural populations [6]. Indeed, there is increasing evidence that community characteristics such as the availability of health services, social capital, and remoteness influence the experience of disease and health [7-10]. However, to date, associations among these factors are relatively unclear, including: whether the impacts of disease in rural areas reflect increases in physical and/or psychological burdens associated with disease; whether the objective indices of community remoteness effectively capture factors that influence quality of life; and whether health burdens associated with disease in rural communities reflect health related adversity or more general difficulties concerning the experience of adversity in rural and remote communities.

**Aims and purpose**

This chapter aimed to examine whether the HRQoL impacts of chronic disease differed with contextual factors that vary across urban-rural areas of New South Wales, Australia. To examine these effects, an objective continuous index of community remoteness (ARIA+) and a subjective continuous index of social capital were used as proxy for the health relevant characteristics of context. Ratings of key psychosocial health determinants including adverse life events, financial difficulty and social support were conceptualised as exerting incremental risk/protective effects upon health outcomes and were also modelled as continuous variables.
To aid interpretation of observed effects, the current chapter also examined the association of the ARIA+ with reported experiences of social capital and health service accessibility from a large representative secondary data source. A supplementary analysis was conducted to examine whether the conclusions of the primary analyses were supported when the moderating influence of an alternative index of health relevant contextual characteristics, namely individual perceptions of social capital, was assessed. The health impacts of other forms of adversity, such as financial difficulty, and whether these effects were influenced by individual social capital was also assessed. Effects were considered to be consistent if they were observed across all statistical models. This is the fourth manuscript of the thesis and has been published in Health and Quality of Life Outcomes.

**Contribution to primary research question**

The current study examined whether the physical and psychological health impacts of personal adversity, particularly in the form of chronic disease, differed with contextual characteristics. As these analyses were exploratory, no assumption regarding the presence of a differential effect of remoteness on these associations, nor about the level of remoteness at which associations may be observed, was made. Thus, interaction terms between these predictors and a continuous index of remoteness in the prediction of HRQoL outcomes were modelled. The HRQoL impacts of chronic conditions did not vary with remoteness, though a trend indicated a lifetime diagnosis of depression or anxiety was associated with lower psychological impairment in more remote areas (Figure 5.0A).

Supplementary analyses assessed the association of often utilized categories of ARIA+ values, known as the Australian Standard Geographic Classification (ASGC) [11], with the health service accessibility and social capital aspects of context. Findings suggested that the ARIA+ index of remoteness provided a poor proxy for these health relevant aspects of context. The majority of the ARIA+ scale (range 0.00-15.00) describes areas for which no differences in
contextual characteristics were reported (i.e., no differences between outer regional and remote ASGC categories: ARIA+ values 2.41-15.00).

Secondary analyses employing a more direct assessment of contextual characteristics, individual perceptions of social capital, revealed that the association of depression/anxiety diagnoses with psychological HRQoL impairment was influenced by social capital (Figure 5.0A). Exploration of this interaction indicated that the impairment associated with a diagnosis of depression/anxiety weakened for those reporting higher perceived social capital. When financial adversity was included in the model, the moderation of the depression-psychological impairment association was attenuated. However, the association of financial difficulty with psychological HRQoL impairment was moderated by social capital (Figure 5.0B), indicating that the impairment associated with financial difficulty weakened for those reporting higher perceived social capital. This chapter provides evidence that psychological, but not physical, health burdens associated with depression/anxiety and financial difficulty may be moderated by context in similar ways. The use of indices of community remoteness as proxy for health related contextual factors should be carefully considered. Assessment of the correspondence of remoteness indices to contextual characteristics of interest, or direct assessment of those characteristics of interest, are recommended.
Figure 5.0. Moderation of the health impacts of health related adversity by context (Model A). From left to right: the association of depression with psychological HRQoL impairment was not moderated by remoteness (Beta = -.03, p = .074); the association of depression with psychological HRQoL impairment displayed a trend indicating moderation by social capital (Beta = -.08, p = .012). Moderation of health impacts of health related adversity and financial adversity by context (Model B). From left to right: the association of depression with psychological HRQoL impairment was not moderated by social capital (Beta = -.05, p = .145); the association of financial difficulty with psychological HRQoL was moderated by individual perceptions of social capital (Beta = -.07, p = .014).

Candidate’s contribution

In addition to the ethics, data collection and data processing tasks mentioned previously, and contributing substantially to the preparation of the current manuscript, the candidate investigated, formulated and undertook statistical analyses relating to: the multiple imputation of missing data; hierarchical linear regression analyses of predictors of physical and psychological HRQoL; and investigating the influence of non-measured cohort effects on model outcomes. In addition, the candidate obtained, applied appropriate population weights, and
analysed data from the Adult Population Health Survey, attending to the required data acquisition and retention procedures.
References


Quality of life impact of cardiovascular and affective conditions among older residents from urban and rural communities

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Abstract

Background

The demographic, health and contextual factors associated with quality of life impairment are investigated in older persons from New South Wales, Australia. We examine the impact of cardiovascular and affective conditions on impairment and the potential moderating influence of comorbidity and remoteness.

Methods

Data from persons aged 55 and over were drawn from two community cohorts sampling from across urban to very remote areas. Hierarchical linear regressions were used to assess: 1) the impact of cardiovascular and affective conditions on physical and psychological quality of life impairment; and 2) any influence of remoteness on these effects (N = 4364). Remoteness was geocoded to participants at the postal code level. Secondary data sources were used to examine the social capital and health service accessibility correlates of remoteness.

Results

Physical impairment was consistently associated with increased age, male gender, lower education, being unmarried, retirement, stroke, heart attack/angina, depression/anxiety, diabetes, hypertension, current obesity and low social support. Psychological impairment was consistently associated with lower age, being unmarried, stroke, heart attack/angina, depression/anxiety and low social support. Remoteness tended to be associated with lower psychological impairment, largely reflecting overall urban versus rural differences. The impacts of cardiovascular and affective conditions on quality of life were not influenced by remoteness. Social capital increased and health service accessibility decreased with remoteness, though no differences between outer-regional and remote/very remote areas were observed. Trends
suggested that social capital was associated with lower psychological impairment and that the influence of cardiovascular conditions and social capital on psychological impairment was greater for persons with a history of affective conditions. The beneficial impact of social capital in reducing psychological impairment was more marked for those experiencing financial difficulty.

**Conclusions**

Cardiovascular and affective conditions are key determinants of physical and psychological impairment. Persons affected by physical-psychological comorbidity experience greater psychological impairment. Social capital is associated with community remoteness and may ameliorate the psychological impairment associated with affective disorders and financial difficulties. The use of classifications of remoteness that are sensitive to social and health service accessibility determinants of health may better inform future investigations into the impact of context on quality of life outcomes.

**Keywords**

Cardiovascular disease, Urban–rural, Social capital, Quality of life, Physical and psychological health, Over 55 years
Introduction

The impact of geographic factors on health outcomes, particularly for persons affected by chronic health conditions, has long been of concern. Rural areas are often characterised by poor access to health services, increased risk of injury, and stress due to adverse environmental conditions and socioeconomic disadvantage [1-4]. However, rural areas typically display high levels of social capital that may be protective against poor health and functioning [5-7]. Social capital is a multidimensional term used to describe social interactions within communities that promote [8] and are embedded within [9] norms of trust, reciprocity and social cohesion, which support the actions of persons in these communities [10,11]. Social capital is thought to influence health both through psychosocial pathways that promote individual adaptation to adversity [12] and by enabling access to health-related resources (i.e., by facilitating the spread of health related information, opportunities and attitudes) [13].

There is increasing evidence that contextual effects, such as availability of health services, socioeconomic deprivation [14,15], aggregate social capital [16-19] and remoteness [20-22] influence the experience of disease and health.

Current estimates suggest that over half of adults report at least one chronic physical health condition [23,24] and among individuals aged 65 and over, this figure is approximately 80% [25]. The 2007 Australian National Survey of Mental Health and Wellbeing revealed that 45.6% of people who met criteria for a 12-month affective or anxiety disorder also reported a current chronic physical health condition [26]. Such mental health conditions are known to exacerbate the disability associated with chronic physical conditions [27] and vice versa [28,29]. These findings suggest chronic physical health conditions are of significant concern, particularly for older persons and those with mental health conditions.
The burden associated with comorbid physical and mental health conditions was more recently raised by the 2012 National Report Card on Mental Health and Suicide Prevention [30], with specific reference to the burden of cardiovascular conditions in persons with a history of mental illness and those living in rural and remote areas of Australia. Consideration of the underlying mechanisms and ways to equitably address the issues of intervention and treatment of comorbid mental-physical conditions in these populations is ongoing [30,31]. However, social capital may be particularly relevant to intervention and understanding regarding the burden associated with cardiovascular conditions and depression, which have been linked to prolonged stress responses [32-34], socioeconomic disadvantage [35] and stressful life events [36,37]. Attention to the role of such contextual factors in health related quality of life (HRQoL) provides an opportunity to improve our understanding of a broad range of potential influences on the burden associated with physical and mental health conditions.

To date, rural and remote regions of Australia have been underrepresented in national surveys and little detailed information from these populations is available for comparison with urban populations. The Extending Treatments, Education and Networks in Depression (xTEND) study is a collaboration between two existing and ongoing longitudinal cohorts, namely the Australian Rural Mental Health Study (ARMHS) and Hunter Community Study (HCS), that aims to investigate the social determinants of well-being in Australia and how these may be influenced by contextual factors associated with increasing remoteness [38]. Combined, these cohorts provide a sample representative of the spectrum of urban to very remote communities, in largely contiguous local government areas. These studies share common baseline assessments of psychological distress and HRQoL outcomes, as well as demographic and health related determinants, such as life time diagnoses of several chronic illnesses and indices of health behaviour. In combining individual level data from these cohorts, due consideration has also been given to similarities and differences in recruitment, methodology,
and assessment techniques and recent work has confirmed that the administered assessment of HRQoL impairment taps divergent aspects of physical and psychological impairment which are invariant across these samples [39]. While physical and psychological HRQoL outcomes have been shown to have different demographic and social determinants, little evidence currently exists regarding the differential impact of chronic disease and contextual factors on these health domains. Such information would have implications for understanding the burden associated with these disorders, as well as tailoring interventions and treatment in light of contextual factors.

Thus, the purpose of the current paper is threefold. Firstly, in the primary analysis, we use data from the xTEND collaboration to represent older persons from across urban to very remote areas of New South Wales (NSW), Australia, and adopt a multi-level framework to investigate the impact of cardiovascular and affective conditions, community remoteness and their interactions upon physical and psychological HRQoL impairment. We also model the additional impacts of personal characteristics known to influence the association between perceived health and health conditions, including demographic characteristics, such as gender, age and socioeconomic status [40,41], as well as other health risk factors, including smoking [41], obesity [42] and social support [43]. Secondly, we use community data from the NSW Adult Population Health Survey, in a secondary analysis, to examine an index of community remoteness in terms of its correspondence with self-reported health service accessibility and aspects of social capital. Finally, in a sub-analysis of the ARMHS data, we examine whether direct measures of social capital influenced outcomes of the primary analysis model and whether the influence of social capital moderates the influence of financial difficulty on HRQoL outcomes.
Methods

Participants

For the purposes of our primary analysis, self-report postal survey data from two NSW population-based cohort studies were combined: the HCS [44]; and the ARMHS [45]. Detailed descriptions of recruitment, sample descriptions and methods employed can be obtained from their respective baseline descriptive papers [HCS: 44, ARMHS: 45]. Briefly, the HCS is a study of persons aged 55–85 years residing in the major regional city of Newcastle and the ARMHS is a study of persons aged 18 years and older residing in nonmetropolitan areas of NSW. Both studies randomly selected potential participants from the state electoral roll. Introduction and recruitment letters were sent to individuals by post and non-responding individuals were followed-up by telephone calls. Overall response rates of 44.5% and 27.3% for the HCS and ARMHS respectively were achieved, with both samples having comparable rates of uncontactable or excluded persons (HCS: 26.9%, ARMHS: 25.2%). Within the ARMHS sample, among those who were contactable and met study inclusion criteria, participation rates varied by age group (under 55 years: 25.4%; 55–70 years: 32.4%; over 70 years: 20.1%). A comparable pattern emerged within the HCS sample, with responders tending to be slightly younger than non-responders (66.3 vs. 68.6 years) [26]. To reduce participant burden, survey items were administered over two postal surveys in both cohorts.

Following ethical approval (Human Research Ethics Committees from the University of Newcastle and Hunter New England Area Health), baseline survey data from the HCS and ARMHS were combined. To maintain comparability with the HCS sample and to address the aims of the current research, only participants aged 55 years and over from the ARMHS cohort (N = 1273) were considered for inclusion in the current (primary and sub) analyses. For the purposes of the current study, only participants who provided complete information on life
time diagnosis variables (depression/anxiety, stroke, heart attack/angina, diabetes, high cholesterol, hypertension) and adequate data on all other variables were included in the current analyses; that is, at least 75% of the item data used to construct primary analysis model variables (primary outcome and predictor variables) and item responses to the Kessler 10 (see Missing data: for handling of missing data). Of the N = 4732 participants in the combined sample, 92.2% (N = 4364) provided adequate data for inclusion in the current analyses (see Appendix 5.1, Figure S1 for further information).

Measures

Dependent variables (primary and sub-analysis)

HRQoL impairment. Self-rated health outcomes were assessed using the Assessment of Quality of Life (AQoL-6D), a 20-item self-report measure of HRQoL and general functioning [46]. The AQoL-6D forms six domains characterised as ‘Independent living’, ‘Relationships’, ‘Mental health’, ‘Coping’, ‘Pain’, and ‘Senses’ [46]. These domain scores form two higher-order factors representing the psychological (Mental health and Coping subscales; range = 1.00-5.00) and physical (Independent living, Relationships, Pain, Senses; range = 1.00-4.88) aspects of HRQoL impairment, with higher scores indicating greater impairment [39]. Significant impairment is indicated by scores greater than 1 standard deviation (SD) above the mean; scores were standardized using normative means and SD values for the physical (mean = 1.73, SD = 0.45) and psychological (mean = 1.98, SD = 0.50) HRQoL domains, from our earlier paper [39].

Predictor variables

Unless otherwise stated, all predictor variables were used in both the primary and subanalysis.

Demographic variables. Age, gender, level of education, marital status and retirement.
**Cardiovascular and affective conditions.** Both cohorts administered items regarding lifetime self-reported diagnoses, including cardiovascular conditions (heart attack/angina or stroke) and depression/anxiety (ARMHS: ‘Has a doctor EVER told you that you have…’; HCS: ‘Have you ever been diagnosed with…’).

**Other health related indicators.** Self-reported diagnoses of metabolic health risk factors: diabetes, hypertension, and high cholesterol.

**Current smoking.** A common yes/no index of current smoking behaviour was constructed from the HCS and ARMHS measures of smoking behaviour.

**Obesity.** Height and weight measurements were undertaken as part of a battery of clinical measures recorded by the HCS, while the ARMHS obtained these measurements through self-reported survey responses. To address the potential for bias in self-reporting height and weight measurements, correction equations were used based on 2007–2008 Australian national survey data [47], which adjusts for known biases in self-reported height and weight by participant age and gender. Body Mass Index was calculated as weight in kilograms divided by height in metres squared and values \( \geq 30 \) used to classify obesity.

**Social support.** Both cohorts collected conceptually related social support measures at baseline and follow-up. A composite index of social support, representing the network (number of supporting friends and relatives, the frequency of contact with these individuals, and involvement in organised social groups) and personal (access to close personal relationships) features of social support has been constructed for the purposes of the xTEND project [48]. For standardization purposes, grand means and SDs for index components were used to create the composite index.

**Recent adverse life events (secondary analysis only).** A self-report questionnaire was used to assess the number of adverse life events experienced in the last 12 months (range 0–12) (i.e.,
‘has a member of your family died?’, ‘have arguments or marital difficulties with your partner worsened?’, ‘have you had a major financial crisis?’) [49].

**Perceived financial difficulty (secondary analysis only).** Assessed using a similar single item question to that used by the Household, Income and Labour Dynamics in Australia Survey [50], namely ‘Given your current needs and financial responsibilities, would you say that you and your family are’ ‘prosperous’, ‘very comfortable’, ‘reasonably comfortable’, ‘just getting along’, ‘poor’, or ‘very poor’, with higher scores indicating a poorer financial position (range 1–6).

**Contextual factors**

**Remoteness (primary analysis only).** Participant remoteness was classified using the Accessibility/Remoteness Index of Australia Plus ARIA+: [51] and geocoded using participant’s postal code. The ARIA + is a continuous index ranging from 0.00-15.00 (higher scores indicating greater remoteness) that is calculated based on the size of the nearest service centre and its average estimated road distance from the location. For descriptive purposes, these scores were collapsed into four categories of remoteness: major cities (range = 0.00-0.20); inner regional areas (range = 0.21-2.40), outer regional areas (range = 2.41-5.92), and remote/very remote areas (range > 5.92) [51].

**Social capital (sub-analysis only).** Social capital was assessed using the Sense of Community Index [52] among the ARMHS cohort. This index comprises a 12 item true/false self-report questionnaire assessing an individual’s psychological sense of belonging to a community, with higher scores indicating greater social capital (range 0–12).

**District level social capital and health service characteristics (secondary analysis only).** Data from the 2006–2009 NSW Adult Population Health Surveys (NSW Population Health Surveys, http://www.health.nsw.gov.au/surveys/Pages/default.aspx) were obtained from the Centre for Epidemiology and Evidence, NSW Health and combined to examine the social capital and
health service characteristics of four levels of community remoteness. Data from this period were selected to coincide with the collection of baseline data from the HCS (2004–2007) and ARMHS (2007–2009). The NSW Adult Population Health Survey is an annual telephone survey of approximately 12,000 people aged 16 and above who are randomly selected from all area health services across NSW. The survey is conducted between February and December each year [53] and achieved response rates of 59-64% between 2006 and 2009. Data were weighted in accordance with procedures adopted by the NSW Adult Population Health Survey [53] to adjust for differential non-response rates by gender, age and by population estimates for each health service area, with raw sample sizes for surveyed remote/very remote participants maintained. Social capital was measured using nine items described by Onyx and Bullen [7] as best reflecting components of social capital (i.e., ‘participating in the local community’, ‘feelings of trust and safety’ and ‘neighbourhood connections’). Responses were provided on a four point Likert scale, with higher ratings indicating higher social capital. We constructed a mean total social capital score based on a minimum of six items to maximise the number of items and observations retained while preserving scale associations with related variables. An index of Health service accessibility was constructed using responses to the question ‘Do you have any difficulties getting health care when you need it?’ Persons who reported any need for health care (97.3%) provided either a ‘yes’ or ‘no’ response and were included in the current analyses.

Data analysis

Analyses were conducted using SPSS (v.20; IBM Corporation, Armonk NY, USA) and graphs produced using SPSS and Microsoft Excel 2010. For an account of data utilised from different datasets for purposes of primary, secondary and sub-analyses, see Appendix 5.1, Figure S1. Continuous variables were described using means and SDs and categorical variables using frequencies and percentages. Effect sizes for group comparisons were expressed as the
proportion of sample variance explained: eta-squared for ANOVA and Cramer’s V for chi-square tests. Effects were considered consistent if their direction and significance as predictors of HRQoL impairment were replicated across all statistical models. Some alternative versions of the regression models reported here are presented in Appendix 5.1 (Tables S1 to S3), together with simple correlations with the outcome measures.

**Missing data**

To address potential bias caused by the exclusion of persons with missing data in ARMHS and HCS studies, five datasets predicting these missing values were generated using the inbuilt SPSS multiple imputation procedure, following the recommendations of Graham [54]. Items from the Kessler 10 [55] were included in the multiple imputation procedure as potentially important model variables along with all predictor and dependent model variables in the primary analyses. Overall, 1% of data were imputed. Body mass index was by far the most frequently missing information (9.5% missing data) however no differences in obesity as a predictor were observed for models using imputed and non-imputed data. Pooled estimates are reported for all descriptive and inferential statistics.

**Primary analyses**

Dependent variables displayed approximate normal distributions, though physical HRQoL impairment displayed a slight positive skew. Two sets of multivariate linear regressions were used to identify factors associated with physical and psychological HRQoL impairment. Overall model fit and change in model fit by step were assessed using the $R^2$ statistic. To assess whether the HRQoL impairment associated with a lifetime diagnosis of cardiovascular or affective conditions was influenced by remoteness, dichotomous indicators of whether the participant reported life time diagnoses of a cardiovascular (stroke, heart attack/angina) or affective (depression/anxiety) condition were produced and interaction terms generated with
remoteness (Z score) to model their two and three way interactions [cardiovascular by affective by (Z)remoteness]. To assess the influence of cohort membership, each regression was run twice: once with cohort included as the last step of the regression (examining its residual contribution) and once with cohort membership included in the first step of the regression (examining its aggregate contribution); this approach facilitates an assessment of cohort membership as a potential effect modifier, which may arise due to a number of factors (e.g., due to participant characteristics, or differences in wording of survey items). The remaining variables were entered into the main analysis model in six steps: demographic factors; life time cardiovascular and affective conditions; the additional explanatory value of other health related indicators; contextual factors; two-way interaction terms; three-way interaction terms. Where present, interactions were explored by plotting the association of the HRQoL factor with the probability of diagnosis by each level of the effect modifier. An $\alpha < .01$ was used as a significance threshold, as a partial control for the number of statistical tests, with marginal effects ($p < .05$) also noted.

Secondary analyses

To examine whether remoteness was associated with resources theorized to influence health outcomes in NSW, secondary data from the NSW Population Health Survey were used to examine the associations of social capital and health service accessibility with four descriptive categories of remoteness. Community members aged 16 and over (N = 42155; mean age = 54.38, SD = 18.03; male gender = 39.3%) provided data to the NSW Adult Population Health Survey during 2006–2009, with 49.5% residing in major cities, 28.2% from inner regional, 19.4% from outer regional, and 2.9% from remote/very remote areas. The corresponding weighted values were: mean age = 45.10, SD = 18.10; male gender = 49.3%; with 66.0% residing in major cities, 22.1% from inner regional, 10.7% from outer regional, and 1.2% from remote/very remote areas.
ARMHS sub-analyses

To further examine the possible effects of health-relevant community resources on HRQoL impairment, we analysed data from the ARMHS cohort which included a direct assessment of social capital; this measure was substituted as the contextual variable in the analysis, in place of remoteness, in conjunction with two other known explanatory variables: 12 month adverse life events and perceived financial difficulty. Participants from the primary analysis who did not have complete data for the social capital, adverse life events and perceived financial difficulty measures were excluded from this analysis. To assess whether the HRQoL impairment associated with a lifetime diagnosis of cardiovascular or affective conditions was influenced by social capital, dichotomous indicators of cardiovascular or affective conditions were used to generate interaction terms with social capital (Z score) to model their two and three way interactions [cardiovascular by affective by (Z)social capital]. Additionally, to assess whether the HRQoL impairment associated with perceived financial difficulty was influenced by social capital, the interaction of these variables was produced and entered with the other two-way interactions in the model. To facilitate comparison of this extended predictor model (including financial difficulty and adverse life events) with the model examined in the primary analysis, a model without the additional predictor variables was examined and is provided in Appendix 5.1, Table S3.

Results

Primary analysis: the influence of remoteness on HRQoL impairment associated with cardiovascular and affective conditions from the xTEND study

For the N = 4364 participants aged 55 and over who provided adequate data for inclusion in the current analyses overall descriptive statistics are reported in Table 5.1 and are compared by cohort membership. The mean age of participants was 66 years and approximately half
were female. There were few differences between HCS and ARMHS participants, although a higher proportion of HCS participants had completed 12 or more years of formal education and a higher proportion of ARMHS participants were current smokers, trends consistent with those of rural populations in Australia [3]. As indices of social support were standardized within each cohort to facilitate assessment of this variable’s association with outcome variables across groups, no group comparisons were conducted. ARMHS participants reported significantly lower physical and psychological HRQoL impairment, with the latter representing a more marked difference (0.17 vs. 0.41 standardised units).
Table 5.1 Descriptive statistics and comparison of HCS (N = 3118) and ARMHS (N = 1246) participants.

<table>
<thead>
<tr>
<th></th>
<th>HCS</th>
<th>ARMHS</th>
<th>p</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Demographic factors %</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age Mean (SD)</td>
<td>66.17 (7.78)</td>
<td>66.10 (7.68)</td>
<td>.783</td>
<td>66.15 (7.75)</td>
</tr>
<tr>
<td>Female</td>
<td>52.92</td>
<td>56.82</td>
<td>.020</td>
<td>54.03</td>
</tr>
<tr>
<td>12 + years education</td>
<td>76.77</td>
<td>60.63</td>
<td>&lt;.001</td>
<td>72.16</td>
</tr>
<tr>
<td>Married/de facto</td>
<td>72.95</td>
<td>71.04</td>
<td>.209</td>
<td>72.41</td>
</tr>
<tr>
<td>Retired</td>
<td>62.69</td>
<td>61.04</td>
<td>.314</td>
<td>62.22</td>
</tr>
<tr>
<td><strong>Cardiovascular &amp; affective conditions %</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stroke</td>
<td>4.14</td>
<td>4.57</td>
<td>.508</td>
<td>4.26</td>
</tr>
<tr>
<td>Heart attack</td>
<td>12.12</td>
<td>11.64</td>
<td>.680</td>
<td>11.98</td>
</tr>
<tr>
<td>Any CVD</td>
<td>15.14</td>
<td>15.09</td>
<td>.999</td>
<td>15.12</td>
</tr>
<tr>
<td>Depression/anxiety</td>
<td>20.97</td>
<td>23.84</td>
<td>.042</td>
<td>21.79</td>
</tr>
<tr>
<td>CVD &amp; depression</td>
<td>3.59</td>
<td>3.85</td>
<td>.369</td>
<td>3.67</td>
</tr>
<tr>
<td><strong>Other health related indicators %</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Diabetes</td>
<td>11.10</td>
<td>11.96</td>
<td>.428</td>
<td>11.34</td>
</tr>
<tr>
<td>Obese</td>
<td>34.96</td>
<td>31.65</td>
<td>.041</td>
<td>34.02</td>
</tr>
<tr>
<td>Current smoker</td>
<td>7.66</td>
<td>10.13</td>
<td>.009</td>
<td>8.36</td>
</tr>
<tr>
<td>High cholesterol</td>
<td>39.58</td>
<td>38.84</td>
<td>.681</td>
<td>39.37</td>
</tr>
<tr>
<td>Hypertension</td>
<td>47.11</td>
<td>47.03</td>
<td>.973</td>
<td>47.09</td>
</tr>
<tr>
<td>Social support Mean (SD)</td>
<td>0.01 (0.81)</td>
<td>0.01 (0.83)</td>
<td>.01</td>
<td>0.01 (0.82)</td>
</tr>
<tr>
<td><strong>Quality of life impairment Mean (SD)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Physical</td>
<td>1.82 (0.47)</td>
<td>1.75 (0.47)</td>
<td>&lt;.001</td>
<td>1.80 (0.47)</td>
</tr>
<tr>
<td>standardize</td>
<td>0.20 (1.05)</td>
<td>0.03 (1.03)</td>
<td>.016</td>
<td>1.05</td>
</tr>
<tr>
<td>Psychological</td>
<td>2.04 (0.51)</td>
<td>1.84 (0.52)</td>
<td>&lt;.001</td>
<td>1.99 (0.52)</td>
</tr>
<tr>
<td>standardize</td>
<td>0.13 (1.01)</td>
<td>-0.28 (1.05)</td>
<td>.01</td>
<td>1.04</td>
</tr>
<tr>
<td><strong>Contextual factors Mean (SD)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Remoteness</td>
<td>0.05 (0.12)</td>
<td>3.96 (3.08)</td>
<td>&lt;.001</td>
<td>1.16 (2.41)</td>
</tr>
</tbody>
</table>

Note: Reported statistics are based on pooled results (across multiple imputation datasets); CVD = cardiovascular disease; ARMHS = Australian Rural and Remote Mental Health Study; HCS = Hunter Community Study; quality of life impairment scores were standardized using normative means and standard deviations for the physical and psychological HRQoL domains reported in Allen et al. [39].
Physical HRQoL impairment

The left hand columns of Table 5.2 show the results of the regression model predicting physical impairment. Demographic indices, cardiovascular and affective conditions and other health indicators (Steps 1 to 3) contributed approximately 23.8% of the 24.6% variation explained by the model. There were no two- or three-way interaction effects of cardiovascular, affective conditions and remoteness on physical impairment (Steps 5 and 6). All demographic, health condition and related indicators, with the exception of high cholesterol, were significantly associated with physical impairment and the magnitude and significance of these predictors was largely unaffected by cohort membership (see Appendix 5.1, Table S1 for comparisons with cohort membership modelled in the first regression step and Figure S2 for the influence of cohort on the association of remoteness with physical HRQoL).
Table 5.2 Primary analysis: hierarchical linear regression analysis of the correlates of physical and psychological quality of life impairment (N = 4364).

<table>
<thead>
<tr>
<th>Step</th>
<th>Physical Impairment</th>
<th>Psychological Impairment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>β</td>
<td>p</td>
</tr>
<tr>
<td>Step 1</td>
<td>Demographic factors</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(Z)Age</td>
<td>0.16</td>
</tr>
<tr>
<td></td>
<td>Female</td>
<td>-0.05</td>
</tr>
<tr>
<td></td>
<td>12+ years education</td>
<td>-0.10</td>
</tr>
<tr>
<td></td>
<td>Married/de facto</td>
<td>-0.08</td>
</tr>
<tr>
<td></td>
<td>Retired</td>
<td>0.06</td>
</tr>
<tr>
<td>Step 2</td>
<td>Cardiovascular &amp; affective conditions</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Stroke</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>Heart-attack/angina</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td>Depression/anxiety</td>
<td>0.19</td>
</tr>
<tr>
<td>Step 3</td>
<td>Other health related indicators</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Diabetes</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>Obesity</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td>Current smoker</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>High cholesterol</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>Hypertension</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>Social support</td>
<td>-0.22</td>
</tr>
<tr>
<td>Step 4</td>
<td>Contextual factors</td>
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<td></td>
<td>(Z)Remoteness</td>
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</tr>
<tr>
<td>Step 5</td>
<td>Interactions (2-way)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Cardiovascular* (Z)Remoteness</td>
<td>0.01</td>
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<tr>
<td></td>
<td>Cardiovascular* Depression</td>
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</tr>
<tr>
<td></td>
<td>Depression* (Z)Remoteness</td>
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<tr>
<td>Step 6</td>
<td>Interactions (3-way)</td>
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<td></td>
<td>Cardiovascular* Depression</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>Depression* (Z)Remoteness</td>
<td></td>
</tr>
<tr>
<td>Step 7</td>
<td>Cohort</td>
<td></td>
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<tr>
<td></td>
<td>0.10</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

Model diagnostics

<table>
<thead>
<tr>
<th>Significance (F value)</th>
<th>70.85, p &lt; .001</th>
<th>86.64, p &lt; .001</th>
</tr>
</thead>
<tbody>
<tr>
<td>R²</td>
<td>24.6%</td>
<td>28.5%</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>24.3%</td>
<td>28.2%</td>
</tr>
</tbody>
</table>

Note: Reported statistics are based on pooled results (across multiple imputation datasets).
There was a small but statistically significant effect of remoteness on physical impairment (accounting for under one percent of the explained variation), which disappeared when cohort membership was accounted for (see Appendix 5.1, Table S1, $\beta = 0.02, p = 0.404$). Since the cohorts were chosen primarily because they differed in remoteness (i.e., it is a group defining characteristic, see Table 5.1), this finding suggests that continuous scores on the remoteness index added little to prediction beyond the urban versus rural comparison. On the other hand, cohort effects remained (see Table 5.2, Step 7) even after all other factors (including remoteness) were controlled for, suggesting that other (non-assessed) cohort related factors were also associated with impaired physical HRQoL; however, in both of these models cohort accounted for under one percent of the explained variation (see Appendix 5.1, Table S1).

**Psychological HRQoL impairment**

The right hand columns of Table 5.2 show the results for the regression model predicting psychological impairment. Demographic indices, cardiovascular and affective conditions and other health indicators (Steps 1 to 3) contributed approximately 24.7% of the 28.5% variation explained by the model. All steps significantly added to the model, with the exception of the three-way interaction (Step 6). Several factors were significantly associated with psychological impairment (most notably, a lifetime affective condition and lower social support) and the magnitude and significance of these predictors were largely unaffected by the inclusion of cohort membership in the first step of the model (see Appendix 5.1, Table S2).

However, the two factors that were associated with cohort differences in Table 5.1 (education and current smoking status) only reached the threshold for statistical significance when cohort membership was controlled. That is, after controlling for urban versus rural differences, lower education and smoking were associated with higher psychological impairment. Conversely, remoteness was significantly associated with lower psychological impairment (accounting for
1.8% of the explained variation, see Table 2) but not after cohort membership was controlled (see Appendix 5.1, Table S2 and Figure S2), raising doubt about the value of continuous scores on the remoteness index beyond the urban versus rural comparison. In addition, the effects of a lifetime affective condition on psychological impairment were worse for those who also reported a lifetime cardiovascular condition (Step 5, \( p < .010 \)), which remained after controlling for cohort (see Appendix 5.1, Table S2; \( \beta = 0.04, p = 0.014 \)).

**Secondary analyses: contextual correlates of remoteness from the NSW Adult Population Health Survey**

Descriptive statistics for social capital and health service accessibility by remoteness category are displayed in Table 5.3. An overall influence of remoteness category on social capital of small effect size was observed (\( F(3, 74909) = 1042.53, p < .001, \text{ eta-squared} = .040 \)). Post hoc tests indicated that all group differences were statistically significant (\( p < .001 \)) with the exception of outer regional versus remote/very remote areas (\( p = .408 \)). Residents of major cities reported the lowest social capital, followed by inner regional, outer regional and remote-very remote areas. Similarly, a chi-squared test indicated that the proportion of people with difficulties accessing health care varied by remoteness category, with a medium effect size (\( X^2(3) = 3455.09, p < .001, \text{ Cramer’s} \ V = .191 \)). Post hoc tests indicated that all group differences were statistically significant (\( p < .001 \)) with the exception of outer regional versus remote-very remote areas (\( p = .995 \)). Major cities had the highest proportion of persons reporting no difficulty accessing health care when needed, followed by inner regional areas and outer regional and remote/very remote areas. Overall 1.79% of participants reported that they did not need health services and the proportion of these participants did not vary by remoteness category (\( X^2(3) = 0.42, p = .936 \)). These secondary analyses support an association between remoteness and both social capital and health service accessibility, though findings of
no difference between outer-regional and remote-very remote areas also suggest a level of insensitivity of our remoteness index to these underlying community characteristics.
Table 5.3 Secondary analysis of subjective social capital and health service accessibility by remoteness category from NSW Adult Population Health Surveys (years: 2006-2009).

<table>
<thead>
<tr>
<th></th>
<th>Major City (MC)</th>
<th>Inner Regional (IR)</th>
<th>Outer Regional (OR)</th>
<th>Remote/Very Remote (R/VR)</th>
<th>Statistically significant comparisons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social capital</td>
<td>N</td>
<td>49267</td>
<td>16712</td>
<td>8030</td>
<td>902</td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>2.44</td>
<td>2.62</td>
<td>2.73</td>
<td>2.70</td>
</tr>
<tr>
<td></td>
<td>SD</td>
<td>0.52</td>
<td>0.53</td>
<td>0.52</td>
<td>0.53</td>
</tr>
<tr>
<td>Health service accessibility</td>
<td>N</td>
<td>62495</td>
<td>20938</td>
<td>10134</td>
<td>1126</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>88.3</td>
<td>77.6</td>
<td>68.4</td>
<td>68.4</td>
</tr>
</tbody>
</table>

Note: Comparisons based on one-way ANOVA with Scheffé post hoc tests (social capital) or chi-squared tests (health service accessibility); significant follow-up comparisons: all \( p < .001 \); Health service accessibility % indicates the proportion of persons reporting no difficulty accessing services when needed; results are weighted to adjust for differential non-response rates by gender, age, remoteness and by population estimates for each health service area.
Sub-analyses: the influence of social capital on HRQoL impairment associated with cardiovascular, affective conditions and perceived financial difficulty from the ARMHS study

Those included in the ARHMS sub-analysis (N = 1176) were marginally younger (mean = 65.96, SD = 7.54 vs. N = 70, mean = 68.34, SD = 9.50; \( p = .012 \)), had experienced fewer adverse life events (mean = 1.32, SD = 1.37 vs. N = 51, mean = 1.84, SD = 1.92; \( p = .009 \)) and reported less perceived financial difficulty (mean = 3.18, SD = 0.76 vs. N = 54, mean = 3.48, SD = 0.92; \( p = .008 \)) compared to those excluded (N = 70). One-way ANOVA revealed a small significant effect of remoteness category on social capital ratings (\( F(2, 1202) = 6.93, p < .001, \text{eta}-\text{squared} = .011 \)) with Scheffé post hoc tests indicating that participants from inner regional areas (N = 484, mean = 9.06, SD = 2.13) reported significantly lower (\( p < .001 \)) social capital than those from remote/very remote areas (N = 285, mean = 9.65, SD = 1.99). Outer regional participants did not differ from those of the other areas (N = 434, mean = 9.14, SD = 2.37).

Two models were used to assess the influence of social capital on physical and psychological impairment: 1) a model identical to that used in the primary analysis but with contextual factors represented by an individual’s rating of social capital; and 2) an expanded model including the influence of recent adverse life events and perceived financial difficulty. As individual level ratings of social support and social capital are likely to be correlated, social capital was included at a subsequent step in the regression model to enhance our capacity to examine the benefits of community level support above those attributable to an individual’s propensity for close social relationships. Results of the former analyses are presented in Appendix 5.1, Table S3, and the latter analysis in Table 5.4.
Table 5.4 Sub-analysis: hierarchical linear regression analysis of the correlates of physical and psychological quality of life impairment (N = 1176).

<table>
<thead>
<tr>
<th></th>
<th>Physical impairment</th>
<th>Psychological impairment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>β</td>
<td>p</td>
</tr>
<tr>
<td><strong>Step 1 Demographic factors</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Z) Age</td>
<td>0.14</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Female</td>
<td>-0.08</td>
<td>.004</td>
</tr>
<tr>
<td>12+ years education</td>
<td>-0.10</td>
<td>.002</td>
</tr>
<tr>
<td>Married/de facto</td>
<td>-0.08</td>
<td>.004</td>
</tr>
<tr>
<td>Retired</td>
<td>0.14</td>
<td>&lt;.001</td>
</tr>
<tr>
<td><strong>Step 2 Cardiovascular &amp; affective conditions</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stroke</td>
<td>0.08</td>
<td>.005</td>
</tr>
<tr>
<td>Heart-attack/angina</td>
<td>0.16</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Depression/anxiety</td>
<td>0.22</td>
<td>&lt;.001</td>
</tr>
<tr>
<td><strong>Step 3 Other health related indicators</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Diabetes</td>
<td>0.06</td>
<td>.029</td>
</tr>
<tr>
<td>Obesity</td>
<td>0.12</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Current smoker</td>
<td>0.03</td>
<td>.266</td>
</tr>
<tr>
<td>High cholesterol</td>
<td>-0.05</td>
<td>.043</td>
</tr>
<tr>
<td>Hypertension</td>
<td>0.07</td>
<td>.01</td>
</tr>
<tr>
<td>Social support</td>
<td>-0.16</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>(Z) Adverse life events</td>
<td>0.13</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>(Z) Fin difficulty</td>
<td>0.22</td>
<td>&lt;.001</td>
</tr>
<tr>
<td><strong>Step 4 Contextual factors</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Z) Social capital</td>
<td>-0.01</td>
<td>.604</td>
</tr>
<tr>
<td><strong>Step 5 Interactions (2-way)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Z) Fin difficulty*</td>
<td>-0.04</td>
<td>.112</td>
</tr>
<tr>
<td>(Z) Social capital</td>
<td>0.02</td>
<td>.454</td>
</tr>
<tr>
<td>Cardiovascular*</td>
<td>0.02</td>
<td>.550</td>
</tr>
<tr>
<td>Depression*</td>
<td>0.03</td>
<td>.285</td>
</tr>
<tr>
<td><strong>Step 6 Interaction (3-way)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cardiovascular* Dep</td>
<td>-0.03</td>
<td>.329</td>
</tr>
<tr>
<td>Depression*</td>
<td>0.00</td>
<td>0.329</td>
</tr>
<tr>
<td>(Z) Social capital</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Model diagnostics**

- Significance (F-value): 22.49, p < .001 22.01, p < .001
- \( R^2 \): 30.03% 29.58%
- Adjusted \( R^2 \): 28.69% 28.24%

Note: Reported statistics are based on pooled results (across multiple imputation datasets). Fin difficulty = perceived financial difficulty.
The inclusion of 12 month adverse events and perceived financial difficulty (at Step 3) did not generally influence the direction or significance of model variables. However, a trend indicating that the impact of depression/anxiety on psychological impairment decreased with greater social capital (Table S3: \( p = .012 \)) was no longer significant in the extended model. Instead, a trend indicating that the impact of financial difficulty on psychological impairment decreased with greater social capital (Table 5.4: \( p = .014 \)) was observed in the extended model.

The null result regarding the interaction of depression/anxiety and social capital in the extended model may be due to variance shared by financial difficulty and depression/anxiety and their interaction with social capital in the prediction of psychological impairment. Figure 5.1 illustrates this association by displaying univariate regression lines for ratings of social capital on psychological impairment for four financial difficulty subgroups. This figure indicates that increased social capital had the greatest positive psychological impact on persons experiencing financial difficulty, with little to no psychological impact on persons who perceived themselves as prosperous or very comfortable financially. There were no significant two- or three-way interactions of cardiovascular, affective conditions or social capital in the prediction of physical impairment in the extended model.
Figure 5.1 Sub-analysis of the association of social capital and psychological impairment by perceived financial difficulty grouping. Variability in psychological impairment attributable to social capital by perceived financial difficulty group: Poor-very poor (N = 37, $R^2 = .12$); Just getting along (N = 337, $R^2 = .09$); Reasonably comfortable (N = 615, $R^2 = .02$); Prosperous/very comfortable (N = 781, $R^2 = .01$). Overall variability in psychological impairment (main effects) attributable to perceived financial difficulty ($R^2 = .09$) and social capital ($R^2 = .04$).

Results of the rural sub-analysis were consistent with those of the overall primary analysis reported in Table 5.2, although the effects of smoking on physical and psychological impairment were no longer apparent, nor was the effect of obesity on psychological impairment. However, retirement status was a predictor of psychological impairment and the influence of age on psychological impairment appeared to be greater. The associations of diabetes and hypertension with physical impairment were now of marginal significance though of similar magnitude. There was no association between social capital and physical impairment, though a marginal association with psychological impairment was observed, with increased social capital associated with decreased psychological impairment. Correlations
reported in Appendix 5.1, Table S3 suggest that the simple association between social capital and psychological impairment was reduced in the multivariate model (−0.21 in Table S3 vs. -0.06 in Table 5.4), likely due to the inclusion of social support in the previous step.

Discussion

This study reports population based findings about factors associated with HRQoL impairment in a sample of older persons from across urban-remote areas of NSW, as well as examining the impact of contextual factors and cardiovascular-affective condition comorbidity on these outcomes. Investigation of the moderating effect of cohort membership on these models revealed that, with the exception of factors directly associated with cohort membership (i.e., remoteness) there were few differences in the magnitude or significance of model predictors, supporting the validity of combining data across different cohorts. Current models explained approximately a quarter of the variance in physical and psychological impairment reported by participants, with demographic indices, cardiovascular and affective conditions and other health indicators accounting for most of the model variance. Physical impairment was consistently associated with increased age, male gender, lower education, being unmarried, retirement, a lifetime history of stroke, heart attack/angina, depression/anxiety, diabetes and hypertension, as well as current obesity and low social support. Psychological impairment was consistently associated with lower age, being unmarried, a lifetime history of stroke, heart attack/angina and depression/anxiety, as well as low social support. In the primary analyses, the influence of participant remoteness on HRQoL impairment was relatively small and varied with the model being examined. Remoteness tended to be more strongly associated with lower psychological impairment, reflecting overall urban versus rural differences, rather than more subtle changes in remoteness. Previous research in the Australian context has also observed a rural advantage for psychological [56,57], but not physical quality of life [56] compared to urban participants. In line with previous research regarding the impact of
comorbid physical and mental health conditions [26], trends suggesting that the lifetime occurrence of both affective and cardiovascular conditions was associated with greater psychological impairment than was explained by either diagnosis alone ($p = .010$) were observed, although they were not significant in the rural sub-analysis ($p = .053$). Moreover, there was no evidence that the impact of cardiovascular and affective conditions were influenced by remoteness. However, these findings must be interpreted with caution. Several factors suggest that chronic conditions may be more likely to be misclassified or of greater severity in our rural populations, particularly: the decreased probability of receiving a diagnosis in remote areas where health services are less accessible [58,59]; the potential for increased severity at diagnosis; the relative infrequency with which rural populations with health conditions consult their physician; the reduced likelihood of surviving an acute health event; and evidence of migration of persons to less remote areas following diagnosis of mental health conditions [60]. Such biases in diagnostic classification (i.e., more persons incorrectly classified as not having the condition) in regional-remote areas would mean that the influence of disease on quality of life would be underestimated in these areas, though it would be difficult to determine the degree to which such an effect could be offset by the increased severity of diagnosed cases. Further, investigations regarding impact of migration patterns on mental health outcomes suggest migration from rural to urban areas to be associated with increased probability of depression, with decreased contact with friends and neighbours a particular burden in this group [61]. Thus, current results may be best characterised as representing the influence of current community remoteness on persons who have received these diagnoses.

Analyses of NSW Adult Population Health Survey data confirm observations that social capital increases [7] and experiences of health service accessibility decrease [59] with remoteness, though no differences were observed for either factor between outer regional and remote/very remote groups. Approximately 32% of persons in outer regional and remote/very
remote areas reported difficulty accessing health services when needed compared to 12% living in major cities. Conversely, outer regional and remote/very remote participants reported levels of social capital approximately half a SD greater than their major city counterparts. These findings provide some support for the use of remoteness indices as a proxy for health related community characteristics, although they also tend to suggest that a three category classification would be sufficient (i.e., major city, inner regional, and other areas), and that the current remoteness indices lack greater sensitivity.

The impact of these supposedly opposing forces (increased social capital and decreased health service accessibility) upon health outcomes requires further research, though it is possible that in light of their co-variation, the protective effects of social capital reported here are underestimated. For example, while we have observed no effect of social capital on physical HRQoL outcomes in our ARMHS sub-analyses, it may be that these community effects are offset by poorer health service accessibility. However, current results are in line with previous investigations of the influence of social capital on HRQoL in Australia, with social capital displaying a particular influence of social capital on psychological HRQoL [62]. Further, while the association of social capital with psychological HRQoL has been observed for both urban and rural participants, evidence suggests that social capital is associated with physical HRQoL only in urban populations [56]. This is consistent with the current null finding regarding the relationship of social capital with HRQoL in our rural sample and may be due to limitations on the capacity of social capital to influence physical health related behaviours in rural areas where health resources are limited.

As discussed above, in line with previous research our sub-analysis of ARMHS data revealed a marginal association of social capital with decreased psychological impairment when controlling for individual level variables such as social support. In our replication of the primary analysis (Appendix 5.1, Table S3), social capital influenced the association of affective
conditions with psychological impairment; as social capital increased, persons with a lifetime diagnosis of depression/anxiety reported less psychological impairment. These effects were observed in the replication despite the fact that other major drivers of well-being were included in the model, such as personal social support. This effect was not significant in the extended model which included recent adverse life events, perceived financial difficulty and a marginal interaction of financial difficulty with social capital, suggesting that these variables shared a portion of the variance in psychological impairment accounted for by the social capital and affective disorder interaction. Both marginal interactions observed suggest that interrelated psychological burdens, such as affective disorders and financial difficulties, are similarly ameliorated by social capital. The previously observed trend for comorbid lifetime diagnoses of cardiovascular and affective disorder to be associated with psychological impairment was of similar magnitude but not significant in this subsample ($p = .053$). The ARMHS cohort sub-analysis also confirmed the influence of recent adverse life events and perceived financial difficulty on HRQoL impairment. Evidence for a moderating effect of social capital on the negative effect of financial difficulty on psychological HRQoL impairment was also observed.

Comparisons between the corresponding analyses (Table 5.4 vs. Appendix 5.1, Table S3) show an increment in explained variation of approximately six percent with the inclusion of the additional predictors (adverse life events, perceived financial difficulty and the interaction of financial difficulty and social capital). We acknowledge that the individual level measures of social capital used in these analyses may themselves be influenced by each person’s own psychological HRQoL. However, the patterns of social capital in this sample are consistent with those observed in the NSW data and elsewhere [5-7], namely, increased social capital across rural locations, suggesting this is a potentially health-sustaining quality of rural living, particularly for those with a history of affective conditions. These results are consistent with
previously hypothesised and observed ameliorating influences of social capital on stressful situations and events [5]. It is possible that community engagement and support plays a greater role in supporting psychological well-being of persons with financial difficulties, suggesting that they have greater engagement with the community in maintaining their psychological well-being. Given that these variables were only assessed in the rural-remote ARMHS cohort and not the overall xTEND sample, a limitation of these analyses is that they do not include persons from urban areas and thus the effects and interactions reported here are likely be truncated representations of the effects present in the community at large.

Current findings have practical implications for research into the influence of comorbidity and context on health outcomes, particularly in Australia. This report informs concerns raised by the 2012 National Report Card on Mental Health and Suicide Prevention regarding the physical health of persons affected by mental illness [30], particularly in light of the burden of cardiovascular disease in these populations. Current results build on past observations of an effect of physical-mental comorbidity on increased days out of role and high health service usage [26], short term disability and suicidal ideation [63], decreased HRQoL [28] and general disability beyond that of diagnoses in isolation [29]. Our results tend to suggest that the disability associated with comorbidity may have a stronger association with psychological HRQoL. In any event, all of the analyses demonstrated clear independent linkages between lifetime cardiovascular and affective conditions and current physical and psychological HRQoL impairment (accounting for between 6.9% and 12.3% of the explained variation).

The strengths of this study are its consideration of data from large community based samples and access to a depth of health information from participants across the spectrum of urban to remote communities that is unprecedented in Australia. Our models include a range of biopsychosocial risk factors that are not only potentially important for understanding the relationship of physical and mental disorders with HRQoL but which also enable us to tease out
some of the contextual, rather than behavioural, influences of remoteness on HRQoL outcomes (such as increased rates of smoking). It should be noted that response rates for these surveys were relatively low, particularly for the oldest persons contacted, among whom the impact of disease on participation is likely to be high. Therefore, we infer that the current subset of participants represents a relatively healthy sub-sample of the population at large, and that the impacts of disease on quality of life depicted here are potentially weaker than those which would be observed in the general population.

The study has several other limitations. Firstly, the use of self-reported lifetime diagnoses for health conditions meant that these variables may reflect a range of symptoms that may not be current and do not account for duration or severity. In the current analyses, self-reported lifetime diagnoses of affective conditions were among the strongest predictors of both physical and psychological impairment. However, the impact of lifetime health conditions may be variable and the effects of current or recent experiences of these conditions on HRQoL impairment may be greater than those represented here. Secondly, apart from the obvious urban versus rural difference, it is unclear what other cohort related factors may have contributed to differences in mean HRQoL impairment. Finally, it should be noted that our urban population was drawn from a major regional industrial city and thus the current observations of factors influencing HRQoL may not generalise to other urban contexts. In particular, differences between characteristics of major urban locations, which are not necessarily delineated by population density or distance from services, and populations residing within these areas, may impact the experiences of social capital and health service accessibility and their association with health between urban centres [13].

A strength of the current study is that our primary outcome measure, the AQoL-6D, has been shown to display metric invariance across these cohorts [39], suggesting that the same constructs are tapped by this measure in both groups. Further, the inclusion of cohort
membership in the models did not substantially change the significance or magnitude of model variables as predictors of HRQoL outcomes. Some aspects of the greater impairment reported by the HCS cohort may reflect cohort differences not assessed by our current measures. For example, a component of the observed differences may be a result of the HCS’s focus on recruitment of older persons with an interest in feedback about their health and by the ARMHS protocol of screening out participants with poor hearing and cognitive performance. However, these potential influences are likely to be small. Equally, the residual cohort effects observed in Table 5.2 (Step 7) may still be due to important elements of urban versus rural differences, but which are simply aspects not captured by the existing remoteness indices. Thirdly, the cross-sectional design of the current study means that we cannot assume that the HRQoL impairments observed here were actually caused by the variables under investigation.

**Conclusion**

The findings from this study support the influence of social capital on HRQoL impairment, with particular focus on co-existing affective and cardiovascular conditions, two of the most common causes of disease burden in the Australian community. Findings suggest that the psychological impairment experienced by persons affected by lifetime affective conditions may be influenced by comorbid cardiovascular conditions (and vice versa) and by low social capital. Awareness of the compounded effects of physical-mental comorbidity on psychological impairment in these populations is necessary to equitably address their experiences of health conditions. Greater remoteness was associated with higher levels of social capital, reflected in overall urban/rural differences in psychological impairment. The findings suggest that personal social capital may ameliorate the psychological impairment associated with affective disorders and financial difficulties. Initiatives with a focus on social support and social engagement may make help to improve the HRQoL of older persons in the Australian community.
References


Chapter six: Characterising the health related characteristics of sparsely populated rural areas: identifying the stable personal, social and contextual correlates of perceived physical and mental health for rural men and women

This chapter was disseminated in the academic literature as:


Synopsis

This chapter assesses the personal, social and contextual factors that are associated with perceived physical and mental health in a rural sample. Stability of these models was assessed across multiple phases of data collection and by gender. The chapter uses data from a large representative secondary data source to assess a novel method of characterising social capital and health service accessibility characteristics of rural areas. The relative strength of assessed psychosocial and contextual factors as predictors of physical vs. mental health outcomes is examined.
Introduction to Chapter six

Previous chapters provide some evidence that contextual characteristics may influence the psychosocial determinants of health. As such, assessment of the determinants of health within rural areas is necessary to design, adapt and implement evidence based health interventions traditionally informed by research from largely urban populations. Identifying the stable personal, social and contextual correlates of physical and mental health in rural areas of Australia, and how these may differ for men and women, will help inform the development of these targeted health interventions.

The measurement of the health related experiential elements of context, such as social capital and health service accessibility in rural areas is difficult due the small, dispersed nature of these populations. Inadequate numbers of observations and contention regarding the relevant area size for which to aggregate data [1-4] present real barriers to characterising the contextual factors in rural areas. Theories addressing how contextual factors are determined suggest that top-down influences of physical and structural factors contribute to shaping these characteristics. Such models may be useful in developing area-level contextual characterisations of rural areas in which remoteness as well as local social and administrative forces are likely to shape the health related contextual characteristics.

Assessing whether predictors display predominant associations with physical or mental health dimensions may further support understanding of the mechanisms through which personal and contextual factors influence health in rural areas. Finally, evidence that the social experiences of men and women may differ within rural areas [5-8] highlights gender as a potential moderating factor, which may help inform these investigations and targeted health interventions for rural populations. To obtain equivalent ratings of individual’s subjective
states of health-related physical and mental well-being, comparable self-ratings of perceived levels of physical and mental health will be assessed as model outcomes.

**Aims and purpose**

The purpose of the multivariate analyses conducted in Chapter six is to: identify the stable personal, social and contextual correlates of physical and mental health in a rural sample; examine whether these differed by gender; and investigate whether predictors displayed stronger association with physical or mental health. This chapter also aimed to assess a novel method of characterising health related contextual characteristics, namely social capital and health service accessibility, in sparsely populated areas. Single item ratings of self-rated perceived physical and mental health are the primary outcome measures. A supplementary model using a multi-item index of nonspecific psychological distress (Kessler 10) as the outcome measure is reported for comparison in Appendix 6.1, Tables S7-S9. As these analyses were exploratory in nature, no model pathways between predictors and outcomes were excluded. Where paths were shown to vary significantly by gender, these paths were allowed to vary in the final analyses. This iterative model modification permits minimal modification to models based on observations and theoretical differences and is consistent with the exploratory nature of the analyses. A maximum likelihood method was used to estimate missing data. These missing data imputation methods model the covariation between all variables, estimate linear regression equations for the relationship of each variable to each other variable, generate potential missing values, and reiterate this process until only minimal variation between estimates generated by each iteration are achieved. This is the fifth manuscript of the thesis and has been submitted to the Journal of Health and Social Behavior.
Contribution to primary research question

This study identified a range of psychosocial and health experiences that were reliably associated with self-rated physical and mental health outcomes in a rural sample. Demographic, factors, individual characteristics, current and past health experiences, individual’s social networks and contextual factors all contributed to these prediction models (Figure 6.0). In light of the correlated nature of the physical and mental dimensions of health, testing the strength of associations between these dimensions provides additional insight into the nature of these associations. Building upon observations in Chapter five, statistical comparison confirmed that cardiovascular diagnoses were more strongly associated with physical health and affective diagnoses were more strongly associated with mental health. This example demonstrates the value of these comparisons in helping us understand the nature of observed predictors of these correlated dimensions of health (e.g., the association of a cardiovascular diagnosis with mental health may in part reflect its impacts on physical health, and the association of depression with physical health may reflect its mental health impacts); such observations may also assist in the development of targeted health interventions for these populations. Though displaying associations with both factors, financial difficulty and cardiovascular diagnoses displayed stronger associations with physical health, while neuroticism, adverse life events and depression displayed stronger associations with mental health. Personal hopefulness, smoking status, social support, and a sense of belonging were equally associated with physical and mental health outcomes.

Ratings of several health predictors were highly stable within persons over the three year follow-up period. However, experiences of personal adversity, social networks and health outcomes did vary considerably over this time. These findings have implications for our capacity to assess causal associations between these predictors and health outcomes over time. Where possible, modelling of causal links between physical and mental health outcomes
and their predictors may provide further information regarding appropriate points of health intervention. These models will be explored in Chapter seven.

Comparison of predictor models by gender indicated that aspects of social networks differed in their associations with health outcomes for men and women (i.e., a sense of belonging, social visibility), as did other characteristics with social significance, including alcohol consumption and living on a farm. These results suggest that gender-related social contexts discussed in the qualitative literature on health in rural Australia do present important considerations for health and targeted health interventions in these populations.

Finally, the development of meaningful indices of the contextual characteristics of areas is an important step towards understanding contextual influences on health and its determinants. Using a theory-driven method of formulating aggregate contextual variables from a secondary data source, the current study identified consistent marginal associations of area-level social capital (Trust) with self-rated physical (Figure 6.0A) and mental (Figure 6.0B) health, as well as a significant association with nonspecific psychological distress (Figure 6.0C). Area-level health service accessibility displayed a marginal association with physical health but not mental health. While it should be noted that these results suggest theory-driven methods present a promising method for characterising contextual characteristics in small, dispersed populations. It should be noted that the single item measure of difficulty accessing health services when needed available within the NSW population health survey cannot provide insight into the nature and degree of difficulty encountered by persons in these communities. Such information would be invaluable in better understating variation in health needs across Australian communities. Due to the lack of specific information available in the current measure, future measures sensitive to the degree and nature of difficulties may produce larger effective sizes and more direction in identifying health needs and targeted interventions for increasing health care accessibility in rural and remote communities.
Candidate’s contribution

The candidate contributed substantially to all elements of this work, including: determination of a theory-driven method of formulating aggregate indices of health and social factors in rural and remote areas of New South Wales (NSW), Australia, using existing data from the NSW Adult Population Health Survey and geocoding these to ARMHS survey participants; extracting and geocoding existing indices of area socio-economic disadvantage to survey participants; creating a longitudinal dataset incorporating three waves of ARMHS data collection; performing data imputation using expectation maximisation methods; investigating and applying structural equation modelling techniques to assess correlates of health outcomes and their invariance by phase and gender groups, as well as assessment of the statistical significance of differences between independent variable contributions to physical and mental health; and contributing to the preparation of the current manuscript.
References


Figure 6.0. Personal and contextual predictors of self-rated physical and mental health in rural Australia. Note: # = effect was significant at p < .05, M = effect for men only, F = effect for women only, M/F = effect stronger for men but was also observed for women, +M, -F = effect was positive for men and negative for women.
Integrated multilevel cross-sectional models of personal, social and contextual predictors of self-reported overall physical and mental health

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Abstract

Knowledge regarding reliable personal, social and contextual correlates of health for rural populations and whether they vary by gender is limited due to the poor representation of these persons in national surveys and difficulties presented by low population density. Stable predictors of physical and mental health were identified using integrated multilevel cross-sectional models of survey data from the Australian Rural Mental Health Study (n = 1132) and New South Wales Adult Population Health Survey (n = 42,115). The health influences of a sense of belonging, social visibility, alcohol consumption, and living on a farm differed for rural men and women. The influence of contextual characteristics on physical health (health service accessibility and Trust) and mental health (socioeconomic status and Trust) were reduced to trend level when controlling for personal and social characterises. Theory-driven methods may help overcome difficulties in characterising the subjective experience of living in areas with low population density.

Keywords

Rural, physical health, mental health, social capital, data aggregation
Background

Concern about health and well-being outcomes in rural areas has increased in recent years. This has been driven, in part, by recognised socio-geographic health inequalities, such as poor access to health services, higher incidence of some conditions, and poorer disease outcomes [1]. Increased risk of occupational injury [2] and the impact of stress due to adverse environmental conditions [3,4] have also been recognised. The influence of rural living on health outcomes for men is of particular concern, with a culture of stoicism [5,6] and poor mental health literacy [7] posited as drivers for poorer health outcomes in this group (e.g., increased mortality, chronic health conditions, injury, alcohol consumption and smoking [8,1]). International data also indicate increased rates of suicide in rural areas, particularly among young men in Western countries [9].

The Australian Rural Mental Health Study (ARMHS) is a cohort study launched in 2007 aimed at identifying the personal, social and contextual factors associated with health outcomes in rural areas. As the third ARMHS data collection phase concludes, several personal characteristics have been identified as key correlates of mental health and distress in this cohort, including demographic, personality, health behaviours and conditions, and individual-level social factors, such as indices of social support and social capital [10,11]. While ‘social support’ refers to the presence and quality of personal relationships, ‘social capital’ encompasses wider social networks that promote trust, reciprocity and social cohesion [12], and support the actions of persons within communities [13,14].

Social capital has been conceptualised both as a property of individuals, built through personal interactions within social networks [15], and as a property of areas, built through the overall accumulation of positive and negative interactions [12]. Both levels of social capital are thought to influence health through psychosocial pathways that promote individual adaptation
to adversity [16] and by enabling access to health-related resources [17]. Dimensions of social capital, such as feelings of trust, neighbourhood connections and civic participation appear to differ in their impact on health [18], with feelings of safety within a community or ‘Trust’ emerging as potentially important for health outcomes [19-21,18,22]. In light of previous research suggesting that the health impacts of social capital may be moderated by gender [23,20,1] and concerns regarding social norms for men in rural areas, the health impacts of the social environment are of particular interest. Although several studies have examined the health impacts of community remoteness, the adequacy of remoteness indices as proxy for health-relevant contextual factors is unclear and has recently been challenged [24,25,10]. A more fine-grained approach to the impact of contextual factors on health may be needed to improve our understanding of the role of community characteristics.

Researchers who conceptualise social capital as a property of areas acknowledge that such contextual resources must be gleaned from the experiences of representative individuals within an area, relying on aggregations of individual perceptions to quantify area-level characteristics. The available data and appropriate spatial scale for this aggregation are thus key considerations in assessing such contextual factors [26], with the latter requiring sound theory and an understanding of the pertinent forces at work [27]. While a range of geographical or nominal boundaries have been used to characterise contextual factors (e.g., postal codes, city blocks, states and countries), it is widely acknowledged that these may not capture the contextual influences on health [26], especially in dispersed rural and remote populations. As the physical and historical contexts of rural areas are thought to shape the social norms, beliefs and behaviours of persons who live in those communities [28,29,27], aggregations based on areas with similar resource and social strains may result in more meaningful characterisations of contextual factors in rural and remote regions.
**Current study**

The primary aims of the current study are to: 1) undertake an integrated multilevel cross-sectional analysis of the personal, social, and contextual correlates of self-reported physical and mental health across three phases of ARMHS data collection; and 2) examine gender differences in these associations. To evaluate a theoretically driven method of characterising health-related contextual factors in rural areas, we also draw on quantitative socioeconomic indices related to place, as well as data from four waves of the New South Wales (NSW) Adult Population Health Survey (relating to health service accessibility and Trust).

**Data and methods**

**Current sample**

Self-report postal survey data were collected across three longitudinal survey phases of the ARMHS project between 2007-2012; see Kelly et al. [30,11] for recruitment and study design details. The baseline ARMHS cohort comprised a stratified random sample of non-metropolitan community dwelling persons aged 18 years and over listed on the NSW state electoral roll and residing in inner-regional to very remote local government areas (see shaded areas of Figure 6.1). Oversampling from remote and very remote areas was undertaken to ensure sufficient representation of these populations. Ethical approval was obtained from the relevant institutional Human Research Ethics Committees.

At baseline (T0), a response rate of 27% (n = 2639) was achieved. Among baseline participants, 64% (n = 1702) responded to the first follow-up survey (T1) and 48% (n = 1261) responded to the second follow-up survey (T2). Of the 1168 participants responding to all three surveys, 97% (n = 1132) provided adequate data (less than 25% missing data at the item level for each phase) for inclusion in a full information maximum likelihood imputation procedure and formed the study sample for the current analyses (years between phases: lag between first
(T0) and second (T1) phase, mean = 1.05, SD = .26; lag between second (T1) and third (T2) phase, mean = 2.10, SD = .33). This dataset represents 43% of baseline respondents and n = 3396 observations over time.

**Measures**

Self-report postal questionnaires were used to assess a range of participant characteristics and were repeated at each survey phase, with the exceptions of education (assessed only at T0) and personality traits (neuroticism assessed only at T0 and personal hopefulness assessed only at T2).

**Primary outcome variables: overall physical health and mental health**

Participants were asked ‘During the last four weeks, how would you rate your overall physical [mental] health?’, with five response options: (1) poor, (2) fair, (3) good, (4) very good, (5) excellent. The use of these highly similar single item variables to assess the physical and mental dimensions of health facilitates more direct comparisons between health prediction models, due to their shared measurement characteristics. These variables are also normally distributed and reflect both positive and negative aspects of health states, as opposed to the presence or absence of specific symptoms or illness. This representation of a spectrum of health states is further evidenced by the correlation of these ratings with impairment scores for the Physical domain (physical health, \( r = -.55, p < .001 \); mental health, \( r = -.36, p < .001 \)) and the Psychological domain (physical health, \( r = -.44, p < .001 \); mental health, \( r = -.60, p < .001 \)) of the Assessment of Quality of Life-6D [31,32] in the ARMHS sample (n = 3333). Outcome variables were treated as continuous for all analyses.
Personal characteristics

Demographic factors. Participants provided information regarding age, gender, education, marital status (married/defacto vs. not), retirement status (retired vs. not), whether they lived on a farm, proportion of life lived in their current district, and perceived financial difficulty. Financial difficulty was assessed using a single item question, namely ‘Given your current needs and financial responsibilities, would you say that you and your family are’: (1) prosperous, (2) very comfortable, (3) reasonably comfortable, (4) just getting along, (5) poor, or (6) very poor [33].

Individual characteristics. Trait neuroticism was assessed using 7 items from a brief version of the Eysenck Personality Inventory [34], as described by Kelly et al. [11]. Personal hopefulness was assessed using the 12-item Hunter Opinions and Personal Expectations Scale [HOPES-12: 35], which assesses aspects of each respondent’s hopeful and despairing perceptions regarding the future. Stability data were available for an ARMHS sub-sample (n = 369) who completed the HOPES-12 at both T0 and T2, suggesting moderate stability over the three year follow-up (T0, mean = 2.95, SD = .59; T2, mean = 2.89, SD = .60; ricc = .65, p < .001). Experiences of recent adverse life events were assessed by a count of negative personal life events reported during the past 12 months [36]. Examples include: ‘has a member of your family died (e.g., parent, brother, wife, child)?’ and ‘...have you been involved in an accident that carried serious risk to the health or life of yourself or others?’.

Current and past health. Participants provided information regarding lifetime diagnoses of depression, stress or anxiety (vs. no lifetime diagnosis) and cardiovascular disease (stroke, heart attack/angina/heart disease vs. no lifetime diagnosis), current smoking status (current smoker vs. not), recent serious injury (occurrence of an injury requiring hospital treatment in the last 12 months vs. not), and alcohol consumption. Alcohol consumption was assessed using
the Alcohol Use Disorders Identification Test, a 10-item questionnaire about alcohol consumption, related behaviours and problems. Responses to each item were scored from 0 to 4, giving a maximum possible score of 40 [37]. Total scores $\geq 8$ are indicative of current hazardous alcohol use [38].

**Social characteristics.** Social support was assessed by responses to the Availability of Attachment subscale of the abbreviated Interview Schedule for Social Interaction [39]. This is a 6-item true/false self-report measure assessing the availability of close personal relationships providing emotional support, with higher mean scores indicating greater social support (range 0-1; $\alpha = .81$). Individual perceptions of social capital were assessed using nine true/false self-report items from the Sense of Community Index [40] selected on the basis of preliminary factor analyses. An exploratory model of three correlated factors was used to produce factor scores (score range 0-1), here referred to as Social cohesion ($\alpha = .56$; sample item ‘If there is a problem in this district, people who live here can get it solved’), Social visibility ($\alpha = .51$; sample item ‘I care about what other residents in the district think of my actions’), and Belonging ($\alpha = .67$; sample item ‘It is very important to me to live in this particular district’). Full description of these analyses, scale items and their factor allocation are presented in the Appendix 6.1, Table S1).

**Contextual factors**

Contextual characteristics (socioeconomic, health service accessibility, and Trust) were conceptualised as being highly stable over the follow-up period and thus single scores were used in all analyses. Indices of area-level health service accessibility and Trust were derived from 2006-2009 NSW Adult Population Health Surveys using data weighted to adjust for differential non-response rates by gender and age, and by population estimates for each health service area in NSW [41] (total unweighted $N = 42,155$; for further details see Appendix
Survey respondents were categorised by area health service and the Australian Standard Geographical Classification [42] of community remoteness (major cities, inner regional, outer regional and remote/very remote; see Figure 6.1) and aggregate indices calculated within these areas. Aggregate values were then geocoded to ARMHS participants by postal code.

Figure 6.1 Remoteness categories (colouring) by New South Wales (NSW) area health service regions (black outline) used in defining area-level social capital and health service accessibility characteristics. Uncoloured area within NSW is the Australian Capital Territory. Shaded areas represent local government areas (LGAs) sampled by the Australian Rural Mental Health Study. NSW has a total area of approximately 809,000 km².

Socioeconomic status (SES) was assessed using the Australian Bureau of Statistics’ Index of Relative Socioeconomic Advantage and Disadvantage for Areas [43]. This is a standardized
continuous index score, from disadvantage (low values) to advantage (high values), which accounts for a range of household factors including income, education, employment, available internet connections, and transport characteristics within an area, using data derived from the 2006 Australian Census (distribution: average area = 1000, with 70% between 900 and 1100). Values were geocoded to ARMHS participants by postal code.

**Health service accessibility (HSA)** was derived from responses to the question ‘Do you have any difficulties getting health care when you need it?’ Persons who reported any need for health care (97.3%) provided either a ‘yes’ or ‘no’ response and were included in the current analyses. Aggregate health service accessibility was calculated as the proportion of persons reporting no difficulty accessing services when needed.

**Trust** was derived from three items described by Onyx and Bullen [44] as best reflecting feelings of trust and safety within areas (α = .68, sample item ‘My area has a reputation for being a safe place’). Item responses were provided on a four point Likert scale, with higher ratings indicating greater Trust and scores were calculated based on mean item responses. Subscale items are presented in Appendix 6.1, Table S2).

**Analyses**

Analyses were conducted using SPSS (v.20; IBM Corporation, Armonk NY, USA) and AMOS 20 (v.20; IBM Corporation, Chicago IL, USA). An α < .01 (corresponding Critical Ratio, CR = +/-2.58) was used as the threshold for all tests of statistical significance. To reduce potential bias caused by the exclusion of persons with missing data, missing values were imputed using SPSS’s built-in expectation-maximization estimation procedure. Participants who had no more than 25% missing item data on model variables within each phase were included in the imputation procedure. Following the recommendations of Graham [45], all model variables as well as auxiliary variables which could inform the estimation of missing model variables were
included in this procedure. No more than 8% of data were imputed for any model variable and overall 1% of data were imputed.

The stability of participant characteristics over time was described using kappa statistics for categorical variables, consistency intra-class correlation coefficients ($r_{icca}$) for age and proportion of life lived in current district, and absolute intra-class correlation coefficients ($r_{icc}$) for all other continuous variables. Following Landis and Koch [46], consistency was interpreted as: 0.00-0.80 slight-substantial and 0.81-1.00 almost perfect.

**Integrated multilevel cross-sectional modelling**

Structural equation modelling (SEM) techniques were used to identify reliable associations of individual-level personal and social characteristics, as well as area-level contextual characteristics, with physical and mental health over three phases of data collection (i.e., integrated multilevel cross-sectional models). SEM is particularly suited to assessing the reliability of models across phases (cross-validation) and the moderating effects of factors such as gender. Correlation matrices used to produce the reported overall associative models and by phase and gender are provided in Appendix 6.1, Tables S3a-S3f. Maximum likelihood estimations were used for all SEM procedures. Squared multiple correlations ($R^2$) were obtained to assess the portion of variability in an outcome explained by the predictors.

The predictors of physical or mental health over all observations were estimated. Chi-squared difference tests were examined to assess whether model fit differed significantly across phase and gender models. Critical ratios for differences between each model path were inspected to identify where differences occurred. Paths were freed one at a time and model fit reassessed in an iterative process beginning with the largest absolute CR value until adequate model fit was achieved. As standardised coefficients may display small differences due to different variances between groups, where coefficients did not significantly differ, standardised
coefficients represent the mean of the male and female standardized coefficients (largest observed difference in standardized coefficients: +/- .02).

Finally, as physical and mental health represent interrelated domains of general health, we assessed whether model predictors differed in their association with the two outcomes. CRs for differences in path strength across the models were inspected, as well as the disturbance to overall model fit when each parameter was constrained to have an equal association across outcomes, which were examined using serial chi-squared difference tests.

**Results**

**Participant characteristics**

Baseline characteristics of participants providing adequate data for the current analysis at all phases were compared with those of excluded participants. Included participants reported better baseline physical and mental health, were less likely to be in a married/defacto relationship or to have completed 12 or more years of education, lived a lower proportion of their lives in their current district, reported lower financial difficulty, greater social cohesion, and were from less remote areas than excluded participants (see Appendix 6.1, Table S4).

Table 6.1 details participant characteristics and their stability over time (see Appendix 6.1, Table S5 for description of characteristics by phase). Just over one-third (35.6%) of the sample was retired and the majority (78.1%) were currently married or in a defacto relationship. Approximately half of the personal characteristics reported in Table 6.1 were considered to be highly stable over the three time periods (e.g., age, marital and retirement status, lifetime depression and cardiovascular disease) and several characteristics varied (e.g., financial difficulty, number of recent adverse life events, physical and mental health, social support, social cohesion, social visibility and belonging). Contextual characteristics indicated that participants resided in areas with below average socioeconomic status. On average, aggregate
indices suggest participants lived in areas where 70% of residents reported no difficulty accessing health services when needed.
Table 6.1 Overall participant characteristics and their stability over three survey phases.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Overall (N = 3396)</th>
<th>Stability</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Demographics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age M (SD)</td>
<td>57.36 (13.06)</td>
<td>( r_{icca} = 1.00^{***} ) S</td>
</tr>
<tr>
<td>Gender (Female %)</td>
<td>62.1</td>
<td>.</td>
</tr>
<tr>
<td>12+ years education %</td>
<td>74.6^</td>
<td>.</td>
</tr>
<tr>
<td>Married/defacto %</td>
<td>78.1</td>
<td>( K = 0.91^{***} ) S</td>
</tr>
<tr>
<td>Retired %</td>
<td>35.6</td>
<td>( K = 0.96^{***} ) S</td>
</tr>
<tr>
<td>Living on a farm %</td>
<td>22.9</td>
<td>( K = 0.89^{***} ) S</td>
</tr>
<tr>
<td>Prop. life lived in district M (SD)</td>
<td>0.47 (0.32)</td>
<td>( r_{icca} = 1.00^{***} ) S</td>
</tr>
<tr>
<td>Financial difficulty M (SD)</td>
<td>3.13 (0.75)</td>
<td>( r_{icc} = 0.69^{***} ) V</td>
</tr>
<tr>
<td><strong>Individual characteristics M (SD)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neuroticism</td>
<td>1.92 (1.82)^</td>
<td>.</td>
</tr>
<tr>
<td>Personal hopefulness</td>
<td>2.86 (0.62)^</td>
<td>.</td>
</tr>
<tr>
<td>Adverse life events (12mth)</td>
<td>1.24 (1.37)</td>
<td>( r_{icc} = 0.33^{***} ) V</td>
</tr>
<tr>
<td><strong>Current and past health</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depression diagnosis (LT) %</td>
<td>36.8</td>
<td>( K = 0.96^{***} ) S</td>
</tr>
<tr>
<td>Cardiovascular diagnosis (LT) %</td>
<td>14.5</td>
<td>( K = 0.95^{***} ) S</td>
</tr>
<tr>
<td>Current smoker %</td>
<td>10.8</td>
<td>( K = 0.86^{***} ) S</td>
</tr>
<tr>
<td>Serious injury (12mth) %</td>
<td>15.1</td>
<td>( K = 0.22^{***} ) V</td>
</tr>
<tr>
<td>Alcohol consumption M (SD)</td>
<td>3.93 (4.03)</td>
<td>( r_{icc} = 0.85^{***} ) S</td>
</tr>
<tr>
<td><strong>Individual social networks M (SD)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social support</td>
<td>0.88 (0.23)</td>
<td>( r_{icc} = 0.52^{***} ) V</td>
</tr>
<tr>
<td>Cohesion</td>
<td>0.83 (0.27)</td>
<td>( r_{icc} = 0.39^{***} ) V</td>
</tr>
<tr>
<td>Social visibility</td>
<td>0.70 (0.34)</td>
<td>( r_{icc} = 0.54^{***} ) V</td>
</tr>
<tr>
<td>Belonging</td>
<td>0.86 (0.22)</td>
<td>( r_{icc} = 0.56^{***} ) V</td>
</tr>
<tr>
<td><strong>Primary outcomes M (SD)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PH: Overall physical health</td>
<td>3.23 (0.93)</td>
<td>( r_{icc} = 0.51^{***} ) V</td>
</tr>
<tr>
<td>MH: Overall mental health</td>
<td>3.63 (0.96)</td>
<td>( r_{icc} = 0.58^{***} ) V</td>
</tr>
<tr>
<td><strong>Area characteristics M (SD)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Socioeconomic status</td>
<td>940.63 (35.88)</td>
<td></td>
</tr>
<tr>
<td>Health service accessibility</td>
<td>0.70 (0.05)</td>
<td></td>
</tr>
<tr>
<td>Trust</td>
<td>2.88 (0.07)</td>
<td></td>
</tr>
</tbody>
</table>

Note: *** p < .001; M (SD), Mean and standard deviation; \( r_{icc} \), intra-class correlation coefficient (absolute); \( r_{icca} \), intra-class correlation coefficient (consistency); K, Kappa coefficient; LT, lifetime; V, characteristic varied over time; S, characteristic was highly stable over time; ^, variable only assessed at one phase of data collection.
Physical health: predictors and modification by phase and gender

Univariate and multivariate associations for the initial physical health model are presented on the left-hand side of Table 5.2. The initial multivariate model accounted for 12.5% of the variability in physical health. Analyses of initial model modification by phase suggested that the effects of retirement varied between T0 and subsequent phases (T0, $\beta = -.12, p < .001$; T1: $\beta = .00, p = .982$; T2: $\beta = -.02, p = .458$) and the association of personal hopefulness varied between T0-T2 (T0, $\beta = .16, p < .001$; T2: $\beta = .28, p < .001$). However, chi-squared difference tests suggest a model in which all variables were constrained to have equal associations with physical health at all time-points resulting in no significant overall model disturbance compared to a model in which parameters were allowed to vary in their associations at each phase (Table 3A).
Table 6.2 Overall cross-sectional predictors of current physical health and the moderating effects of phase and gender.

<table>
<thead>
<tr>
<th>Model variables</th>
<th>Initial model</th>
<th>Gender constrained model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$r$</td>
<td>$p$</td>
</tr>
<tr>
<td></td>
<td>T0-T1</td>
<td>T1-T2</td>
</tr>
<tr>
<td>Demographics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>-.07</td>
<td>***</td>
</tr>
<tr>
<td>Gender (Female)</td>
<td>.02</td>
<td>.282</td>
</tr>
<tr>
<td>12+ years education</td>
<td>.09</td>
<td>***</td>
</tr>
<tr>
<td>Married/defacto</td>
<td>.09</td>
<td>***</td>
</tr>
<tr>
<td>Retired</td>
<td>-.10</td>
<td>***</td>
</tr>
<tr>
<td>Living on a farm</td>
<td>.01</td>
<td>.441</td>
</tr>
<tr>
<td>Prop. life lived in district</td>
<td>-.01</td>
<td>.720</td>
</tr>
<tr>
<td>Financial difficulty</td>
<td>-.26</td>
<td>***</td>
</tr>
<tr>
<td>Individual characteristics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neuroticism</td>
<td>-.15</td>
<td>***</td>
</tr>
<tr>
<td>Personal hopefulness</td>
<td>.31</td>
<td>***</td>
</tr>
<tr>
<td>Adverse life events (12 mth)</td>
<td>-.17</td>
<td>***</td>
</tr>
<tr>
<td>Current and past health</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depression diagnosis (LT)</td>
<td>-.18</td>
<td>***</td>
</tr>
<tr>
<td>Cardiovascular diagnosis (LT)</td>
<td>-.18</td>
<td>***</td>
</tr>
<tr>
<td>Current smoker</td>
<td>-.10</td>
<td>***</td>
</tr>
<tr>
<td>Serious injury (12 mth)</td>
<td>-.12</td>
<td>***</td>
</tr>
<tr>
<td>Alcohol consumption</td>
<td>.00</td>
<td>.965</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*** $p < .001$; $r$, correlation coefficient; CR, Critical Ratios $> |2.58|$ indicate that the difference between path coefficients significantly differed from zero; T0, first survey phase; T1, second survey phase; T2, third survey phase; hyphenation of phases (e.g., T0-T1) indicates that the CR is for the comparison of variable coefficients between these two phases; LT = lifetime; $\beta$ = standardized regression weight.
Table 6.2 continued. Overall cross-sectional predictors of current physical health and the moderating effects of phase and gender.

<table>
<thead>
<tr>
<th>Model variables</th>
<th>Initial model</th>
<th>Gender constrained model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>r</td>
<td>p</td>
</tr>
<tr>
<td><strong>Individual social networks</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social support</td>
<td>.17</td>
<td>***</td>
</tr>
<tr>
<td>Cohesion</td>
<td>.09</td>
<td>***</td>
</tr>
<tr>
<td>Social visibility</td>
<td>.07</td>
<td>***</td>
</tr>
<tr>
<td>Belonging</td>
<td>.11</td>
<td>***</td>
</tr>
<tr>
<td><strong>Area characteristics</strong></td>
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<tr>
<td>Socioeconomic status</td>
<td>.06</td>
<td>***</td>
</tr>
<tr>
<td>Health service accessibility</td>
<td>.05</td>
<td>.009</td>
</tr>
<tr>
<td>Trust</td>
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<td>.001</td>
</tr>
<tr>
<td></td>
<td>R²</td>
<td>.125</td>
</tr>
</tbody>
</table>

*** p < .001; r, correlation coefficient; CR, Critical Ratios > |2.58| indicate that the difference between path coefficients significantly differed from zero; T0, first survey phase; T1, second survey phase; T2, third survey phase; hyphenation of phases (e.g., T0-T1) indicates that the CR is for the comparison of variable coefficients between these two phases; LT = lifetime; β = standardized regression weight.
Table 6.3 Nested model comparisons for phase and gender moderation in (A) physical and (B) mental health outcome models.

<table>
<thead>
<tr>
<th>Model disturbance</th>
<th>Model</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>(A) Physical health model</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Phase</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unconstrained vs.:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fully constrained</td>
<td>$\Delta \chi^2 (46) = 39.74$, $p = .731$</td>
<td></td>
</tr>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unconstrained vs.:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fully constrained</td>
<td>$\Delta \chi^2 (22) = 42.45$, $p = .006$</td>
<td></td>
</tr>
<tr>
<td>1 free parameter (Belonging)</td>
<td>$\Delta \chi^2 (21) = 41.18$, $p = .005$</td>
<td></td>
</tr>
<tr>
<td>2 free parameters (Alcohol consumption)</td>
<td>$\Delta \chi^2 (20) = 31.99$, $p = .043$</td>
<td></td>
</tr>
<tr>
<td>3 free parameters (Social visibility)</td>
<td>$\Delta \chi^2 (19) = 27.00$, $p = .105$</td>
<td></td>
</tr>
<tr>
<td><strong>(B) Mental health model</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Phase</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unconstrained vs.:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fully constrained</td>
<td>$\Delta \chi^2 (46) = 46.19$, $p = .464$</td>
<td></td>
</tr>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unconstrained vs.:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fully constrained</td>
<td>$\Delta \chi^2 (22) = 39.68$, $p = .012$</td>
<td></td>
</tr>
<tr>
<td>1 free parameter (Belonging)</td>
<td>$\Delta \chi^2 (21) = 37.06$, $p = .017$</td>
<td></td>
</tr>
<tr>
<td>2 free parameter (Living on a farm)</td>
<td>$\Delta \chi^2 (20) = 30.97$, $p = .056$</td>
<td></td>
</tr>
</tbody>
</table>
Inspection of model fit differences between free and constrained gender models suggested that allowing the three greatest path differences (belonging, alcohol consumption and social visibility) to vary by gender resulted in no significant model misfit between genders (Table 3A). Model coefficients on the right-hand side of Table 6.2 present the gender constrained model of standardized predictors of physical health. The final model explains 15.0% of the variance in physical health for men and 11.6% of the variance for women. For both men and women, better physical health was associated with a lower proportion of life lived in the current district, lower financial difficulty, lower neuroticism, greater personal hopefulness, fewer adverse life events, absence of a lifetime depression diagnosis, absence of a lifetime cardiovascular diagnoses, not being a current smoker, absence of a recent serious injury and greater social support. Gender modified associations indicated better physical health was associated with greater belonging for men, but not for women.

**Mental health: predictors and modification by phase and gender**

Univariate and multivariate associations for the initial mental health model are presented on the left-hand side of Table 6.4; an alternative model using current symptoms of psychological distress (Kessler 10) as the outcome is provided in Appendix 6.1, Tables S7-S9. The initial multivariate model accounted for 21.0% of the variability in mental health. Analyses of path modification by phase suggested that personal hopefulness was more strongly associated with mental health at T2 compared to T1 and T0 (T0: $\beta = .18$, $p < .001$; T1: $\beta = .24$, $p < .001$; T2: $\beta = .34$, $p < .001$). However, chi-squared difference tests suggest there was no significant difference in mental health model fit between phases (Table 3B).
Table 6.4 Overall cross-sectional predictors of current mental health and the moderating effects of phase and gender.

<table>
<thead>
<tr>
<th>Model variables</th>
<th>Initial model</th>
<th>Path moderation (CR)</th>
<th>Gender constrained model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>r</td>
<td>p</td>
<td>p</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Demographics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>.12</td>
<td>.09</td>
<td>***</td>
</tr>
<tr>
<td>Gender (Female)</td>
<td>-.02</td>
<td>.316</td>
<td>.02</td>
</tr>
<tr>
<td>12+ years education</td>
<td>.01</td>
<td>.689</td>
<td>.01</td>
</tr>
<tr>
<td>Married/defacto</td>
<td>.10</td>
<td>.017</td>
<td>.01</td>
</tr>
<tr>
<td>Retired</td>
<td>.04</td>
<td>.015</td>
<td>.02</td>
</tr>
<tr>
<td>Living on a farm</td>
<td>-.01</td>
<td>.528</td>
<td>-.03</td>
</tr>
<tr>
<td>Prop. life lived in district</td>
<td>.06</td>
<td>.001</td>
<td>-.01</td>
</tr>
<tr>
<td>Financial difficulty</td>
<td>-.21</td>
<td>***</td>
<td>-.06</td>
</tr>
<tr>
<td><strong>Individual characteristics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neuroticism</td>
<td>-.37</td>
<td>***</td>
<td>-.22</td>
</tr>
<tr>
<td>Personal hopefulness</td>
<td>.37</td>
<td>***</td>
<td>.25</td>
</tr>
<tr>
<td>Adverse life events (12 mth)</td>
<td>-.28</td>
<td>***</td>
<td>-.15</td>
</tr>
<tr>
<td><strong>Current and past health</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depression diagnosis (LT)</td>
<td>-.32</td>
<td>***</td>
<td>-.19</td>
</tr>
<tr>
<td>Cardiovascular diagnosis (LT)</td>
<td>-.03</td>
<td>.044</td>
<td>-.04</td>
</tr>
<tr>
<td>Current smoker</td>
<td>-.13</td>
<td>***</td>
<td>-.05</td>
</tr>
<tr>
<td>Serious injury (12 mth)</td>
<td>-.08</td>
<td>***</td>
<td>-.02</td>
</tr>
<tr>
<td>Alcohol consumption</td>
<td>-.05</td>
<td>.002</td>
<td>.02</td>
</tr>
</tbody>
</table>

*** p < .001; r, correlation coefficient; CR, Critical Ratios > |2.58| indicate that the difference between path coefficients significantly differed from zero; T0, first survey phase; T1, second survey phase; T2, third survey phase; hyphenation of phases (e.g., T0-T1) indicates that the CR is for the comparison of variable coefficients between these two phases; LT = lifetime; β = standardized regression weight.
Table 6.4 continued. Overall cross-sectional predictors of current mental health and the moderating effects of phase and gender.

<table>
<thead>
<tr>
<th>Model variables</th>
<th>Initial model</th>
<th>Gender constrained model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>r</td>
<td>p</td>
</tr>
<tr>
<td>Model variables</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model variables</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individual social networks</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social support</td>
<td>.26</td>
<td>***</td>
</tr>
<tr>
<td>Cohesion</td>
<td>.12</td>
<td>***</td>
</tr>
<tr>
<td>Social visibility</td>
<td>.11</td>
<td>***</td>
</tr>
<tr>
<td>Belonging</td>
<td>.20</td>
<td>***</td>
</tr>
<tr>
<td>Area characteristics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Socioeconomic status</td>
<td>.07</td>
<td>***</td>
</tr>
<tr>
<td>Health service accessibility</td>
<td>.02</td>
<td>.370</td>
</tr>
<tr>
<td>Trust</td>
<td>.06</td>
<td>.001</td>
</tr>
<tr>
<td>R²</td>
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<td></td>
</tr>
<tr>
<td>M: .224</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F: .203</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*** p < .001; r, correlation coefficient; CR, Critical Ratios > |2.58| indicate that the difference between path coefficients significantly differed from zero; T0, first survey phase; T1, second survey phase; T2, third survey phase; hyphenation of phases (e.g., T0-T1) indicates that the CR is for the comparison of variable coefficients between these two phases; LT = lifetime; β = standardized regression weight.
Inspection of model fit differences between free and constrained gender models suggested that allowing the two greatest path differences (belonging and living on a farm) to vary by gender resulted in no significant model misfit between genders (Table 3B). Model coefficients on the right-hand side of Table 6.4 present the gender constrained model of standardized predictors of mental health. The final model explains 22.4% of the variance in mental health for men and 20.3% of the variance for women. For both men and women, better mental health was associated with lower financial difficulty, lower neuroticism, greater personal hopefulness, fewer recent adverse life events, absence of a lifetime depression diagnosis, absence of a lifetime cardiovascular diagnoses, not being a current smoker, and greater social support. For women living on a farm was associated with poorer mental health. Greater belonging was associated with better mental health for both men and women however this effect was stronger for men.

Comparison of coefficients across physical and mental health models

Critical ratios for parameter differences and disturbance to overall model fit when parameters were constrained are presented in Table 6.5. Comparisons suggest that age, neuroticism, recent adverse life events, and lifetime depression were more strongly associated with mental than physical health. Financial difficulty, cardiovascular disease and recent serious injury were more strongly associated with physical health. Significant path moderation and a marginal disturbance in model fit suggests retirement to be more strongly associated with physical health. Personal hopefulness, current smoking status, social support and belonging displayed comparable associations with both physical and mental health.
Table 6.5 Comparison of parameter strength across physical and mental health outcome models.

<table>
<thead>
<tr>
<th>Model parameter constrained</th>
<th>Physical health $\beta$</th>
<th>Mental health $\beta$</th>
<th>Parameter CR</th>
<th>Overall model fit $\Delta \chi^2(1)$</th>
<th>$p$</th>
<th>Strongest association</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demographics</td>
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<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>.00</td>
<td>.09</td>
<td>-4.03</td>
<td>8.85</td>
<td>.003</td>
<td>MH</td>
</tr>
<tr>
<td>Gender (Female)</td>
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<td>.02</td>
<td>-6.66</td>
<td>.36</td>
<td>.546</td>
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<tr>
<td>Married/defacto</td>
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<td>-.01</td>
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<td>.609</td>
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<tr>
<td>Retired</td>
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<td>.02</td>
<td>-2.66</td>
<td>4.07</td>
<td>.044</td>
<td>(PH)</td>
</tr>
<tr>
<td>Living on a farm</td>
<td>-.02</td>
<td>-.03$^{#G}$</td>
<td>5.1</td>
<td>.24</td>
<td>.627</td>
<td></td>
</tr>
<tr>
<td>Prop. life lived in district</td>
<td>-.05</td>
<td>-.01</td>
<td>-1.81</td>
<td>2.72</td>
<td>.099</td>
<td></td>
</tr>
<tr>
<td>Financial difficulty</td>
<td>-.14</td>
<td>-.06</td>
<td>-3.94</td>
<td>12.84</td>
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</tr>
<tr>
<td>Individual characteristics</td>
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<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Neuroticism</td>
<td>-.05</td>
<td>-.22</td>
<td>7.61</td>
<td>45.76</td>
<td>***</td>
<td>MH</td>
</tr>
<tr>
<td>Personal hopefulness</td>
<td>.21$^{#T}$</td>
<td>.25$^{#T}$</td>
<td>-1.68</td>
<td>2.15</td>
<td>.143</td>
<td>GH</td>
</tr>
<tr>
<td>Adverse life events (12 mth)</td>
<td>-.08</td>
<td>-.15</td>
<td>3.32</td>
<td>9.72</td>
<td>.002</td>
<td>MH</td>
</tr>
<tr>
<td>Current and past health</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depression diagnosis (LT)</td>
<td>-.08</td>
<td>-.19</td>
<td>4.52</td>
<td>17.35</td>
<td>***</td>
<td>MH</td>
</tr>
<tr>
<td>Cardiovascular diagnosis (LT)</td>
<td>-.14</td>
<td>-.04</td>
<td>-4.59</td>
<td>17.81</td>
<td>***</td>
<td>PH</td>
</tr>
<tr>
<td>Current smoker</td>
<td>-.05</td>
<td>-.05</td>
<td>.00</td>
<td>.00</td>
<td>.999</td>
<td>GH</td>
</tr>
<tr>
<td>Serious injury (12 mth)</td>
<td>-.09</td>
<td>-.02</td>
<td>-3.14</td>
<td>9.47</td>
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<td>PH</td>
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<tr>
<td>Alcohol consumption</td>
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<td>.02</td>
<td>-.59</td>
<td>.29</td>
<td>.588</td>
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<td>Individual social networks</td>
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</tr>
<tr>
<td>Social support</td>
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<td>.11</td>
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<td>4.28</td>
<td>.039</td>
<td>GH</td>
</tr>
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<td>Cohesion</td>
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<td>-.03</td>
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<td>1.19</td>
<td>.276</td>
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</tr>
<tr>
<td>Social visibility</td>
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<td>-.01</td>
<td>.32</td>
<td>.07</td>
<td>.795</td>
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</tr>
<tr>
<td>Belonging</td>
<td>.04$^{#G}$</td>
<td>.08$^{#G}$</td>
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<td>1.46</td>
<td>.226</td>
<td>GH</td>
</tr>
<tr>
<td>Area characteristics</td>
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<td></td>
</tr>
<tr>
<td>Socioeconomic status</td>
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<td>-2.53</td>
<td>4.79</td>
<td>.029</td>
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<td>Health service accessibility</td>
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<td>.00</td>
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<td>1.92</td>
<td>.166</td>
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</tr>
<tr>
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<td>.04</td>
<td>.09</td>
<td>.01</td>
<td>.929</td>
<td></td>
</tr>
</tbody>
</table>

*** $p < .001$; CR = critical ratio; $^{#T}$ = association moderated by phase; $^{#G}$ = association moderated by gender; MH = mental health association stronger; PH = physical health association stronger; GH = association did not differ by health outcome (general health factor); (PH) = trend suggesting stronger association with physical health; LT = lifetime; $\beta$ = standardized regression weight.

**Discussion**

The current study revealed personal and social predictors of overall physical and mental health that were reliably observed over three survey phases. Several factors were associated with both health outcomes, with model fit indices used to determine those equally associated with physical and mental health (i.e., not being a current smoker, personal hopefulness, social
support, and a sense of belonging), and those displaying a somewhat stronger association with physical health (lower financial difficulty, absence of a lifetime cardiovascular diagnosis) or mental health outcomes (lower neuroticism, fewer recent adverse life events, absence of a lifetime depression diagnosis). Other factors were only associated with physical health (i.e., lower proportion of life lived in the current district, absence of recent serious injury).

The current study observed an association between a greater proportion of life lived in the current district and poorer physical but not mental health. While little is known regarding the association of migration and health in Australia, these results are consistent with research suggesting that Australians living in rural areas have a lower likelihood of moving to more urban areas following the onset of chronic physical, but not mental, illness [47]. Thus the current results may indicate that poor physical health either prevents or is not seen as a reason for persons to leave a community.

Our models suggest a key role of personal adversity in mental and physical health outcomes. Recent adverse life events [48] and financial difficulty [49] contributed considerably to the prediction of physical and mental health, despite the inclusion of potential confounders such as trait neuroticism [50] and area-level disadvantage [49]. Further, financial difficulty and adverse life events had the greatest impact on physical and mental health respectively. These observations may raise awareness of the impacts of stress on health as well as improving our understanding of the nature of burdens associated with these specific factors i.e., the association of stressful life events with physical health may be primarily driven by their mental health burdens.

Some correlates of physical and mental health differed for men and women (i.e., living on a farm, a sense of belonging, alcohol consumption, social support and social visibility) while others, in line with previous research [51], did not (i.e., demographic, personality, financial stress, adverse life events, social support factors). In the physical health model, alcohol
consumption, social visibility and a sense of belonging differed by gender however, only a sense of belonging yielded statistically significant parameters in the gender-specific models. A greater sense of belonging associated with greater physical health for men, but not for women. In the mental health model, living on a farm was associated with poorer mental health for women, but not for men, and a sense of belonging was more strongly associated with greater mental health for men compared to women. Current models indicate a (trend level) association of greater social visibility with poorer physical health for men only. Differential associations of social visibility with health for men and women have been previously observed in Australia, with greater area-level ‘neighbourhood alienation’ (e.g., If I no longer lived here, hardly anyone around here would notice; I have little to do with people in this neighbourhood) associated with poor self-rated health for men (negative association) and women (positive association) [23]. Differential influences of social visibility by gender were also observed for our supplementary analyses of psychological distress (Appendix 6.1, Table S8) and at a trend level for analyses of mental health (Table 6.4, CR = 2.37).

These results highlight the possibility that social and physical conditions may have different influences on health for men and women. Potential differential effects of isolation (i.e., social visibility and living on a farm) on health outcomes for men and women are of particular relevance for rural and remote populations. The finding of a differential health association of alcohol consumption by gender contrast with previous research [51], with women displaying the common positive association (reflecting lower consumption by persons in ill health [52,8]) but with no association for men in the current sample. Reasons for the absence of this effect for men are unclear but may be related to a strong drinking culture and reluctance to seek medical advice among rural Australian men [53], lessening the positive association between drinking and health in this group.
Several factors were highly stable over the three year follow-up period (marital status, retirement status, living on a farm, lifetime depression or cardiovascular diagnoses, smoking status and alcohol consumption) while others varied (perceived financial difficulty, recent life events, social networks and physical and mental health). These observations have potential implications for investigations into the relationships between such factors and health outcomes over time; for example, if retirement status is highly stable over a particular follow-up period, the capacity to examine its causal relationship with health is limited. Additionally, knowledge that correlates of health varied over the study time period may have important implications for treatment settings; for example, variations in personal adversity and social characteristics suggest that it may be important to undertake ongoing assessment of factors such as the presence of adequate supportive relationships. Finally, knowledge regarding the stability of participant characteristics aids in our understanding of these factors and their utility as predictors within cross-sectional models. For example, retirement was associated with poorer physical health at baseline, but not follow-up phases. As retirement status was observed to be highly stable over this assessment period, this finding may indicate that greater time since retirement weakened the association between retirement and experiences of lower physical health. Similarly, an apparent increase in the association of personal hopefulness with physical and mental health over time was observed, likely due to the sole measurement of this variable at T2.

No significant association between health and contextual indices was observed. Marginal associations of higher area-level health service accessibility ($p = .017$) and Trust ($p = .013$) with better physical health, and increased socioeconomic status ($p = .013$) and Trust ($p = .010$) with better mental health were observed. There was a corresponding negative association of Trust with increased current psychological distress in our supplementary analyses (Appendix 6.1, Table S8: $\beta = -.06$, $p < .001$). Trust has been identified as a multilevel predictor of health in
previous studies [20,21,54,19]. The current study builds on previous work [55] demonstrating an association of individual-level Trust and psychological distress in the NSW adult population health survey, when controlling for a range of demographic and socioeconomic indices, by exploring the association of area-level Trust with physical and mental health outcomes.

With a few exceptions [56], characterisation of social contextual factors has been rarely attempted in Australia and, to our knowledge, is the first study to apply a theory-driven method of aggregation to overcome challenges associated with characterising rural and remote contexts. Several researchers suggest that the relevant physical scale of the environment for characterising ‘area’ effects is likely to differ between urban and rural areas [26,57]. Contention also exists regarding whether the health-relevant characteristics of non-urban areas are spread over larger spatial units, as the relevant resources, including population, are spread over greater distances [26], or smaller spatial units, as townships exist in smaller areas [57]. The observation of consistent marginal (and univariate) associations of this fairly well established effect across three health outcomes provides some support for our larger area-level conceptualisation of social capital for sparsely population areas; and potentially reinforces its ability to be characterised using broader environmental factors, as opposed to small area classifications. However, whether this is the most appropriate characterisation is yet to be established and statements regarding the relative importance of contextual social capital for health in urban versus rural areas should be made with due caution.

Finally, the current study found no evidence of a differential association of contextual variables with health outcomes by gender. Analyses of a representative sample from Tasmania, Australia, found interactions between health and political participation, neighbourhood safety and neighbourhood alienation by gender; although these associations are in line with current results, interactions with socioeconomic status and Trust were not observed [23].
**Usage of integrated multilevel cross-sectional models**

The use of an integrated analysis strategy allowed us to not only replicate the current models of physical and mental health at three different phases of data collection but to formally test whether the observed associations significantly differed between these models. Previously, assessment of model comparisons and cross-validation have involved running analyses independently within each phase or group, followed by a non-statistical comparison of model parameters (e.g., coefficients and/or the proportion of variance explained) or explored further using non-equivalent overall models with interaction terms (i.e., [23]). A limitation of the current application of this relatively advanced method (i.e., integrated cross-sectional analyses) is that while our model was confirmed to be stable over phases (within the current sample), the extent to which these findings would replicate in a broader sample remains unclear.

**Limitations**

Results suggest persons who met criteria for inclusion in the current analyses represent a somewhat healthier, socioeconomic ally advantaged and less remote sub-sample of the baseline ARMHS cohort. Thus, the generalizability of the current results are limited and the observed associations of individual and area-level factors with health are potentially weaker than those present in the general population. The relative magnitude of the associations with health domains should be similarly interpreted in light of the sample limitations.

The current cross-sectional analyses cannot provide information regarding the causal nature of the observed associations. The interpretation offered here is sensitive to the existing literature and potential for observed associations to represent not only the influence of model predictors on health outcomes, but also health outcomes on predictors. An additional potential for the true causal associations between these variables to include mediating
pathways, through which the modelled predictor variables are associated with health outcomes, means that some associations may be inflated or spurious. Further analyses utilising the temporal features of the ARMHS dataset will allow exploration of the direct and indirect nature of the health related effects reported here.

**Conclusions**

The various layers of data (e.g., individual-level, area-level) and statistical analysis (e.g., integrated cross-sectional analyses and moderation effects) within the current study improve our overall understanding of physical and mental health in rural areas. The current study suggests that social support and a sense of belonging are positively associated with a global health factor, while the association of other variables with the modelled outcomes may have primarily indirect effects on physical and mental health outcomes, commonly assessed in isolation, representing correlated dimensions of health. The value placed on living in the current community displayed a greater association with health for men while factors associated with isolation had different effects for the health experiences of men and women. Information from the current cross-sectional analyses will support further modelling of causal influences, which may help to identify factors that represent potential points of health intervention, relative to non-causal personal or social factors that largely co-vary with health outcomes.

The often observed association of area-level Trust with health was detectable in the current study, reinforcing the potential utility of aggregating data from broader areas sharing common environmental and social forces. This knowledge may facilitate further research into the role of contextual forces on health outcomes in areas with low population density, where obtaining adequate area-level data for meaningful characterisation is often difficult, but may present important areas for health intervention [58].
References


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Chapter seven: Potential causal pathways between personal adversity, social networks and perceived physical and mental health outcomes for rural men and women

This chapter was disseminated in the academic literature as:


Synopsis

The causal pathways between perceived physical health, mental health, personal adversity and social networks in a rural sample are assessed using cross-lagged panel analyses across three phases of data collection for men and women. The direct and indirect impacts of personal adversity and social networks on perceived health outcomes are examined.
Introduction to Chapter seven

Effective targeting of resources is essential in rural environments where populations are dispersed and barriers to accessing health services are many. Understanding causal pathways between health and its predictors enhances our understanding of cross-sectional associations and helps identify suitable targets for intervention. In Chapter six, social networks and experiences of personal adversity displayed stable associations with health outcomes and displayed variability within participants over the baseline, one and three year follow-up periods of the ARMHS. Theories of the health impacts of social networks and adversity propose that these factors have direct, indirect and reciprocal associations with health outcomes, though these effects are rarely tested. Models of the health impacts of social networks suggest that an individual’s social networks both influence health, and are influenced by health states [1]. Social networks are also thought to protect individuals from experiencing personal adversity, thus reducing the health impacts of personal adversity [2]. To date, few analyses have modelled these effects simultaneously and to our knowledge this is the first to investigate these processes in rural areas. Further, recent models of the causal association between individual level social capital and health have not attempted to tease out the physical versus mental health related natures of these associations, nor have they modelled the influence that personal social support may exert upon these associations. Additionally, few causal models have been examined by gender and none have included statistical comparison of these models. Finally, knowledge of the time periods over which factors influencing health operate is crucial to understanding the nature of these associations as well as for the evaluation of health interventions.

Chapter seven builds upon findings of Chapters three and five that the associations of social and adversity factors differ with contextual effects, as well as the findings of Chapter six regarding the significance and stability of health determinants by gender and over time in a
longitudinal rural cohort study. The ARMHS data set presents a unique opportunity to assess the causal associations of social networks, personal adversity and perceived health over two follow-up periods, and to assess whether these models differ for men and women from rural areas of NSW, Australia.

**Aims and purpose**

This chapter aimed to examine the potential causal associations between personal adversity, social networks and health factors, the time periods over which these effects operate, and whether they differ for men and women in rural areas. Specifically, the purpose of this chapter was to explore whether aspects of personal adversity and social networks represent direct and/or indirect points of health intervention and whether these effects can be observed over one and two year follow-up periods. The potential causal nature of the gender modified cross-sectional associations of social visibility with physical health and a sense of belonging, observed in Chapter six, are also of interest. This is the sixth manuscript of the thesis and has been submitted to the Journal of Health and Social Behavior.

**Contribution to primary research question**

Current results suggest that in rural areas, social networks, personal adversity and health are causally linked in ways similar to those observed in theoretical and urban-based data models. Causal associations between these conceptual variable groups are depicted in Figure 7.0. Social support and financial difficulty have independent direct impacts on both physical and mental health outcomes. Social support also displayed an indirect effect on health outcomes by protecting against financial adversity. Mental health presents an important point of intervention for physical health concerns over two years. Men who report high social visibility in rural areas, that is, they report being known and identifiable in the area, may also be susceptible to poor physical health over a two-year period.
Figure 7.0 Causal associations between variable groups over one and two year time lags.

Candidate’s contribution

The candidate: created a longitudinal dataset across multiple ARMHS data collection waves; performed imputation using expectation maximisation methods; investigated and applied a multilevel three phase cross lagged panel design to assess the potential reciprocal associations between personal adversity, social and health factors over two time lags, as well as their invariance by groups; and contributed substantially to the preparation of the current manuscript.
References


A three phase cross-lagged analysis of relationships between personal adversity, social networks and health in rural areas

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Abstract

Reciprocal associations between personal adversity, social network factors and health outcomes have frequently been posited but rarely assessed. We investigate these relationships using multivariate autoregressive cross-lagged panel analyses of 1132 adults (62% female) responding to three phases of the Australian Rural Mental Health Survey. Surveys assessed aspects of personal adversity (financial difficulty, adverse life events, and injury), social network factors (e.g., social support, social capital), and health (self-rated physical and mental health). Results demonstrate greater financial difficulty and lower social support were associated with poorer physical and mental health over time. Poorer mental health was associated with higher financial difficulty and adverse life events as well as poorer physical health. Higher social support was associated with lower financial difficulty. Social capital was associated with greater social support over time. Few differences between men and women were observed. These findings offer useful information for health interventions and their evaluation.

Keywords

Rural areas, physical health, mental health, social capital, social visibility, cross-lagged panel design, Australia.
Introduction

Theoretical models have long suggested links between health outcomes, personal adversity and social network factors, such as social support and social capital [1,2]. These factors may directly influence health outcomes by influencing stress [1,3,4], the availability of material resources and exposure to health related information [2]. The potential for poorer health to influence future personal adversity and social networks has also been acknowledged [5] but has received less research attention. As a range of social connections and related terms are discussed in this literature, we use the expression social networks to collectively refer to the social resources available to individuals through their close personal networks (social support) and the broader community (social capital). Similarly, we use the term personal adversity to refer to potentially stressful events or situations to which persons in the general community may be exposed.

Despite the potential for reciprocal associations of health personal adversity and social network factors, few causal studies have simultaneously modelled these relationships, potentially distorting the observed causal associations between these factors [6]. Additionally, social theorists also suggest social network factors may have an indirect influence on health due to their potential to reduce exposure to personal adversity such as financial hardship, unemployment or relationship breakdown [2] or their associated effects [7,8]. To examine causal relationships, cross-lagged panel (CLP) analyses simultaneously estimate the cross-sectional associations, stability and reciprocal associations of two or more factors over time. These designs allow for the specification of covariation between error terms, which accounts for the systematic variation of both factors attributable to some third unobserved variable [9]. Estimation of such models requires factors measured over multiple time points and with reasonable variation over the assessment period (e.g., it is impossible to assess the reciprocal
influence of retirement on health if either retirement or health status display little variation over the assessment period).

Cross-lagged panel analyses have been used to assess the associations between: mental and physical health over time [10-15]; social factors and physical [16-23] and mental [24-28,23,29] health over time; and personal adversity and physical health [30-32] over time. However, casual associations of personal adversity and social factors with health outcomes remain under-examined and necessitate studies using longitudinal cohorts. Further, the absence of multivariate assessments in such designs may lead to inappropriate causal inferences. For example, the concurrent assessment of personal social support is considered necessary to understand the independent effects of broader social resources, such as social capital (i.e., the social networks within the communities that people live that promote trust, reciprocity and social cohesion [33]), on an individual’s health [34]. Omission of such important control variables mean that findings of a causal influence of reported social capital on health outcomes [23] may simply reflect elements of an individual’s in personal social support characteristics and capacities.

The current study builds on recent integrated cross-sectional analyses identifying several personal adversity (namely, financial difficulty, recent adverse life events and serious injury) and social (namely, social support and two dimensions of social capital: social visibility and a sense of belonging) correlates of physical and mental health outcomes across three phases of data collection in a sample of persons drawn from rural and remote areas of New South Wales, Australia [35]. These analyses revealed some factors displaying different associations with physical health outcomes (financial difficulty, injury factors) and mental health outcomes (adverse life events factors) and some differential associations by gender.

The current analyses explore reciprocal causal relationships between personal adversity, social factors and physical and mental health outcomes over two time lags in a large community
sample using a multi-group multivariate three phase cross-lagged panel design. Drawing on previous work by our group and others, in addition to a base model (M0) – that these factors will display cross-sectional correlations and some stability over time – we hypothesize: 1) reciprocal health associations (M1) – that physical and mental health outcomes will display ongoing associations over time; 2) lagged health predictors (M2) - that personal adversity and social factors will predict health outcomes over time; 3) lagged health consequences (M3) – that health outcomes will also predict subsequent adversity and social factors; and 4) other potential paths (M4) – that personal adversity and social factors will display associations over time. Both the significance of paths and their additional contribution to explained model variance will be assessed. Finally, we will assess whether these causal model are influenced by participant gender.

Data and methods

Participants

The current study is based on self-report postal survey data from three phases of the Australian Rural Mental Health Study (ARMHS), collected 2007-2012; see Kelly et al. [36,37] for details of recruitment and study design. ARMHS is a five year longitudinal cohort study examining the determinants of health outcomes over time in non-metropolitan areas of New South Wales (NSW), Australia. The ARMHS cohort comprises a stratified random sample of community dwelling persons aged 18 years and over listed on the NSW state electoral roll and residing in inner-regional to very remote local government areas. Ethical approval was obtained from the relevant institutional Human Research Ethics Committees. At ARMHS baseline (T0), a response rate of 27% (n = 2639) was achieved. Of the 1168 participants responding at all three phases, 97% (n = 1132) provided adequate data (less than 25% missing data) for inclusion in the current analyses (years lag: between T0 and 1 year follow-up (T1),
mean = 1.05, SD = 0.26; between T1 and 3 year follow-up (T2), mean = 2.10, SD = 0.33). The current longitudinal sample represents 43% of baseline respondents. As previously reported, this represents a somewhat less remote and less socioeconomically disadvantaged subsample of baseline participants [35].

**Current measures**

Detailed information regarding participant characteristics and measures of personal adversity, social factors and physical and mental health have been reported previously [35]. Briefly, data were obtained by postal surveys assessing a range of participant characteristics at each survey phase. Measures included in the current analyses were selected due to their: a) association with physical or mental health, and b) low to moderate stability over the three year follow-up period.

Current overall physical health and mental health perceptions were each rated on a single five point scale (range 1-5) with higher scores indicating greater health. Temporal stability and multivariate correlation of factors associated cross-sectionally with health outcomes are reported in Table 7.1. Indices of personal adversity included self-reported financial difficulty [38] (range 1-7), a count of endorsed recent (12 month) adverse life events (range 0-12) [39] and occurrence of an injury requiring hospital treatment in the last 12 months. Social support was assessed using the 6-item Availability of Attachment subscale of the abbreviated Interview Schedule for Social Interaction [40] with higher scores indicating greater social support (range 0-1). Two aspects of individual’s social capital were assessed using subscales derived from the Sense of Community Index [41], referred to here as Social visibility (sample item: ‘I care about what other residents in the district think of my actions’), and Belonging (sample item: ‘It is very important to me to live in this particular district’).
Table 7.1 Temporal stability and cross-sectional multivariate associations of selected adversity and social factors with physical and mental health (N = 3396).

<table>
<thead>
<tr>
<th>Variables</th>
<th>Stability</th>
<th>Physical</th>
<th>Mental</th>
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<tbody>
<tr>
<td></td>
<td>$r_{icc}$</td>
<td>$\beta$</td>
<td>$\beta$</td>
</tr>
<tr>
<td><strong>Personal adversity</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Financial difficulty</td>
<td>.69***</td>
<td>-.14***</td>
<td>-.06***</td>
</tr>
<tr>
<td>Adverse life events (12mth)</td>
<td>.33***</td>
<td>-.08***</td>
<td>-.15***</td>
</tr>
<tr>
<td>Serious injury (12mth)</td>
<td>.22***</td>
<td>-.09***</td>
<td>-.02ns</td>
</tr>
<tr>
<td><strong>Social factors</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social support</td>
<td>.52***</td>
<td>.06***</td>
<td>.11***</td>
</tr>
<tr>
<td>Visibility</td>
<td>.54***</td>
<td>$^M$.05*, $^W$.03ns</td>
<td>-.01ns</td>
</tr>
<tr>
<td>Belonging</td>
<td>.56***</td>
<td>$^M$.10**, $^W$.02ns</td>
<td>$^M$.12**, $^W$.06**</td>
</tr>
<tr>
<td><strong>Health factors</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Physical</td>
<td>.51***</td>
<td>.</td>
<td>.51***</td>
</tr>
<tr>
<td>Mental</td>
<td>.58***</td>
<td>.51***</td>
<td>.</td>
</tr>
</tbody>
</table>

Note: Table summarises relevant results from our previous integrated cross-sectional analyses [Allen et al. (under review)]; $r_{icc}$, intra-class correlation coefficient (absolute); $\beta$, standardized multivariate model coefficient; $r$, univariate correlation; *** p < .001, ** p < .01, * p < .05; $^W$ (women) and $^M$ (men) indicate the gender specific association for paths that displayed significant modification by gender. Multivariate models included additional factors: demographic (age, gender, education, marital status, retirement status, living on a farm, proportion of life lived in district), individual (neuroticism, personal hopefulness), current and past health (life time diagnoses of depression and cardiovascular diagnoses, current smoking status, alcohol consumption), social (social cohesion) and contextual characteristics (socioeconomic status, health service accessibility and Trust).

**Analyses**

Analyses were conducted using AMOS (v.20; IBM Corporation, Chicago IL, USA). An $\alpha < .01$ (corresponding Critical Ratio, CR = +/-2.58) was used as the threshold for all tests of statistical significance, with trends of $p < .05$ noted (corresponding CR = +/-1.96). As reported previously [35], missing values were imputed using SPSS’s built-in expectation-maximization estimation.
procedure to address potential bias caused by the exclusion of respondents with missing data. Participants who had no more than 25% missing item data on cross-sectional model variables within each phase were included in the imputation procedure. Following the recommendations of Graham [42], all model variables, as well as auxiliary variables which could inform the estimation of missing model variables, were included in this procedure. No more than 8% of data were imputed for any model variable and overall 1% of data were imputed.

Structural equation modelling (SEM) was used to assess the auto-regressive and reciprocal associations between personal adversity, social factors and physical and mental health outcomes over time. SEM is particularly suited to the simultaneous assessment of reciprocal influences using cross-lagged panel (CLP) models and the influence of potential moderating factors such as gender. In CLP models, the reciprocal influences of two or more time lagged variables can be estimated while accounting for their stability over time [6]. The potential influence of unobserved variables can be taken into account by modelling the potential correlation of error terms, thus addressing interpretational concerns that associations may be produced by co-variation with some third variable. Three phase autoregressive cross-lagged predictive models allow the simultaneous estimation of the stability, cross-sectional and longitudinal associations between predictors and outcomes, informing whether a variable is influenced not only by its own previous state, but also some other variable, as well as whether it influences another factor at a later phase [43]. A three phase CLP analysis was conducted to assess the reciprocal associations of personal adversity, social factors, physical health and mental health. The correlation matrices used to produce the reported overall and gender specific CLP models are provided in the supplementary documentation (Appendix 7.1, Tables S1a-1c).
Maximum likelihood estimations were used for all SEM procedures. Squared multiple correlations (SMC) were obtained to assess the portion of variability in longitudinal outcomes explained by lagged predictors. Chi-squared difference tests were examined to assess whether model fit differed significantly with increasing model complexity (nested models M0 to M4) and gender. Critical ratios for differences between each model path were inspected to identify where differences occurred. Figure 7.1 depicts the autoregressive cross-lagged model used to assess the potential for simultaneous reciprocal causation between individual personal, social and health characteristics over time. The model includes: correlations between baseline factors, disturbance terms within phases, and autoregressive associations of variables at adjacent phases (M0: base model); lagged effects of physical and mental health from a previous phase onto physical and mental health at the following phase (M1: reciprocal lagged health associations); lagged effects of personal adversity and social factors from a previous phase onto physical and mental health states at the following phase (M2: lagged health predictors); lagged effects of physical and mental health states from a previous phase onto personal adversity and social factors at the following phase (M3: lagged health consequences); and cross-lagged effects of personal adversity and social factors from a previous phase onto personal adversity and social factors at the following phase (M4: other potential paths). The potential for path moderation by gender was assessed using a backward sequential release strategy and assessing the decrement in model fit [44] to achieve a parsimonious account of model differences. Structural parameter coefficients were constrained to be equal across male and female groups and model fit compared with that of a model unconstrained by gender. Where model fit was impacted by parameter constraints, critical ratios were examined and freed one at a time starting with the largest difference and the model fit reassessed until the chi-squared difference test suggested there was no significant decrement to overall model fit. As standardised coefficients may display small differences due to different variances between
groups, where coefficients did not significantly differ, standardised coefficients represent the mean of the male and female standardized coefficients (largest observed difference in standardized coefficients: $\beta = +/- .02$).
Figure 7.1 Hypothesised multi-level cross-lagged models of personal adversity, social experiences and health. Note: model M1: reciprocal lagged health associations; model M2: lagged health predictors; model M3: lagged health consequences; model M4: other indirect paths. Covariation between baseline variables, disturbance terms (δ) specified within Time 1 and Time 2, and single phase auto regressive paths are not shown but were included in all models (model M0); black lines indicate new paths introduced in each model and grey lines indicate paths introduced in previous models.
**Results**

Chi-squared difference tests of nested models suggested that more restrictive models provided poorer model fit in all cases (Table 2). The final model specifying baseline covariation, autoregressive paths and cross-lagged paths between all variables displayed inadequate model fit. As previous analyses suggested, these variables displayed low to moderate consistency over the three year period (Table 7.1). Eight additional autoregressive paths linking T0 and T2 variables were specified (which has been referred to as a Within construct model [45]: Model M5). This model provided excellent fit to the data, suggesting that an additional component of longer term consistency over the three year period accounted for the misfit in model M4. While increasing model fit, inspection of model M5 revealed little additional increase in the variability explained for lagged outcomes and few differences in cross-lagged associations compared to Model M4 (see Appendix 7.1, Table S4 for reporting of Model M5). Thus, CLP models including reciprocal casual associations between personal adversity, social factors and health outcomes and single phase autoregressive lags (M4) were retained for subsequent analyses.

Assessment of gender modification of the CLP models suggested constraining paths to be equal across male and female groups significantly worsened model fit. Inspection of path CRs suggested the co-variation of baseline social support and mental health displayed the greatest difference across genders (CR = -3.32), followed by the lagged association of social visibility at T1 with physical health at T2 (CR = 3.21, see Appendix 7.1, Table S2 for all CR for path differences across gender models). Consequently, we compared three sub-models with one in which all parameters were estimated freely by gender: constraining all parameters to be equal across genders (M4a); estimating T0 covariation of social support and mental health freely by gender (M4b); and finally estimating the lagged association of T1 social visibility and T2 physical health freely by gender (M4c). This analysis suggested that the third model (M4c)
provided the most parsimonious account of the data. All following results refer to effects observed in Model M4c.
Table 7.2 Nested model comparisons (comparing the fit of less constrained models against those with greater constraints).

<table>
<thead>
<tr>
<th>Model</th>
<th>Model complexity</th>
<th>Parameters estimated (N)</th>
<th>Overall chi-square test (df)</th>
<th>TLI</th>
<th>CFI</th>
<th>RMSEA</th>
<th>Physical health SMC</th>
<th>Mental health SMC</th>
<th>Chi-squared difference (df) ΔX²</th>
</tr>
</thead>
<tbody>
<tr>
<td>M0</td>
<td>Cross-sectional associations and T₀ → T₁ and T₁ → T₂ autoregressive paths</td>
<td>124</td>
<td>648.28(176), ***</td>
<td>.80</td>
<td>.87</td>
<td>.17 (.16, .18)</td>
<td>.29</td>
<td>.22</td>
<td>.33</td>
</tr>
<tr>
<td>M1</td>
<td>+ reciprocal lagged health associations</td>
<td>128</td>
<td>631.19(172), ***</td>
<td>.80</td>
<td>.88</td>
<td>.08 (.07, .09)</td>
<td>.31</td>
<td>.27</td>
<td>.34</td>
</tr>
<tr>
<td>M2</td>
<td>+ lagged health predictors</td>
<td>152</td>
<td>583.05(148), ***</td>
<td>.78</td>
<td>.88</td>
<td>.08 (.07, .09)</td>
<td>.33</td>
<td>.29</td>
<td>.37</td>
</tr>
<tr>
<td>M3</td>
<td>+ lagged health consequences</td>
<td>176</td>
<td>519.43(124), ***</td>
<td>.76</td>
<td>.89</td>
<td>.08 (.08, .09)</td>
<td>.36</td>
<td>.31</td>
<td>.40</td>
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<tr>
<td>M4</td>
<td>+ other indirect paths</td>
<td>236</td>
<td>384.08(64), ***</td>
<td>.62</td>
<td>.91</td>
<td>.09 (.08, .09)</td>
<td>.36</td>
<td>.30</td>
<td>.41</td>
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<tr>
<td>M5</td>
<td>+ T₀ → T₂ autoregressive paths</td>
<td>244</td>
<td>64.64(56), p = .200</td>
<td>.99</td>
<td>1.00</td>
<td>.02 (.00, .04)</td>
<td>.36</td>
<td>.36</td>
<td>.41</td>
</tr>
<tr>
<td>Gender moderation</td>
<td>vs. previous model:</td>
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<tr>
<td>M4a</td>
<td>Gender constrained</td>
<td>236</td>
<td>1090.17(284), ***</td>
<td>.83</td>
<td>.91</td>
<td>.05 (.05, .05)</td>
<td>(156) 195.25, p = .018</td>
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<tr>
<td>M4b</td>
<td>1 free parameter</td>
<td>237</td>
<td>1082.52(283), ***</td>
<td>.83</td>
<td>.91</td>
<td>.05 (.05, .05)</td>
<td>(155) 187.60, p = .038</td>
<td></td>
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<tr>
<td>M4c</td>
<td>2 free parameters</td>
<td>238</td>
<td>1071.58(282), ***</td>
<td>.83</td>
<td>.92</td>
<td>.12 (.12, .12)</td>
<td>(154) 176.66, p = .102</td>
<td></td>
<td></td>
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</table>

Note: TLI, Tucker-Lewis Index; CFI, Comparative Fit Index; RMSEA, root mean square error of approximation and 90% confidence interval; SMC, squared multiple correlation; +, indicates addition of paths to previous model (nested models); gender constrained model holds baseline covariances and all regression weights to be constant across models; SS₀, social support at Time 0; MH₀, Mental health at Time 0; SV₁, social visibility at Time 1; PH₂, physical health at Time 2.
The associations of model factors over the one and two year lagged observation periods are reported in Table 7.3. SMCs are presented at the bottom of Table 7.3 and suggest the model explained roughly equal variability for outcomes in both the male and female models. Approximately a third of the variability in health and social outcomes was explained by the model, while a slightly higher proportion of variability was explained for financial difficulty and a lower proportion for adverse life events and injury. All covariance parameters and CRs for gender differences are presented in supplementary Tables S2 and S3. Standardized coefficients for significant cross-lagged paths are presented in Figure 7.2.
Table 7.3 Path coefficients from cross-lagged panel model (M4).

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Table 7.3 continued. Path coefficients from cross-lagged panel model (M4).

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<td><strong>T0 IV --&gt; T1 DV</strong></td>
<td>B: .32 p: .003</td>
<td>B: .43 p: ***</td>
<td>B: -.22 p: .002</td>
<td>B: -.11 p: .503</td>
<td>B: .08 p: .087</td>
<td>B: .52 p: ***</td>
<td>B: .03 p: .538</td>
<td>B: .06 p: .024</td>
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<tr>
<td><strong>T1 IV --&gt; T2 DV</strong></td>
<td>B: .07 p: .538</td>
<td>B: .15 p: .149</td>
<td>B: -.02 p: .834</td>
<td>B: -.01 p: .968</td>
<td>B: .02 p: .708</td>
<td>B: .44 p: ***</td>
<td>B: .09 p: .019</td>
<td>B: .07 p: .009</td>
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<td><strong>T0 IV --&gt; T1 DV</strong></td>
<td>B: .03 p: .666</td>
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<td>B: .01 p: .815</td>
<td>B: .11 p: .343</td>
<td>B: -.04 p: .215</td>
<td>B: .04 p: .017</td>
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<td><strong>T1 IV --&gt; T2 DV</strong></td>
<td>B: F: .15 p: .100</td>
<td>M: -.27 p: .014</td>
<td>B: -.08 p: .312</td>
<td>B: -.10 p: .065</td>
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<td>B: -.02 p: .605</td>
<td>B: .03 p: .102</td>
<td>B: .48 p: ***</td>
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<td><strong>T0 IV --&gt; T1 DV</strong></td>
<td>B: -.08 p: .489</td>
<td>B: .15 p: .208</td>
<td>B: .00 p: .958</td>
<td>B: -.20 p: .285</td>
<td>B: -.05 p: .324</td>
<td>B: .00 p: .991</td>
<td>B: .21 p: ***</td>
<td>B: .53 p: ***</td>
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**Variance explained (SMC)**

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**Note:** IV, independent variable (predictor); DV, dependent variable (outcome); SMC, squared multiple correlation; B, unstandardized coefficient; *** p < .001; coefficients significant at the p < .01 level are shaded in dark grey and trends at the p < .05 level in light grey; box indicates coefficients that differed for female (F) and male (M) groups.
Figure 7.2 Significant (solid lines, $p < .01$) and trend level (broken lines, $p < .05$) cross-lagged associations (model M4), standardized coefficients.
**M0 autoregressive paths**

Physical health, mental health, social support, social visibility, and belonging displayed comparable autoregressive associations (range $B = .43-.55$). Financial difficulty displayed the highest overall autoregressive associations, while experiences of recent serious injury and adverse life events displayed the lowest autoregressive associations over time ($B = .65$ vs $B = .21$ and .12, respectively).

**M1 reciprocal lagged health associations**

Better physical health was predicted by better mental health over a two year period ($B = .15$, $p < .001$). A trend ($p = .014$) indicating a weaker reciprocal effect, that is, better mental health predicted by better physical health, over a two year period was also observed.

**M2 other lagged health predictors**

Better physical health was predicted by lower financial difficulty ($B = -.17$, $p < .001$) and greater social support ($B = .32$, $p = .003$) over a one year period and by lower financial difficulty ($B = -.12$, $p < .001$) over a two year period. A trend indicating better physical health for men was predicted by lower social visibility over a two year period ($B = -.27$, $p = .014$) was also observed. Better mental health was predicted by lower financial difficulty ($B = -.11$, $p < .001$) and greater social support ($B = .43$, $p < .001$) over a one year period. Trends indicating better mental health to be predicted by a greater financial difficulty ($B = -.07$, $p = .050$) and greater sense of belonging ($B = .28$, $p = .025$) over a two year period were also observed.

**M3 lagged health consequences**

A trend suggesting better physical health to predict lower financial difficulty over a two year lag was observed ($p = .012$). Better mental health predicted fewer adverse life events over a
two year period and trends suggesting better mental health to predict fewer adverse life events over a one year period \((p = .015)\) and lower financial difficulty over a two year period \((p = .012)\) were also observed.

**M4 other indirect paths**

**Personal adversity predicting social network factors.**

There was little evidence of personal adversity factors impacting on social networks over one or two year periods. A trend suggesting a greater sense of belonging to be predicted by fewer adverse life events over a one year period \((p = .011)\) was observed.

**Social network factors predicting personal adversity.**

Impacts of social support and social capital factors on experiences of personal adversity over one and two year periods were observed. Financial difficulty was predicted by lower social support over a one year period \((p = .002)\). A greater number of adverse life events were predicted by greater social visibility \((B = .35, \ p = .005)\) and lower sense of belonging \((B = - .69, \ p < .001)\) over a two year period.

**Associations within personal adversity variables and social network variables.**

A greater number of adverse life events were predicted by greater financial difficulty over both one-year \((B = .22, \ p < .001)\) and two-year \((B = .17, \ p = .002)\) periods. A trend suggesting adverse life events to be predicted by injury over a two year period \((p < .011)\) was also observed. Injury was predicted by a greater number of adverse live events over a one-year period. No other adversity factor predicted financial difficulty over one- or two-year lags.

Greater social support was predicted by a greater sense of belonging over a two-year period and a trend suggesting social support to be predicted by greater social visibility \((p = .017)\) over a one-year period was also observed. Social visibility was predicted by a greater sense of...
belonging over both one-year (B = .21, p < .001) and two-year (B = .15, p = .001) periods and a
trend suggesting greater social visibility to be predicted by greater social support over a two-
year lag (p < .019) was also observed. Finally, a greater sense of belonging was predicted by
greater social support (B = .07, p = .009) and greater social visibility (B = .05, p = .005) over a
two-year period, with trends additionally suggesting a sense of belonging to be predicted by
greater social support over a one year period (p = .024).

Discussion

This paper presents a multivariate cross-lagged panel model of the predictive associations
between personal adversity, social factors and physical and mental health across two time
lags. As hypothesised, models introducing lagged associations between personal adversity,
social networks and physical and mental health each contributed significantly to explaining the
overall associations between these important factors. These results develop our understanding
of the observed cross-sectional relationships of these variables over time [35].

The findings suggest that physical and mental health displayed little causal association over a
one-year lag, when the stability of these factors over time and the influence of other social and
adversity factors are taken into account. However, a positive influence of good mental health
on better physical health was observed over the two-year lag. This evidence confirms the
causal impacts of these important health domains on each other, suggesting that these
processes function over longer periods of time, and that the impacts of mental health on
physical well-being are greater than the reciprocal effect. These results support calls for a
holistic view of health to be applied to the treatment of physical and mental health conditions
to achieve positive outcomes [46]. Recent discussions regarding the physical health
disadvantages of persons with serious mental health disorders [47] should perhaps be
broadened to acknowledge that poor perceived mental health may also have negative consequences for persons in the general community.

Examination of the direct impacts of personal adversity and social factors on health outcomes revealed that financial difficulty and personal social support influenced physical and mental health over the one-year lag, as did financial difficulty over the two-year lag. A trend level association suggesting a greater sense of belonging to predict better physical health over two year period was also observed. These results support previous findings of a direct influence of financial [48] and social support [49] on experiences of physical and mental health outcomes over time. The current work builds on existing analyses of the causal impacts of personal social capital on health outcomes [23] by simultaneously evaluating the impact of personal social support. The distinction between social support and personal social capital has been extensively discussed in the literature [34] but, to date, has not impacted on the development and evaluation of causal models.

Examination of the impacts of health on personal adversity and social factors revealed that better mental health was associated with a lower number of adverse life events over two year period. Trend level associations of an influence of mental health on adverse life events over the one year lag were observed. An association between poorer physical and mental health on financial difficulty over the two year lag was also identified. These results suggest that poorer health may increase the likelihood of personal adversity and that these effects may be best observed over a time period longer than one year.

Finally, the associations between personal adversity and social factors over time were examined to explore the potential indirect effects of these factors on health outcomes as hypothesised in models such as stress buffering [8,7] and social capital [2] theories. While there was little support for an influence of adversity on social networks, potential indirect links
between social networks and health through lower personal adversity were observed. Greater social support appeared to be protective against financial difficulty over the one-year period. Measures of community connectedness (i.e., social visibility and sense of belonging) also predicted fewer future adverse life events over the two year period. Overall these effects provide support for processes in which social support protects individuals from experiences of personal adversity which may in turn have negative health consequences. Current modelling suggests social support may protect against financial adversity which displayed relatively consistent negative health impacts, thus presenting an indirect influence of these factors on health outcomes. In turn, adversity factors may erode social factors such as social capital which are positively associated with social support, confirming that experiences of stressors such as adverse life events may have negative impacts on health resources. These are in line with models of social support and social capital [2] in which social resources protect against the experiences of adversity and promote opportunities such as employment.

The models developed in this study were generally consistent for both men and women, suggesting similar processes influenced the experiences and consequences of personal adversity, social networks, and health (cross-sectional associations [35]) for men and women. However, the cross-sectional influence of social support and mental health was significantly stronger for men than for women. Further, the causal influence social visibility on physical health was moderated by gender with a trend level influence of higher social visibility on poorer physical health observed for men but not for women. These moderating effects suggest that evaluation of social support and self-reported mental health are more strongly related in men than women. Additionally, there is some evidence that social visibility, that is, the degree to which a person feels they are known or recognisable in the community, may lead to poorer physical health outcomes in men.
As discussed previously [35] these results may be particular to the sample population, which was drawn from rural and remote areas of New South Wales, Australia. Current analyses build on these results by revealing that the differential association between social visibility and physical health for men represents a potential causal pathway as opposed to a cross-sectional association. The current observation that social visibility is positively associated with physical health for women but negatively for men, are of particular interest. These findings highlight the potential for social capital to have both positive and negative valence for health outcomes [4], as well as the importance of examining moderating effects such as gender when examining social determinants of health outcomes. Research has previously identified certain types of community interactions to be associated with higher current psychological distress in Australian community samples, namely ‘expressing opinions publicly’ and ‘political protest’ which were more frequently endorsed by men, while others were generally associated with lower distress [e.g., ‘contact with neighbours’, ‘participating in organised community activities’, ‘religious observance’: 50]. Thus current observations of an association of social visibility with poorer health outcomes for men may reflect an increased visibility due to participation in community interactions that are associated with stress. In contrast, the increased social visibility for women may reflect engagement in activities which are health promoting or in which women with poor health cannot, or do not, engage.

**Strengths and limitations of cross lagged analyses**

The current paper assessed potential causal impacts of personal adversity and social networks previously identified as associated with health. The current analyses contribute to our knowledge of these potential causal impacts by identifying whether personal adversity and social networks directly impact health outcomes and/or act indirectly through their causal influence on each other. This study examines the interplay of these important personal, social
and health factors simultaneously using sophisticated modeling to examine the interplay of these factors over one and two year periods to identify their causal relationships across time. Evidence provided here confirms that some factors impact on health over one- to two-year time periods. However, factors not displaying health impacts in our study, or for which marginal significance was observed (i.e., effect of physical health on mental health over a two year period or the impact of mental health on financial difficulty over a two year period) may still be important for health. Specifically, while in the current study causal associations were assessed over two discrete time lags, the underlying processes should be conceptualised as dynamic and continuous (e.g., the mental health impact of poor physical health may act and be resolved over a shorter or longer time period than those assessed). Thus, current results must be interpreted with caution.

**Other limitations**

The current sample was derived from rural and remote areas of Australia, where indices of income and access to infrastructure are lower than those of urban residents, as reflected by the low average post-code level SEIFA score (population average is 1000, while ARMHS participant values range 816.10-1049.42). Thus, the potentially health promoting consequences of socioeconomic advantage may not have been strongly represented in the current sample. However it should be noted that the current analyses are based on participants with relatively complete data over three survey phases and represent a relatively less remote and disadvantaged subsample of the Australian Rural Mental Health Survey sample. Further, the current sample was older than many community studies, and over one-third were retired, which may have contributed to better current mental health. Thus, the rural but relatively older and advantaged nature of the sample may limit underestimate the effects
present in the wider rural population, for whom factors such as financial adversity and social networks may be more dynamic.

Conclusions and practical recommendations

The current study demonstrates the complex interplay of personal adversity social factors and health outcomes that have long been discussed in the literature but rarely concurrently modelled. Findings of a direct impact of mental health on physical health, the importance of financial difficulty and social support for health outcomes and the indirect protective influences of social factors on adversity all provide evidence for potential points of health promotion and intervention programs (Figure 7.3). The negative effect of social visibility for men reinforces the need to examine important moderating factors such as gender. Finally, future studies aiming to examine theoretical causal associations between these variables or indeed the efficacy of public health interventions should attend to the relevant time lag over which these processes are likely to be observed (i.e., interrelationships of mental health interventions and subsequent physical outcomes may be better examined over two as opposed to one year time lags).
Figure 7.3 Causal paths between personal adversity, social networks and physical and mental health observed in the current study.
References


Chapter eight: Discussion and conclusions
Thesis overview: the impact of context on determinants of health across urban to remote areas of Australia

This thesis aimed to examine the impact of contextual characteristics on determinants of health across urban to remote areas of Australia utilising existing community and state survey data. In combining existing datasets, careful consideration was given to the potential benefits as well as threats to inference presented by this endeavour (Chapter two). Chapter three examined whether the demographic and social support determinants of high psychological distress were influenced by remoteness with a particular focus on social networks. Analyses of the validity and invariance of best available indices of health related quality of life (HRQoL) were conducted to ensure optimal comparability of physical and mental health constructs across urban and rural cohorts (Chapter four). Chapter five examined whether the personal adversity determinants of HRQoL were influenced by contextual remoteness and individual social capital. Data collected by the state health department was also used to explore the association of health service accessibility and social capital with remoteness (Chapter five). Applying a novel theory-driven method of aggregation, these data were subsequently used to characterise the health service accessibility and social capital characteristics of rural areas, allowing assessment of their association with self-rated health in these areas (Chapter six). Finally, the causal interactions of health, social networks and personal adversity in rural settings were examined (Chapter seven).

This thesis presented findings utilising two existing cohort studies and a state survey of population health. Participants were drawn from the Hunter Community Study (HCS) to obtain data regarding the mental, physical and social health of persons living in urban and inner regional areas of New South Wales. The overall response rate to the baseline HCS survey was
44.5% and a 3-5 year follow-up survey represented a subsample of 68.6% of baseline participants. Participants were also drawn from the Australian Rural Mental Health Study (ARMHS) to obtain data regarding the mental, physical and psychosocial health of persons living across inner regional to very remote areas of New South Wales. Overall baseline response rate for the ARMHS was 27.3%, and persons responding across three follow-up periods (utilised in Chapters six and seven) represented a subsample of 48% of baseline participants. Data from the 2006-2009 New South Wales Adult Population Health Surveys were utilised to examine the association of health service accessibility and social capital with remoteness, as well as to create contextual indices of these health-related factors for the purpose of examining their association with health in rural areas of Australia. The New South Wales Adult Population Health Surveys attracted a response rate of 59-64% during this period and data were weighted for nonresponse by age, gender and NSW Area Health Service administrative area. Neither questions regarding the impact of remoteness on determinants of health, nor the association of contextual factors with health in rural Australia, could have been explored using any of these datasets in isolation.

The purpose of this final discussion chapter is to link the published research chapters presented here to the overarching research thesis goals. This chapter provides an overview of the four key questions posed in the introduction and how they were addressed within the preceding six research chapters. Methodological factors limiting interpretation of the work overall are also discussed. In the following sections, each finding and its associated evidence and interpretation are detailed and the limitations specific to these analyses highlighted. The thesis concludes with the overall lessons and policy implications of the current work.
**Key thesis findings**

**Key finding one: The combination of individual participants data across multiple studies can be valuable for addressing new research questions**

The current research addresses questions that could not be addressed by existing resources in isolation. In considering the merits of utilising existing resources, it was believed that seeking additional funding and additional community responses to questions of interest would introduce too much redundancy with respect to existing resources. Further, it would place excess burden on the populations of interest, particularly within small rural communities in which a large proportion of persons had previously been contacted and surveyed for similar purposes.

Combining existing individual participant data from the HCS and ARMHS projects supported a systematic approach to address new research questions. These questions include the comparability of findings across studies, such as the operationalization of remoteness and measurement invariance of key concepts, as well as questions regarding the effects of community remoteness on determinants of health. Traditional methods of addressing questions using existing data typically involve comparisons of the strengths of associations observed within cohorts and meta-analytic techniques. By combining individual participant data, we were able to use statistical methods with greater power to detect differences across the spectrum of remoteness, such as the inclusion of relevant interaction terms. Further, a consistent method of operationalizing remoteness across datasets was applied by geocoding Australian Remoteness Index for Australia (ARIA+) values to participant postal codes. This circumvents a key issue in research on the influence of remoteness on health, that is, the use of varied and often over-simplified definitions and operationalization of remoteness between studies. Similarly, individual participant data analysis of these cohorts allowed questions of
measurement invariance in the conceptualisation of HRQoL impairment to be addressed. This increased confidence that inferences made regarding differences between populations were due to effects of interest, as opposed to differences in the measurement and meaning of constructs between populations.

These findings indicate that combining data from multiple cohort studies can address questions beyond those that can be addressed by existing cohorts in isolation. The use of existing data can maximise the use of collected resources, decrease burden on populations of interest, assist in the timely delivery of results and provide a basis for identifying populations who may benefit from targeted and tailored interventions. It may also address methodological differences between studies which may otherwise present barriers to addressing questions of interest.

**Key finding two: There is little evidence that remoteness moderates the impact of psychosocial health determinants**

The current study is the first to examine how health determinants vary across urban to remote regions of Australia. Little evidence of a moderating effect of remoteness on the psychosocial determinants of health was detected. In an exploratory analysis (Chapter three), social support displayed a weaker association with psychological distress in remote areas than it did in regional and urban areas. In primary analyses (Chapter five), personal adversity in the form of chronic disease (life time diagnoses of cardiovascular conditions or of affective conditions) was not associated with physical or psychological HRQoL impairment. While dual diagnoses of cardiovascular and affective diagnoses had a negative interactive effect on psychological quality of life, this was also not influenced by remoteness.
In light of observations that the index of remoteness used may not be sensitive to health relevant contextual characteristics (Chapter five, and discussed below), individual social capital ratings were employed as an alternative proxy of health relevant aspects of context in the ARMHS sample. In this rural sample, trends suggested that social capital moderated the association of a lifetime affective condition with psychological HRQoL impairment and also the presence of personal financial difficulty with psychological HRQoL impairment. While these findings indicate that there is some impact of context on the psychosocial determinants of psychological health, the observed effects were small.

When proxies for context such as individual social networks were examined, there is some evidence that the influences of affective conditions and financial difficulty on mental HRQoL impairment are influenced by individual social capital. However, no evidence of a differential influence of health determinants on physical HRQoL impairment with remoteness was observed.

Key finding three: Remoteness is associated with, but is a poor proxy for, health related contextual factors

No association of remoteness with indices of psychological distress or physical HRQoL impairment were observed. A weak association of remoteness with psychological HRQoL impairment was observed. This association was attenuated when participant cohort was controlled for, suggesting this may reflect overall urban-rural differences in psychological HRQoL impairment. These findings indicate that remoteness per se is not associated with health measures in the current sample. It is unclear whether this result reflects ‘ecological’ effects [1, 2], in which aspects of rural or urban context itself may influence health and its geographical distribution, or ‘urban drift’ effects [2], in which residence within, or selective migration from, rural or urban contexts may influence health and its geographical distribution.
Remoteness indices were associated with reported social capital and health service accessibility in state survey data. With increasing remoteness, social capital increased and experiences of health service accessibility decreased. However, no differences were observed between outer regional and remote/very remote groups. These findings indicate that when using the ARIA+ both continuous and the four-category Australian Standard Geographic Classification (ASGC) indices of remoteness lack sensitivity to the health relevant characteristics of context.

In multivariate analyses of the ARMHS cohort, individual social capital displayed a marginal negative association with psychological HRQoL impairment. When assessing the influence of established indices of contextual socioeconomic disadvantage and theory-driven indices of contextual health service accessibility and generalised Trust (a dimension of social capital) on the individual’s self-rated physical and mental health and psychological distress in a rural sample: physical health displayed association with contextual health service accessibility and generalised trust; mental health displayed an association with socioeconomic disadvantage and generalised Trust, and; psychological distress displayed an association with generalised Trust. The creation of theory driven methods to circumvent often encountered limitations of assessing the contextual, service and social characteristics of sparsely populated areas may provide useful information regarding health related characteristics of areas.

**Key finding four: Social networks and personal adversity are key determinants of health in rural Australia**

Current findings confirmed the association of a range of individual level psychosocial factors with health outcomes. Several findings were evident across multiple indices of health, including psychological distress, HRQoL impairment, and self-reported health. Even when assessing the health impacts of social support, a beneficial influence of individual ratings of
social capital in rural areas of Australia was observed. These results differed by gender, as did the physical effects of alcohol consumption, the mental health effects of living on a farm. For physical health, a sense of belonging displayed a positive association for men, while social visibility displayed a negative association for men. For mental health, a sense of belonging displayed a positive association for both men and women, but was significantly stronger for men. When assessing correlates of psychological distress, social visibility displayed a negative association for men and a sense of belonging displayed a negative association that did not differ by gender. These results were consistently observed across three phases of data collection, increasing confidence in their measurement and validity.

Results of causal modelling suggest that in rural contexts, social networks, personal adversity and health are causally linked in ways similar to those observed elsewhere [3, 4] and in theoretical models [5, 6]. Social support and financial difficulty displayed independent direct impacts on both physical and mental health outcomes. Social support also displayed an indirect effect on health outcomes by protecting against financial adversity. Social visibility aspects of social capital had a marginal negative impact on physical health for men. Mental health influenced physical health over two years. In line with theoretical models of social capital [6-8], aspects of social capital, namely social visibility and a sense of belonging, were important antecedents of social support and the probability of experiencing adverse life events.

These findings indicate that in addition to contextual effects of generalised trust, health service accessibility and socioeconomic status, social networks and financial difficulty present meaningful points of health intervention in rural Australia. Rural living presents different health stressors for men and women in Australia and social visibility may have negative consequences for the physical health of men in rural communities, perhaps reflecting the
different demands of context exerted upon masculine and feminine identities in rural areas [9-12].

**Methodological factors affecting interpretation of key findings**

**Sample representativeness**

**Response rate/bias.** Both the HCS and ARMHS randomly selected potential participants from the New South Wales state electoral roll. Introduction and recruitment letters were sent to individuals by post and non-responding individuals were followed-up with telephone calls. Informed written consent was obtained from all participants. Overall response rates of 44.5% (N = 3253) and 27.3% (N = 2639) for the baseline HCS and ARMHS samples respectively were achieved, with both samples having comparable rates of non-contactable or excluded persons (HCS 26.9% and ARMHS 25.2%). Within the ARMHS sample, among those who were contactable and met study inclusion criteria, participation rates varied by age group (under 55 years: 25.4%; 55-70 years: 32.4%; over 70 years: 20.1%). A comparable pattern emerged within the HCS sample, with responders tending to be slightly younger than non-responders (66.3 vs. 68.6 years) [26]. These low rates of response suggest that the current results may represent a somewhat older, educated and potentially healthier section of the general community population. In light of these sample biases, statements regarding prevalence of disorder and expression of associations in terms of relative risk in the current sample have been avoided.

**Exclusion of persons with sight and hearing disabilities and poor literacy.** The ARMHS utilised a protocol screening participants with poor hearing and cognitive performance. This may have resulted in the ARMHS not representing this section of the population and added to disparities in psychological HRQoL impairment observed between the ARMHS and HCS cohorts (Chapters four and five). While some efforts were made to assist persons with literacy issues to complete
surveys in both cohorts, it is similarly likely the current postal survey method meant that persons with poor sight and low levels of education and literacy are not represented in the current results.

**Urban setting.** Our urban population was drawn from a major regional industrial city and thus the current observations of factors influencing health may not generalise to other urban contexts. Differences between characteristics of major urban locations, which are not necessarily delineated by population density or distance from services, and populations residing within these areas, may impact the experiences of social capital and health service accessibility, and their association with health, between urban centres [13].

**Aboriginal and Torres Strait Islander people.** While Aboriginal and Torres Strait Islander people make up 2.9% of the New South Wales population, this group represent 5.7% of persons in regional and 24.1% of persons in remote areas of the state [14]. However, the Aboriginal and Torres Strait Islander people are underrepresented in the current sample population. Several issues may have contributed to this situation. The ARMHS study engaged in a separate strategy to foster community engagement within communities with a high proportion of Aboriginal and Torres Strait Islander persons. This was undertaken, with the approval of the Aboriginal Health and Medical Research Council, to appropriately design specific approaches within aboriginal communities and undertake pilot work regarding appropriate protocols around surveying for mental health research. This led to the exclusion of these local government areas from the main component of the ARMHS survey. As can be seen in Figure 8.0, while largely contiguous areas of northern New South Wales were sampled, several local government areas in which a high proportion of Aboriginal and Torres Strait Islander people reside were not sampled, including the Central Darling Shire, Walgett Shire, Gwydir Shire, Guyra Shire, Brewarrina Shire, Uralla Shire and Walcha Council.
Figure 8.0. Local government areas sampled by the ARMHS (green) and Hunter Community Study (Red).

Representation impacted by need to make studies comparable. To maintain comparability with the HCS and address the aims of the current research, only participants aged 55 years and over from the ARMHS cohort (54.3%) were considered for inclusion in analyses of the combined datasets (Chapters three and five). As a result younger people were not represented in analyses assessing the impact of context on determinants of health (Chapters three and five) and current findings may not be generalizable to this section of the population.
Primarily cross sectional design

The current work represents largely cross-sectional observations and analyses and thus results need to be interpreted with care. The use of primarily cross-sectional analyses of baseline ARMHS and HCS datasets reflects in part the ongoing nature of these surveys, with limited longitudinal data available across these cohorts available at the time of the preparation of this thesis. Where available, preliminary follow-up datasets made available for the purposes of the current research were used for purposes of validation of selected measures, including social support (Chapter three) and HRQoL as assessed by the AQoL-6D (Chapter four). In Chapters three though six, the association of a range of psychosocial determinants (including education, personal adversity and social networks), with health outcomes are examined in the cross-sectional analyses are presented. Causal inferences regarding the health impacts of objective demographic factors such as age and gender, which are not themselves influenced by health states, may be made with greater confidence than those for factors which may themselves be influenced by health outcomes. Importantly for the current thesis, these cross sectional designs were used to create common indices of social support using harmonization methods (Chapter three) and also facilitated assessment of the stability of associative models over multiple phases of data collection (Chapter six), the results of which could then be utilised to implement targeted analyses of longitudinal design (Chapter seven).

The combination of individual participant data across multiple studies may be valuable for addressing new research questions

Examination of the moderating influence of community remoteness on known determinants of health outcomes was a key objective of this thesis. However, the capacity of existing studies to address this issue is limited by the under-representation of rural and remote communities in
state and national surveys of well-being, a lack of measurement of key psychosocial health
determinants in these surveys, and the omission of urban comparison samples in studies of
rural and remote populations. With an aim of addressing these limitations, the current study
combined data from two existing cohort studies assessing the psychosocial determinates of
health which, in combination, had the capacity to represent communities from across urban to
very remote areas of New South Wales. Evaluation of the efficacy of this strategy and its
potential to enhance and distort current findings presented a key challenge to the current
program of research.

**Chapter two** outlined the motivations, considerations and threats to scientific inference that
should be considered when undertaking such combined analyses of cohort data, also known as
‘individual participant data analysis’. This work formed the basis for the statistical
considerations of **Chapters three through five** which addressed elements of comparability of
measures and methods between datasets and the capacity of the combined dataset to address
research questions of interest. In **Chapter three**, cohorts were combined to examine whether
individuals’ demographic and psychosocial characteristics varied in their association with an
established index of psychological distress across urban to remote areas of New South Wales.
In the absence of a common measure of social support, data from a common follow-up phase,
in which social support indices from each cohort were administered to both cohorts, was used
to identify common conceptual and measurement elements between baseline measures. In
**Chapter four**, the metric invariance of a relatively new index of HRQoL, the AQoL-6D, was
assessed across the ARMHS and HCS cohorts. **Chapter five** examined whether the HRQoL
impacts of personal adversity, primarily in the form of chronic disease, differed with
community remoteness. This analysis subsequently also drew upon previously unanalysed data
from the New South Wales population Health Surveys 2006-2009 regarding the social capital
and health service accessibility correlates of remoteness. These results indicated that a more
in-depth examination of the contextual characteristics of rural areas and their impact on
determinants of health was needed. These investigations were conducted in Chapters five
and six. In the following section, discussion focusses on the strengths and limitations of combining
multiple cohorts for individual participant data analyses in the current thesis for the purposes
of the xTEND project.

**Strengths**

**Utilizing existing data reduces the burden on resources and populations of interest.**

Using existing data in the current thesis meant that results were obtained in a time and
resource efficient manner compared to beginning a new study. More generally, for similar
aggregate studies, answers to research questions can be expedited, particularly where
outcomes are of importance to the public, or preliminary results are required to leverage
support for a larger study, or common follow-up study, which may be able to more fully
address the questions of interest. Such results are relatively cost efficient, and can often be
obtained without unnecessary duplication of tasks or additional burden on the target
population. In the case of survey-based cohort studies, reducing the necessity of identifying
additional participants, and sending, receiving and processing survey data for analysis, may
mean that the greatest costs associated with survey methods are eliminated. Resources can be
refocused on the analyses and dissemination. Further, in sparsely populated remote areas of
New South Wales, a large proportion of the population had been contacted for participation in
the ARMHS project (and other projects, such as the “45 and Up Study” [15]) and recontacting
these persons for participation in a similar study to one that was ongoing was determined to
be excessively burdensome on the community and would duplicate already collected information.

Combining individual participant data from multiple cohorts allowed the consistent classification of remoteness and other personal and contextual characteristics.

Differences in the definition and operationalization of remoteness are a major barrier to understanding the influence of remoteness on health and its determinants. In Australia and elsewhere, the development of standard statistical indices of geographical remoteness is helping to address this limitation. Combining individual participant data from the ARMHS and HCS provided an opportunity to geocode participant remoteness (and other contextual factors such as socioeconomic status of areas) in a consistent manner across cohorts and in ways that corresponded with those used in the New South Wales Adult Population Health Survey data. Other studies considering combing cohort data may be presented with similar opportunities for geocoding statistical indices. Further, combining individual participant data from these independent cohorts allowed the application of consistent classification and cut offs for the independent and dependant variables across both datasets (e.g., the classification of participant scores on the Kessler 10 [16] into high and low psychological distress categories as in Chapter three).

Combining individual participant data from multiple cohorts allowed the assessment of geographic generalizability and heterogeneity in health determinants.

The representation of remoteness in state and national surveys of health and well-being is severely limited. By pooling individual participant data from the HCS and ARMHS cohorts, the xTEND study accessed data representative of the spectrum of urban to very remote regions of NSW. The location of these regions in largely contiguous local government areas added to the
capacity to infer the potential of observed effects to reflect influences of community remoteness as opposed to other influences (as outlined in Chapter two, Table 2.2).

Further, combining these studies allowed us to assess geographic remoteness as a source of heterogeneity in determinates of health. Assessment of the generalizability of findings from urban samples regarding the determinants of well-being will help inform the identification of targets for health interventions in rural and remote populations.

Combining individual participant data from multiple cohorts allowed the assessment of unknown or potential sources of heterogeneity between studies.

Other sources of heterogeneity not related to specific research questions (such as study inclusion/exclusion criteria) are perhaps better viewed as potential threats to inference (Chapter two, Table 2.2) which need to be considered throughout the process of combining, analysing and interpreting combined data. It was recognised that factors associated with cohort characteristics and the manner in which data were collected may influence the viability of inferences made using these data. Combining individual participant data across cohorts facilitated assessment of the impact of these factors on results. In Chapter five, the influence of these unknown cohort-related factors on observed associations was examined by assessing the moderating effect of cohort when included in the primary statistical models. This provided an indicator of whether other factors that were not included in the model, and were perhaps unmeasured, contributed to the main or interactive effects that were of interest to the current research. Combining data across cohorts may also provide opportunities for more formal analysis of quantitative bias and sensitivity than those conducted for the purposes of the current thesis [17].
Combining individual participant data from multiple cohorts allowed assessment of measurement equivalence/invariance of key concepts such as HRQoL.

Measurement methods or characteristics may differ across cohorts or change differentially and the invariance properties of key concepts of interest should be considered [18]. While studies comparing summary statistics across cohorts often assume invariance of the construct being assessed, pooled individual participant data presents a unique opportunity to test these assumptions.

In light of the differing age profiles and research contexts for the HCS and ARMHS projects, assessment of measurement equivalence/invariance was considered particularly important. In Chapter four, the measurement and structural equivalence of the Assessment of Quality of Life-6D (AQoL-6D) [19] was assessed across cohorts and phases using nested multi-group confirmatory factor analyses. These analyses identified a two-factor physical-psychological domain structure for the AQoL-6D. The combining of individual participant data in a single analysis allowed the confirmation of the measurement invariance of this construct across these samples. The two factor structure of the AQoL-6D displayed structural and metric invariance across the ARMHS and HCS cohorts, providing strong evidence that comparable latent constructs were assessed by the AQoL-6D subscales across these urban and rural cohorts. This knowledge allowed us to compare factors affecting quality of life across cohorts and time points, providing an opportunity to contribute to the psychometric literature on this instrument and in Chapter five, allowed us to assess whether determinants of physical and psychological quality of life impairment differed with remoteness.
**Limitations**

While guided by substantiative theoretical interest and evaluation of the commonalities between cohorts, the factors investigated in the current thesis were limited by the comparability of samples and measures collected by these separate cohorts. This reflects the retrospective nature of the data combination undertaken for the xTEND study, that is, the synthesis of studies that have been planned and conducted without the intention of later harmonization in mind [20-22].

**Questions addressed are limited by sample comparability of cohorts.**

Differences in the populations sampled presented a major limitation to the value of combining individual participant data across the ARMHS and HCS cohorts. As the HCS cohort was a study of persons aged 55 years and over, we were unable to use the full age range available in the ARMHS cohort when examining the differential effects of psychosocial characteristics on health outcomes across urban to remote areas of New South Wales. These issues highlight that mismatches between the sampling base across cohorts will essentially determine the range of questions that can be addressed when combining individual participant data from multiple cohort studies. Future analyses of mechanisms driving participant attrition over time (i.e., whether samples are differentially biased by non-random attrition) will assist in determining whether the comparability of cohorts established in the baseline samples is maintained over time or whether the implementation of techniques to compensate for these biases are required (e.g., quantitative bias analysis) [17].

**Questions addressed are limited by measurement comparability of cohorts.**

While some exploratory efforts were undertaken (*Chapter three*), a lack of overlap in the concepts and measures administered by the cohorts limited our capacity to examine the
impact of remoteness on the health relevance of this key psychosocial determinant of health. Questions remain regarding the sensitivity of the disparate measures of social support. While the questions raised by the combined analysis regarding the importance of omitted factors across cohorts may inform the design of follow-up phases, and future new studies investigating these factors, the lack of comparable constructs and measures across cohorts presented a major limitation in the current thesis. Inconsistencies between the questions administered across cohorts will essentially determine the range of questions that can be addressed by combining individual participant.

The moderating influence of remoteness on health and its determinants

Chapters three and five examined how the impact of key psychosocial health determinants may vary across urban to remote regions of Australia. Models of population health highlight the importance and interrelated nature of personal and contextual factors in shaping the influence of these factors on health outcomes [13, 23-26]. However it is unclear whether this theoretical and intuitive interaction translates to meaningful differences in the impact of health determinants across urban and rural areas. This limits our capacity to design and implement targeted population health interventions, particularly where one population is understudied, such as is the case for many rural populations, as generalisation of knowledge from urban populations is largely unsubstantiated.

This section discusses thesis findings regarding the relative impacts of demographic and social support factors on psychological distress (Chapter three), and the impacts of chronic and current adversity on physical and psychological HRQoL with increasing remoteness (Chapter five). Current results indicate weak evidence that remoteness influences the psychological
impacts of psychosocial health determinants. As will be discussed in the next section ‘Remote
teness and health related contextual factors’, exploration of the sensitivity of objective
indices of remoteness to the health related contextual factors led us to examine other
potential indices of health related aspects of context. In the current section, the influence of
individual social capital on the health impacts of adversity is explored in the rural subsample is
also discussed. In the final section of our discussion, ‘Health determinants in rural Australia’,
methods of assessing the health impacts of contextual factors in rural Australia are
investigated.

Demographic and social support factors and psychological distress

Demographic factors and remoteness.

Chapter three assessed whether the association of an individual’s demographic and social
support characteristics with high levels of psychological distress differed across the spectrum
of urban to remote areas of New South Wales among community participants aged 55 years
and over. In these analyses, remoteness was conceptualized as a continuous variable indexed
by road distance of a community from populations of given sizes (ARIA+). Results of these
analyses revealed little evidence of such an interactive association of demographic factors
(including age, gender, education and marital status) with community remoteness.

A small, marginally significant, interaction of age and remoteness was observed. This result
indicated that older persons were less likely to be highly distressed in more remote areas.
Graphical investigation of this interaction suggested that increased age was associated with a
decreased likelihood of high distress in remote participants, although this had little or no
impact on distress in urban areas, with regional participants displaying an intermediate
association.
These results suggest that there may be some benefits associated with aging in non-metropolitan communities among those aged 55 and over. It may be that positive determinants of health are enhanced in remote areas with increasing age. For example, older persons may feel more valued, experience decreased exposure to stress or greater life satisfaction with age in remote areas. Alternatively, these effects may reflect a migration effect in which older persons who are highly distressed move to less remote areas as they age.

Social support and remoteness.

Preliminary evidence of a differential association of social support with high levels of psychological distress with increased remoteness was observed (Chapter three, Table 3.3). A significant interaction term indicated that as remoteness increased, the strength of association between low social support and higher levels of distress diminished. Graphical exploration of this effect showed low levels of social support to be associated with high psychological distress in urban and regional areas; however this association was weaker in remote areas (Chapter three, Figure 3.3).

Moderation of the impacts of age and social support on psychological distress with increased remoteness is in line with theoretical models (i.e., Dahlgren and Whitehead [26], Bernard et al. [13]) of an impact of context on individual-level health determinants. That is, the characteristics of the context or place persons live may moderate the protective effects of health determinants such as social support. However, as discussed in Chapter three, there are several potential interpretations and mechanisms for the interaction of social support and remoteness in the prediction of high psychological distress. The interaction may reflect a real difference in the association between social support and psychological distress that is borne of the social and environmental characteristics associated with remote, relative to urban, contexts. Specifically, it may indicate that the social relationships examined, namely access to
close confiding relationships (personal support) and group participation (network support), do not describe the types of social interactions that are important for the maintenance of well-being in remote communities. This latter interpretation is in line with empirical evidence that the health association of all facets of social support and social networks on psychological well-being are not uniform between urban and rural environments [27-29], though this is the first to empirically test the presence of a differential effect. Additional explanations for the observed interaction include the presence of more salient stressors (i.e., drought, financial stress, poor access to resources) that underlie psychological well-being in remote communities. While the mechanisms are unclear, current results provide some preliminary evidence that the association of social support with high psychological distress varied with community remoteness. The current results indicate that, when a range of variables are accounted for, the experience of demographic and social factors has a similar association with psychological distress across urban and rural areas. This finding provides some basis for generalising the findings of studies of the health impacts of demographic and social support in urban areas to rural communities.

**Strengths and limitations of Chapter three analyses of the differential association of demographic and social characteristics with health across urban to remote communities.**

**Psychological distress as an indicator of health.** The dichotomous indicator of ‘health’ used in Chapter three was the presence or absence of high psychological distress as indicated by a score greater than 21 on the Kessler 10 psychological distress scale. The Kessler 10 asks participants to indicate the frequency of their psychological distress symptoms over the past four weeks. It has been used extensively as part of the World Health Organization World Mental Health surveys [30], and has been shown to be sensitive to non-specific psychiatric distress [16, 31]. Data from the 2007 National Survey of Mental Health and Wellbeing suggests
that this cut-off is associated with a 63% likelihood of meeting 12 month ICD-10 criteria for any affective, anxiety or substance use disorder in an Australian community sample (compared to 15% of persons scoring < 21) [32]. As discussed in Chapter four, the continuous Kessler 10 score displayed a strong association with psychological HRQoL impairment (r = .71, p < .001).

Thus, our current outcome measure may be interpreted as an indicator of experiences of affective disturbance occurring with a frequency and is likely to be related to psychological health impairment. A limitation of the current investigation is that this outcome provides no information regarding whether the association of demographic and social support characteristics of individuals on physical health differed with increasing remoteness. Chapter four indicated that the Kessler 10 was only moderately related to ratings of physical HRQoL impairment (r = 0.44, p < 0.001; Table 4.7). Thus, further research is needed to determine whether the demographic and social determinants of physical health are influenced by remoteness.

**Cross sectional data and lack of migration history.** In addition to the potential for these results to reflect a differential association of social support with psychological distress outcomes with remoteness, other theoretically plausible explanations of this finding exit. A limitation is that our conclusions are based on cross-sectional data. Thus, it was not possible to determine whether the current interactions represent causal influences of psychosocial and contextual factors on mental health. These effects may represent a number of reverse processes (e.g., an influence of mental health on psychosocial and contextual effects) or that these factors have reciprocal influences on each other.

Further, in the absence of data relating to personal migration history, selective migration persons with particular personality and health profiles may also contribute to the effect observed. Selective migration of persons towards and away from rural areas, potentially
influenced by social preferences and health needs, as outlined in ‘social cognitive’ theories of social support such as Lakey et al.’s ‘Relational Regulation Theory’ [33] and Uchino et al.’s [34] ‘Reactivity hypothesis’, is likely to be present in the population. Specifically, individuals who have a lesser reliance on social support for maintenance of their psychological well-being may be more likely to move to or remain in remote areas, whereas individuals who require high levels of social support for maintenance of well-being will move to regional or urban areas, where there is a greater opportunity to have these needs met. Future research employing a longitudinal design, and with life time migration history, is needed to address these limitations.

**Calibration of social support indices.** A further limitation of our results in regards to the differential association of social support with remoteness lays in our use of different, though calibrated, indices of social support in our ‘urban’ and ‘rural’ cohorts. As discussed in Chapter two, several methodologists have written on the potential for calibrating different psychometric measures to assess a single construct [35-37]. A strength of the current method was that calibration was performed using follow-up data in which both measures had been administered to the HCS cohort; thus, the correspondence of these measures with each other and with a common outcome could be assessed. Follow-up data indicated these measures of social support to display a moderate correlation (Chapter three results; \( r = .65, p < .001 \)); moreover, the overlapping confidence intervals for the adjusted odds ratios of the different composite measures of social support in the prediction of high distress suggest that the association between social support and high distress did not differ between the two indices. These methods provide some confidence that the difference in remote, compared to urban and regional environments, was not wholly attributable to differences in the sensitivity of our social support indices to high distress.
Personal adversity and remoteness.

Experiences of personal adversity have been identified as key psychosocial determinants of physical and mental health outcomes in rural Australia [38]. The 2012 National Report Card on Mental Health [39] highlighted concerns regarding the impacts of affective and cardiovascular illness in rural Australia, particularly among those affected by mental illness who may face additional barriers to seeking help and self-care. While there were limited indicators of adversity common across the ARMHS and HCS cohorts, lifetime experiences of several chronic diseases were collected in comparable ways.

Chapter five presented a primary analysis that examined whether the association of personal adversity, as indicated by diagnosed lifetime cardiovascular and affective disorders, with physical and psychological HRQoL differed across urban to remote areas. As in Chapter three, remoteness was operationalised using an established continuous index of road distance from major service centres of different sizes, the ARIA+, and analyses included persons aged over 55 from across urban to remote areas of New South Wales. Analyses revealed no evidence that the impact of cardiovascular and affective conditions or their comorbidity were influenced by remoteness. Further, when the cohort of participant origin was included in the first step of the analyses (Chapter five, comparison of results in Table 5.1 with those reported in Appendix 5.1, Table S1), the coefficients for the association of affective and cardiovascular conditions on physical and psychological health did not change, providing evidence of no overall differences in these associations between our urban and rural cohorts.
Personal adversity and individual social capital.

As discussed further in the following section (‘Remoteness and health related contextual effects’), the potential that the ARIA+ index of remoteness was relatively insensitive to health relevant aspects of rural contexts was examined in a supplementary analysis in Chapter five utilizing data from the New South Wales Adult Population Health Survey [40]. This analysis revealed that while remoteness categories derived from the ARIA+ were related to social capital and health service accessibility, this relationship was severely non-linear, with no differences in social capital and health service accessibility present between outer regional and remote/very remote areas of New South Wales which encompass the majority of the ARIA+ range (scores 2.41-15.00). This suggested that this standardized continuous index of remoteness provided a poor proxy for health related aspects of context.

Acknowledging that individual’s perceptions of social capital are shaped with broader social norms and behaviours [41], it was determined that individual-level ratings of social capital, which were available in the ARMHS survey dataset, would be employed as a preliminary proxy of health relevant aspects of context in a ‘rural’ sub-analysis. Indices of current personal adversity (recent adverse life events and financial difficulty) were also present in the ARMHS sample. The influence of the inclusion of these measures of current adversity in the primary analysis model and whether the association of financial difficulty with HRQoL was impacted by social capital were of interest. Thus, two analyses were conducted in this sub-analysis: 1) a replication of the primary analysis assessing whether the impact of affective and cardiovascular diagnoses on HRQoL domains were influenced by social capital; and 2) an analysis that also included recent adverse life events and financial difficulty, and additionally assessed whether the impact of financial difficulty on HRQoL domains was influenced by social capital.
In our replication of the primary analysis, social capital influenced the association of affective conditions with psychological impairment. As social capital increased, persons with a lifetime affective disorder reported less psychological HRQoL impairment ($\beta = -0.08$, $p = .012$; Appendix 5.1). In the extended sub-analysis model which included current adversity factors, the beneficial impact of individual social capital in reducing psychological HRQoL impairment was greater for those experiencing financial difficulty. The interaction of affective conditions and social capital in the prediction of psychological HRQoL was not significant in the extended model, which included recent adverse life events, perceived financial difficulty and a marginal interaction of financial difficulty with social capital (Chapter five, Table 5.4). This suggests that these variables shared a portion of the variance in psychological impairment accounted for by the social capital and affective disorder interaction observed in the previous analysis model.

Both marginal interactions observed suggest that interrelated psychological burdens, such as affective disorders and financial difficulties, are similarly ameliorated by social capital. There was no influence of social capital on the association of lifetime affective, cardiovascular or current financial difficulty with physical HRQoL impairment.

Strengths and limitations of Chapter five analyses of the differential association of personal adversity with health across urban to remote communities and individual ratings of social capital.

Multidimensional HRQoL assessed by the AQoL-6D. A key strength of these analyses is the use of the Assessment of Quality of Life – 6D as the primary outcome measure. As demonstrated in Chapter four, this HRQoL assessment provides a valid measure of the physical and psychological dimensions of HRQoL; that is, it assesses the functional outcomes of individuals’ physical and psychological health states. This scale assesses both the physical and mental dimensions of health and taps the concept of ‘well-being’ by assessing the impairment.
experienced in these domains. These scores provide assessment of a range of functional health experiences, including physical mobility, the impact of physical health on relationships, impairment associated with pain and sensory capacities, as well as experiences of distress and coping. Unlike many other HRQoL indices, the AQoL-6D includes ratings of other positive and negative capacities, providing increase sensitivity to the range of capacities associated with both positive and negative health states, making it particularly appropriate for use in community surveys.

As discussed, **Chapter four** also provided evidence of the invariance of these factor scores across the ARMHS and HCS cohorts, providing strong evidence that the constructs assessed by the physical and psychological HRQoL factor scores were consistent across these samples. With this knowledge, the combined analyses may be interpreted with confidence that the observed effects are not attributable to measurement or conceptual differences related to our outcome measure between these cohorts.

**Consistency of model across cohorts.** As discussed in **Chapter two**, a concern with combining multiple cohorts for individual participant data analyses is that the constructs assessed may be confounded by unmeasured factors across cohorts. A strength of the primary analysis of the combined ARMHS and HCS cohorts is that by comparing models with cohort included and excluded from the first step of the multiple regression models, we can assess the impacts of cohort on the association of model variable with outcomes. This test provided convincing evidence of the stability of the model weights when cohort was and was not included in the model. This suggested that the cohort of origin did not influence the association of model variables with the outcome and, therefore, that they were probably not confounded by unmeasured cohort influences. The one exception to this was our remoteness variable, on which the cohorts were largely defined. The influence of remoteness on psychological HRQoL
was significantly diminished when cohort of origin was modelled. This may indicate an overall urban-rural difference in psychological health, as opposed to any more fine-grained influence of remoteness.

**Misclassification of chronic illness may differ across cohorts.** A possible limitation of these findings is the potential for lifetime diagnoses of chronic illness to be differentially misclassified across urban and rural locations. Chronic conditions may be more likely to be miss-classified or of greater severity in our rural populations, due to a range of factors including: the decreased probability of receiving a diagnosis in remote areas [42, 43]; the potential for increased severity of disorder at diagnosis; the reduced likelihood of surviving an acute health event; and evidence of migration of persons to less remote areas following diagnosis of mental health conditions [44]. Such biases in diagnostic classification (i.e., more persons incorrectly classified as not having the condition) in regional-remote areas would mean that the influence of disease on HRQoL would be underestimated in these areas.

**Availability of measures across cohorts.** As already mentioned, a strength of the current analyses was that a range of important cardiovascular and affective diagnoses were collected in comparable ways across cohorts. However, a limitation of the primary analyses of Chapter five is that little information regarding experiences of current adversity and social capital was comparable across the cohorts. As such, the investigation of how current adverse life events are associated with HRQoL and how this association is influenced by social capital was limited to our sub analyses of the rural ARMHS cohort. A limitation of these sub analyses is that they do not represent persons from urban areas, where social capital is observed to be significantly lower than in inner regional and outer-regional/remote areas. As such, the effects and interactions reported in Chapter five are likely to be truncated representations of the effects present in the community at large. As discussed in Chapter two, this limitation may be
explored in the common follow-up survey in which the overlap in such important measures between the cohorts was improved.

**Individual ratings of social capital.** In Chapter five, individual’s subjective ratings of social capital were used to examine the influence of social capital on the health impacts of personal adversity. Current results indicated that social capital was associated with better psychological HRQoL and provided some ameliorating effect on the impacts of personal adversity on psychological HRQoL (Table 5.4). A limitation of the use of individuals’ social capital ratings for these analyses is that these impressions of the social environment may themselves be influenced by the individual’s own psychological HRQoL and cannot characterise experiences representative of those within a given context, though may be related to it. A strength of the current findings is that these effects were present despite controlling for individual ratings of social support.

The current results are consistent with previously hypothesised and observed ameliorating influences of social capital on stressful situations and events [45]. While individual social capital is a problematic proxy for contextual social capital, due to the unclear causal chain as well as questions regarding the generalizability of individuals’ perceptions of social capital to that of an area’s resourced, results of Chapter five discussed under ‘Remoteness and health related contextual effects’ provide evidence that individual social capital is associated with contextual remoteness.

An alternative measure of social capital often used in the literature is ‘area’ social capital indices which are comprised of aggregate social capital ratings within a given area. However, due to the limited number of observations in dispersed rural samples such as the ARMHS sample, established methods of aggregation were not possible in the current analyses. Development of such methods is addressed in the following section.
Remoteness and health related contextual effects

In the sociological and psychiatric literature, health related contextual effects are often characterised by objective indices obtained from statistical bodies and public registers (e.g., Socioeconomic Indexes for Areas [46], rates of persons engaged in community groups [41]) and aggregate or summary indices of subjective factors influencing health obtained from population surveys [47]. It has been argued that the aggregate subjective experience of a population may provide a less confounded index of health related aspects of context, particularly social capital [23, 48]. However, such characterisations of the small, dispersed populations present in rural contexts has been limited, due to the small number of observations that can be obtained within a given area, as well as controversy regarding the appropriate area over which such aggregation should occur. The current thesis acknowledged remoteness as a factor shaping the health related aspects of context, such as health service accessibility, social capital and socioeconomic disadvantage. However, the nature of the relationship of indices of remoteness with these contextual characteristics remains unclear.

In an attempt to reliably quantify the nature of intra-country remoteness, standardized indices of remoteness have been introduced such as the ARIA+ and associated Australian Standard Geographical Classification (ASGC) categories (major cities, inner regional areas, outer regional areas, remote, and very remote areas) [49]. However, the adequacy of objective remoteness indices as a proxy for health-relevant contextual factors has rarely been examined and has been repeatedly challenged [50-52]. In addition to identifying the influence of remoteness on health determinants as addressed in the primary analyses of Chapters three and five, the current thesis addressed the adequacy of remoteness as a proxy for health relevant contextual factors such as social capital and health service accessibility. As a result a theoretically driven method of producing aggregate characterisations of the social capital and health service
accessibility characteristics of rural areas was examined. The influence of both objective remoteness classifications and administrative health service areas in shaping these contextual characteristics were considered.

**Remoteness as a proxy for health-related contextual factors.**

In **Chapter five**, the utility of the existing ASGC categories as proxy for health related contextual characteristics (health service accessibility and social capital) was assessed using data from the New South Wales Adult Population Health Survey. Analyses confirmed previous observations that social capital increases [53] and health service accessibility decreases [43] with remoteness. Significant differences in these contextual factors were observed between major cities, inner regional and outer regional to remote areas. However, no differences were observed between outer regional and remote categories. Thirty two percent of persons in outer regional and remote areas reported difficulty accessing health services when needed, compared to 22% living in inner regional areas, and 12% living in major cities. Outer regional and remote participants reported levels of social capital approximately half a SD greater than those in major cities.

These results indicate a severely non-linear relationship between the ARIA+ and health related characteristics of context, with no differences in social capital and health service accessibility present between outer regional and remote areas of New South Wales which encompass the majority of the ARIA+ range (scores 2.41-15.00). These findings also provide some support for the use of remoteness indices as a proxy for health related community characteristics. However, these results also indicate that the ARIA+ provides an insensitive proxy for health related aspects of context and that a three category classification of the ASGC classification (i.e., major city, inner regional and other areas) provides a better index than a four five category classification (i.e., major city, inner regional, outer regional, and remote/very
remote). These findings and recommendation may be used to inform future studies employing this measure, to better capture remoteness for health research purposes.

However, whether this proposed three level classification adequately captures health related contextual factors remains undetermined. A more direct approach to quantifying health related contextual factors may improve our understanding of the contribution of community characteristics to health outcomes in rural areas. These results contribute to our understanding of this standardised index of remoteness, which has been widely used in Australia in relation to key health related factors.

**Strengths and limitations of analyses assessing the association of remoteness indices with health related contextual factors**

A strength of our analyses examining the association of social capital and health service accessibility with remoteness are that they are based on the NSW Adult Population Health Survey, a large representative sample of the general population. Further, these data were weighted for a range of demographic and area nonresponse factors. As a result, we can infer that the data provide a good characterisation of the experiences of persons across the range of urban to remote areas of New South Wales. However, it is unclear whether the observed influence of remoteness on social capital and health service accessibility generalise to other states of Australia. New South Wales is the most densely populated state of Australia. Features associated with living in rural contexts also vary considerably by state and are perhaps particularly shaped by environmental factors, population density, industry and state government policy. Further, state based governmental and health administration factors may significantly alter the condition experienced by communities within states. For similar reasons, these effects may not generalise to other countries. State or national surveys of well-being
may provide greater insight into the influence of these factors on the contextual correlates of remoteness in Australia.

The findings presented in Chapter five provide guidance to future studies using the ARIA+ and ASGC remoteness classifications. These analyses enhance our understanding of the limitations of the ARIA+ index of remoteness employed in the primary analyses of Chapters three and five, which may have been insensitive to important health related aspects of context. However, the current results cannot determine whether the standardised cut offs employed in the ASGC are the best or most appropriate characterisations of the health related aspects of context that are influenced by remoteness and drive concerns regarding this population.

**Aggregation of contextual factors in rural areas**

Chapter six explored the characterisation of area-level factors using a theory driven approach to characterising the contextual characteristics of rural areas. As discussed, the available data and appropriate area over which to aggregate observations, are key considerations in assessing contextual factors which are best assessed by subjective experience, such as social capital [47]. Determining the appropriate area for aggregation requires an understanding of the forces shaping these characteristics [54]. It is widely acknowledged that the nominal boundaries used to characterise contextual factors in urban areas (e.g., postal codes, city blocks, states and countries) do not represent optimal spatial scales over which to characterise the health related aspect of context but are employed largely for convenience [47]. It is likely that the use of these contiguous small area boundaries and the availability of relatively large numbers of observations within these areas have alleviated the theoretical deficits of these methods. However, the characterisation of rural and remote populations that are generally both small and dispersed requires a different approach. Consideration of factors that are thought to shape the social norms, beliefs and behaviours of persons who live in rural
communities may provide practical and theory driven method of identifying areas for aggregation relevant to capturing the health related aspects of context. In short, aggregations based on areas with similar resources and social strains may provide more meaningful characterisations of contextual factors in rural and remote regions.

Chapter six examined the sensitivity of such a theory driven method of characterising the health relevant contextual characteristics of rural populations. In this method, respondents to the NSW Adult Population Survey were categorised by the administrative Area Health Service division in which they lived, as well as the remoteness of their community within this area as indicated by the Australian Standard Geographical Classification of remoteness [55]. While Chapter five provided evidence that there was no significant differences between outer regional and remote categories of remoteness in terms of overall social capital and health service accessibility, it was decided that a more fine grained approach to characterising these areas would be employed, as differences in these characteristics also differed by Area Health Service division (results not reported), which may influence differences in the health related correlates of remoteness within and between these areas.

Several studies have noted that dimensions of social capital vary in their association and influence on health outcomes [56-60]. The generalised Trust dimension of social capital was selected for inclusion in models examined in Chapter six due to the consistent association of this dimension with health outcomes in previous research [56-60]. Subjective experiences of the generalised Trust dimension of social capital, as well as the proportion of persons who experienced difficulties accessing health services when needed, were aggregated within these service-by-remoteness area designations. These aggregate values were geocoded to ARMHS participants by postal code and associations were examined with self-rated physical and mental health as well as participant ratings of psychological distress, as assessed by the Kessler
These models also included indices of area socioeconomic advantage-disadvantage at the postcode level to account for these established objective influences, which are also shaped by remoteness and administrative factors.

These area-level aggregations of Trust and health service accessibility displayed univariate associations with self-reported physical health, and Trust displayed univariate associations with self-reported mental health and symptoms of psychological distress. Multivariate analyses related associations of health service accessibility \((p = .015)\) and social capital \((p = .013)\) with self-rated physical health that were consistently observed across three phases of data collection (Table 6.2). Similarly, multivariate analyses revealed an association of social capital with self-rated mental health \((p = .012; \text{Table 6.4})\) and psychological distress \((p < .001; \text{Appendix 6.1, Table S6})\) that was consistently observed across data collection phases. These associations did not vary significantly across multivariate models for male and female participant groups. These observations provide some support for our conceptualisation of factors influencing area-level characteristics in rural areas as well as methods of aggregation based on these factors which can be used for sparsely populated areas; and supports the capacity for contextual factors to characterised based on broader environmental influences, as opposed to small statistical area classifications.

**Strengths and limitations of analyses assessing the aggregation of health related contextual characteristics in rural areas**

As in our discussion of the analysis of the contextual correlates of remoteness, the utilisation of New South Wales Adult Population Health Survey data is a strength of the current analyses due to its superior representation of the NSW population. The data addressed the subjective experiences of the social and service accessibility characteristics of respondent’s local communities – factors that are difficult to assess from objective data. These subjective indices
take into account a range of factors to provide an index of the conditions experienced by persons across a range of urban to remote communities in NSW.

As with our other cross-sectional analyses, causal inferences related to these associations must be considered with caution. A strength of these analyses is that the area-level characteristics and associated subjective health outcomes were obtained from separate individuals and datasets and thus intra personal factors could not account for these associations. A limitation of the method is that it assumes that the contextual social capital and health service accessibility characteristics of areas are consistent over time. Three waves of the Adult Population Health Service Data (2006-2009) were employed to provide adequate representation of populations in remote areas of Australia, for whom random selection for inclusion in population surveys is low due to their extremely small population size. The stability of these characteristics are key to questions regarding the causal influence of these factors, their susceptibility to changes in the social and political environments and thus factors which could be accounted for in theory driven models of aggregation such as ours, as well as to their potential as points of health intervention.

**Determinants of health in rural Australia**

As discussed in the previous section ‘Remoteness and health related contextual effects’, an association between contextual social capital and health outcomes was identified in Chapter six using a theory driven method of characterising social capital that can be applied to overcome difficulties of measurement in small dispersed rural populations. As discussed in the previous section, ‘Aggregation of contextual factors in rural areas’, contextual health service accessibility was associated with physical health, while social capital (Trust) and socioeconomic status were associated with both self-rated mental health and psychological distress indices of mental health. These effects were stable over the three observation periods, did not differ
significantly by gender, and were confirmed by comparisons of the strength of these associations with the alternate health outcome (e.g., health service accessibility was more strongly associated with self-rated physical health than with self-rated mental health). The following discussion will focus on what analysis models revealed regarding the personal psychosocial determinants of health in our rural sample from the Australian Rural Mental Health Study. Previous chapters indicate that the health related contextual characteristics of urban areas, inner regional areas and outer regional-remote areas differ (Chapter five) and provide some evidence that the impacts of health determinants may vary in these contexts (Chapter three and five).

**Chapters six and seven** build upon prior chapters and add to the epidemiological literature on the psychosocial determinants of health in rural areas by using three phases of data collection from the longitudinal cohort of the ARMHS to examine: 1) the determinants of health in rural areas; and 2) their causal associations. In light of previous discussion, this thesis must conclude that these effects should be interpreted with an understanding that health relevant contextual factors may exert some influence the measurement of and associations between these factors, perhaps particularly for mental health outcomes.

**Associative models**

Chapter six examined multivariate associative models of health determinants using three phases of data collection from the ARMHS. These comprehensive models accounted for a range of demographic, health and contextual factors. These analyses aimed to identify factors reliably associated with physical and mental health outcomes in rural Australia factors which may present appropriate variables for further investigation as potential points targeted health intervention for rural populations. To this end, the stability of prediction models was assessed across each phase of data collection. The strength and significance of these predictors for men
and women, whose health may be differently influenced by the rural context [9-12], was also assessed. To further assist the interpretation of these models for informing health intervention strategies, a final analysis was conducted to compare the strength with which each model predictor was associated with the correlated physical and mental dimensions of health.

**Reliable correlates of physical and mental health**

Chapter six revealed reliable psychosocial predictors of overall physical and mental health, their moderation by gender and where factors displayed particular association with the physical or mental health dimension in a rural sample. Better physical health was associated with a lower proportion of life lived in the current district, lower financial difficulty, lower neuroticism, greater personal hopefulness, fewer adverse life events, absence of a lifetime depression diagnosis, absence of a lifetime cardiovascular diagnosis, not being a current smoker, absence of a recent serious injury and greater social support. Better physical health was also associated with greater belonging for men, but not for women. There was also some evidence that better physical health was associated with lower social visibility for men, but not for women, and with increased alcohol consumption for women, but not for men. Better mental health was associated with lower financial difficulty, lower neuroticism, greater personal hopefulness, fewer recent adverse life events, absence of a lifetime depression diagnosis, absence of a lifetime cardiovascular diagnoses, not being a current smoker, and greater social support. Better mental health was also associated with not living on a farm for women, but not for men. Further, while better mental health was associated with a higher sense of belonging for both men and women, this association was significantly stronger for men.

While displaying associations with both factors, financial difficulty and cardiovascular diagnoses displayed stronger associations with physical health than mental health. In contrast,
neuroticism, adverse life events and depression displayed stronger associations with mental health. Personal hopefulness, smoking status, social support and a sense of belonging were equally associated with physical and mental health outcomes. These observations improve our understanding of the nature of burdens associated with these specific factors (i.e., the association of stressful life events with physical health may be in part driven by their dominant mental health burden). This analysis of the association of personal characteristics, social networks and experiences of personal adversity with health outcomes in a rural sample represents an important initial step in identifying potential points of health intervention in rural Australia.

**Gender differences in correlates of physical and mental health in a rural sample**

Evidence that gender moderates the association of psychosocial factors with health outcomes was observed. These effects highlight the potential for gender to influence the determinants of health and the need to consider gender when designing targeted health interventions. Results indicate that the value placed on living in the current community (sense of belonging) displayed a greater association with health for men compared to women. Further, the opposing impacts for men and women (participant social visibility with physical health and psychological distress, and participant identification of living on a farm with mental health) could reduce aspects of social isolation, as they appear to have different effects on the health of men and women. Differential associations of social visibility with health for men and women have been previously observed in Australia [61]. Such findings may have particular relevance for persons residing within the rural and remote context and should be considered in targeting health interventions for these populations.

The observation of a differential health association of alcohol consumption with physical health by gender contrast with previous research [62]. In the rural sample, women displayed
the often observed positive association between higher alcohol consumption and greater health (reflecting lower consumption by persons in ill health [63, 64]), however no association was observed for men. Reasons for the absence of this effect for men are unclear but may be related to contextual factors associated with rural areas in Australia, such as a strong drinking culture and reluctance to seek medical advice among rural Australian men [43]. These gender specific risk factors may weaken the positive association between drinking and health in this group. These results highlight the potential for gender to moderate the determinants for health in rural Australia, as was hypothesised in light of the different contextual social expectations and demands on men and women in rural Australia.

**Strengths and limitations of associative models**

**Inclusive multilevel models.** A strength of the associative models reported in Chapter six is the inclusion of a range of psychosocial and contextual risk factors. These variables represent a range of demographic, personality, adversity, behavioural, social and contextual factors that are potentially important for understanding the relationship of psychosocial factors with health outcomes.

**Integrated analysis strategy.** A particular strength of these analyses is the integrated method in which analyses were conducted. Using structural equation modelling techniques cross-sectional associations of predictors with health outcomes over three phases of data collection were simultaneously assessed and the strength of model parameters compared over each phase. Using these techniques, the strength of these associative models by gender groups were also compared. Finally, the strength of variables as predictors of physical versus mental health outcomes were compared. These analyses enabled the examination of: the reliability with which personal and contextual factors operated as multivariate predictors of health outcomes; the potential for models to be moderated by gender; and the relative strength of
variables as predictors of physical and mental health outcomes. The integrated analysis of three phases of data collection also allowed evaluation of the reliability of the measures and associations.

Analyses of the stability of these models over three separate phases of data collection add to the confidence with which the current prediction models may be interpreted. Successive confirmation of these models suggests that the reported significance and magnitude of these associations are reliable estimates within this population. Further, while several factors displayed marginal associations with health outcomes, the size of these effects was consistent across multiple phases, providing confidence in these effects as potential points of future investigation and health intervention.

Such model comparisons and cross-validation are often undertaken by running analyses independently within each phase or group, followed by a non-statistical comparison of model parameters (e.g., coefficients and/or the proportion of variance explained) or explored further using non-equivalent overall models with interaction terms (e.g., [61]). Thus, the current analysis strategy represents a relatively advanced method of comparing results by survey phase, outcome measure and gender group.

**Limitations of sample representation of the rural population.** A limitation of the current strategy is that the analyses were restricted to persons who provided adequate data at all three phases of data collection (N = 1132, 43% of baseline ARMHS sample). Persons who met criteria for inclusion in the current analyses represent a somewhat healthier, socioeconomically advantaged, and less remote sub-sample of the baseline ARMHS cohort. Further, the current sample was older than many community studies, and over one-third were retired, which may have contributed to better current mental health. Thus, while our observations
were confirmed to be stable within the current sample, the extent to which these findings would replicate in a broader sample remains unclear.

**Interaction of individual and contextual determinants in predicting health outcomes were not assessed.** A final limitation of these analyses is that they do not model the potential moderation of psychosocial predictors of health with contextual factors in these rural areas. While Chapters three and five provide some evidence that these effects may be present, the need to develop methods of characterising health related aspects of context were prioritised in the current analysis. Thus, current findings, particularly in relation to the association of social support, depression and financial difficulty (factors identified in Chapters three and five as potentially moderated by context) should be interpreted with caution, and may particularly overestimate the impact of these variables on health in areas of Australia with greater social capital.

**Within-participant stability of variables over time.** Assessment of the stability of participant characteristics over time revealed that several participant characteristics were highly stable over the three year follow-up period (marital status, retirement status, living on a farm, lifetime depression or cardiovascular diagnoses, smoking status and alcohol consumption), while others varied (perceived financial difficulty, recent life events, social networks and physical and mental health). These analyses assisted in our interpretation of associative models, but they also revealed a limitation in our capacity to comment on the causal nature of the relationship between some predictors and health using the current longitudinal dataset. As causal models assess the influence of variables on outcomes over time, the capacity to examine these associations is limited where variables do not display variation over the observation period. As such, current analyses of causal pathways in the ARMHS data are
limited to examination of the relationships between perceived financial difficulty, recent life events, social networks and physical and mental health.

**Causal models**

**Chapter seven** presented an analysis of potential causal pathways through which health and its correlates identified in **Chapter six** were related over 1 year and 2 year time lags. These analyses build on previous research by exploring the potential direct and indirect causal pathways through which health determinants may influence health outcomes, using three-phase cross lagged panel analyses. This analysis strategy allowed for modelling of associations between social networks, personal adversity and physical and mental health over time. These analyses simultaneously model the multivariate cross-sectional, autoregressive (variables as predictors of themselves over time) and cross-lagged (variables as predictors of other variables over time) associations between variables using three phases of data collection. Knowledge regarding the time over which these processes occur is important to aid understanding of the nature of these processes, as well as to inform subsequent intervention and evaluation models. For example, understanding of the time over which a factor influences health, or health influences an outcome, will inform us regarding our capacity to assess whether a given intervention influences this process. If this is unknown, the presence or absence of effects following intervention can be uninformative, if the process acted over a long or shorter period of time.

The nature of the gender modified associations between social capital variables with health outcomes were also explored by comparing the overall model fit and parameter estimates of these models for men and women in the sample. For the purposes of our discussion, and in light of theoretical models of the impact of these factors in health outcomes, these psychosocial factors were classified as ‘social networks’ (i.e., social support, belonging, and the
gender modified influence of social visibility) and ‘personal adversity’ (i.e., financial difficulty, recent adverse life events and recent injury).

Psychosocial factors and health states as direct determinants of health

Social networks. An effect of social support on physical and mental health outcomes was observed over a one-year lag, but not a two-year lag. A trend level association also suggested that a greater sense of belonging predicts better physical health over a two-year period. Previous research has demonstrated a direct effect of individual social capital on health outcomes [65]. However, while the distinction between social support and individual social capital has been extensively discussed in the literature [57], to date, it has not been assessed in the evaluation of causal models. By simultaneously evaluating the impact of personal social support, the current analyses provide stronger evidence regarding the nature, strength and probability of this association. Thus, Chapter seven provided evidence for a direct influence of social support on mental and physical health outcomes. Increasing social support presents a feasible target for improving health outcomes in rural communities. Increasing a sense of belonging in a community may also have benefits for physical health outcomes in communities. However, the influence of this aspect of individual social capital on health may only demonstrate this effect over a longer period of time than personal social support networks.

Personal adversity. Financial difficulty influenced physical and mental health over both a one-year lag and a two-year lag. Unlike results observed for social networks, aspects of personal adversity displayed reciprocal relationships with health outcomes. That is, health also influenced future experiences of personal adversity. An influence of poorer physical and mental health on financial difficulty over the two-year period was observed. Adverse life events displayed a reciprocal relationship with mental health, although these effects were
observed to operate over different time lags. Better mental health was associated with a lower
number of adverse life events over two year period and this effect was also observed at a
trend level over a one year period. These results suggest that poorer health may increase the
likelihood of personal adversity and that these effects may be best observed over a time
period longer than one year. Protecting individuals from financial difficulty may have positive
influences on physical and mental health in both the long and shorter term. Improved health
may also have the benefits of protecting individuals in rural areas from personal adversity,
such as adverse life events and financial difficulty.

**Health.** Physical and mental health ratings were the strongest determinants of themselves
over time. However, analyses indicated little causal association between physical and mental
health over a one-year period, suggesting that beyond the stability and cross sectional
associations of these factors, poor health in one domain did not influence health in the other
domain over this time period. However, a positive influence of better mental health on better
physical health, and a trend level association indicating a positive influence of better physical
health on better mental health (P = .014), was observed over the two-year period, suggesting
that improving mental health outcomes in rural communities may have benefits for physical
health and vice versa. Rural areas face particular burdens associated with environmental
adversity, such as drought, flood, bushfire and animal disease, which are associated with
financial burdens and undermine social networks, and which may have negative effects on
health over time. In terms of a holistic health care model, it is potentially beneficial to
acknowledge that the factors that influence poor mental health outcomes will also have
negative consequences for physical health in the general population.
Psychosocial factors as indirect determinants of health

The associations between personal adversity and social factors over time were also examined to explore the potential indirect effects of these factors on health outcomes as hypothesised in theories of the health influence of social capital [13]. In line with these theories, results indicated that indirect links between social networks and health may function by influencing future experiences of personal adversity. Greater social support protected against financial difficulty over the one-year period. Social visibility and sense of belonging which were modelled as indices of social capital predicted fewer future adverse life events over the two year period. These effects provide support for processes in which social support protects individuals from experiences of personal adversity, which may in turn have negative health consequences. Social support may protect against financial adversity, which displayed relatively consistent negative health impacts, thus presenting an indirect influence of these factors on health outcomes. These are in line with models of social support and social capital [13] in which social resources protect against the experiences of adversity and promote opportunities such as employment.

There was less support for an influence of personal adversity on social networks, suggesting that over these time periods social networks were not improved or worsened by experiences of adversity. A trend level pathway between adverse life events and social capital indices suggested that experiences of adversity may undermine an individual’s social capital, or perceptions of their community. This is of concern for health, as social capital was positively associated with social support in these models which in turn had a direct effect on health. These results provide some support for anecdotal evidence that personal stressors such as adverse life events may have negative impacts on health resources such as social networks.
Gender differences in causal models of health, social networks and adversity

Causal models were generally consistent for both men and women, suggesting similar processes influenced the experiences and consequences of personal adversity, social networks, and health for men and women. The cross-sectional association of social support and mental health displayed the greatest difference across genders, followed by the lagged association of social visibility with physical health over a two year period. The cross-sectional association of social support and mental health was significantly stronger for men than for women. However, a trend level causal association of higher social visibility with poorer physical health was observed for men but not for women. These differential associations are consistent with the effects observed in the associative models reported in Chapter six; they also build upon these associations, to reveal the cross-sectional and longitudinal nature of these differential gender effects, and provide interesting insights into factors influencing perceived mental health of men living in rural areas. Differential cross-sectional associations provide important evidence regarding factors influencing experiences of mental health for men and women, suggesting that social support, in this case the availability of an attachment figure, was particularly important for men’s perceptions of their mental health. Higher social visibility, or the degree to which a person feels they are known or recognisable in the community, may have a causal effect on the experience of poorer physical health outcomes over time in men. Building on our previous discussion of these results, Chapter seven analyses support interpretations of cross-sectional associations between mental health and social visibility in rural men that reflect negative mental health consequences of social visibility, as opposed to increased social visibility resulting from poor mental health.
Strengths and limitations of causal models of health, social networks and adversity

Cross-lagged panel analyses. The use of multivariate cross-lagged panel models to assess the pathways through which health and its correlates are interrelated is a strength of the current analyses. Cross-lagged panel analyses simultaneously estimate the cross-sectional associations, stability and reciprocal associations of two or more factors over time. These designs allow for the specification of co-variation between error terms, which accounts for the systematic variation of both factors attributable to some third unobserved variable [66]. By simultaneously modelling social support and social capital, personal adversity factors and two dimensions of health outcomes, the multivariate implications of these factors were identified, which is perhaps particularly important for interpreting the influences of the interrelated social network variables modelled (i.e., social support and social capital). This strategy also allowed exploration of the direct as well as indirect pathways through which these variables may influence and be influenced by health, which aids our understanding of the potential efficacy of targeting social and adversity experiences of individuals in rural areas in developing health interventions.

As already noted, a limitation of these analyses is the reduced capacity to examine causal relationships for variables that are highly stable over the three year follow-up period (i.e., living on a farm, alcohol). The analyses reported in Chapter six in relation to the stability of these factors may inform future research into the causal influences on health outcomes; for example, they suggest that longitudinal assessment of these factors may not be useful over a three year follow-up period and that a longer follow-up period is probably necessary to assess these effects in the general population.

In many causal models, a predictor’s association with an outcome at a subsequent time point is assessed; however, these models rarely account for the stability of both predictor and
outcome factors over time, the cross-sectional association of variables at baseline, follow-up and over time, and the potential for reciprocal associations between factors. Omissions of these associations may inflate the size and significance of the association of interest, namely, between a predictor and health outcome. For example, the potential for health and its correlates to have reciprocal associations also have implications for modelling. By simultaneously modelling both the stability of factors over time, their cross-sectional associations, as well as their reciprocal associations, autoregressive cross-lagged models provide a useful model through which the exploratory casual analyses of the health predictors identified in Chapter six may be investigated.

**Exploratory analysis.** It should be noted that these analyses are exploratory in nature and a large number of effects were identified as of potential interest. Under these circumstances Structural Equation Models have been recommended [67]. However, confirmation of these results are necessary. There is potential for these models to be confirmed using ARMHS participants excluded from the current analyses (i.e., persons who responded at baseline and one year follow-up but not the three year follow-up), as well as from data collected during the final five year follow-up ARMHS survey, which has recently concluded. Techniques such as Marginal Structural Models [68] may be used to perform more targeted analyses of the effects identified in these exploratory analyses.

**Static assessment of dynamic effects.** Further, while evidence provided here confirms the hypothesised influence of social support and adversity factors on health over one- to two-year time periods, limitations of the current models suggest that factors not displaying health impacts in our study may still be important for health. Specifically, while in the current study causal associations were assessed over two discrete time lags, the underlying processes should be conceptualised as dynamic and continuous (e.g., the physical or mental health impacts of
serious injury may act and be resolved over a shorter time period than the assessed one-year lag). Thus, current results must be interpreted with caution.

**Limitations of sample representation of the rural population.** As mentioned in the previous section ‘Associative models’, participants who met criteria for inclusion in the current analyses represented a somewhat healthier, socioeconomically advantaged and less remote sub-sample of the baseline ARMHS cohort. The rural but relatively older and advantaged nature of the sample may limit the effects present in the wider rural population, for whom factors such as financial adversity and social networks may be more dynamic.
Conclusions and recommendations

Identification of the personal and contextual factors associated with health in rural and remote areas of Australia, and the implementation of appropriate and targeted health interventions sensitive to the needs and stressors experienced by these populations, are of high priority. The current thesis addressed two key limitations in the epidemiological literature addressing rural health in Australia: i) an underrepresentation of rural populations in investigations of the psychosocial determinants of health; and ii) a lack of examination as to whether determinants of health differ across urban and remote contexts. These factors present barriers to the formulation and targeting of health policy and interventions for rural areas of Australia.

Chapter one highlighted the conceptual and methodical barriers to assessment of the effects of contextual factors on health and health determinants, as well as the particular limitations and concerns present in Australia. In light of research suggesting social networks and experiences of adversity are key predictors of health in rural NSW, this chapter proposed investigation of whether these associations are influenced by the rural context. While such investigations are important to inform the targeted development and implementation of health related interventions, no single dataset in Australia provided sufficient representation of both the geographical area and psychosocial measurement needed to assess these questions. Chapter two examined issues related to combining data from existing cohort surveys assessing the psychosocial determinants of health, to obtain adequate representation of the spectrum of urban to remote communities from available data. Chapter three demonstrated that, among persons aged 55 and over, the association of low social support with high psychological distress was lesser in rural areas. Chapter four demonstrated the invariance of a new measure of physical and psychological HRQoL impairment, across the urban and rural cohorts utilised. Chapter five demonstrated that the positive associations of
depression and financial difficulty with greater psychological HRQoL impairment were similarly lessened with increased remoteness and increased perceived social capital, respectively. Chapter five also provided evidence that objective indices of community remoteness have some limitations as proxies for health related aspects of context. Chapter six proposed a theory driven method of characterising health related aspects of contact in rural areas and identified a range of reliable correlates of physical and mental health for rural men and women. Chapter seven identified both direct and indirect causal impacts of social networks and elements of personal adversity for men and women in rural areas. These causal models identified factors which may present useful points for intervention in rural areas.

In summary, the current thesis must conclude that there is some evidence that the psychosocial determinants of mental, but not physical health, are moderated by remoteness. However, existing objective indices of community remoteness may be poor proxies for the health related aspects of context. Alternative conceptualisation of contextual factors based on multiple physical, social and economic forces (such as remoteness and health service administrative areas) may provide more meaningful characterisations of the health related resources available across the range of highly heterogeneous rural areas. The current thesis also builds on this evidence of the potential moderating effect of remoteness on the determinants of health, identifying a range of reliable correlates of physical and mental health for men and women, and using causal analyses to identify potential points of health intervention. Both low social support and personal adversity may have decreased impacts on psychological health within rural contexts, suggesting that elements of the rural context may protect persons from the psychological burdens of psychosocial stress.

The current findings suggests that conducting research into the psychosocial determinants of mental health and assessing the generalizability of these models across a range of contexts, is
worthwhile. The use of health measures that have demonstrated construct validity across a range of populations and contexts facilitates the interpretation of such studies. Health related policy needs to attend to the potential for important targets for health intervention to differ across different contexts. Identifying factors for which the greatest, or at least equal, benefit to health outcomes may be obtained as a result of intervention efforts is an important consideration for the targeted and equitable distribution of health related resources.
References


