Effectiveness in Mental Health: A Review and Rethink
of Some Basic Assumptions and Common Practices

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Abstract

Despite recent advances in mental health research and treatment, prevalence rates remain high and stable in many countries around the globe. Current efforts to address the problem largely focus on identifying biological causes and correlates of mental disorders on the one hand, and large-scale structural reform of the health system on the other. This thesis took a different approach. It reflected on the role that psychological theory, research and practice plays in this predicament and what steps could be implemented to help improve effectiveness and efficiency in mental health programs.

This was done by firstly examining effectiveness of the mental health sector at the national level. A review of the national mental health programs in Australia was undertaken and found that most programs had demonstrated efficacy in pilot studies, but evidence of effectiveness post-implementation was thin and efficiency reports were practically non-existent. This represents an important gap in knowledge and practice. Next, effectiveness at the intervention level was examined. A focussed review of psychological approaches and intervention models found that the different models were approximately equivalent to each other in treatment settings and, on average, helped around 40% of participants.

To understand why effectiveness at the intervention level might be consistently limited, the focus of the thesis turned to common practices and basic assumptions that underpin psychological research and practice - specifically, how mental health is conceptualised, operationalised and analysed. It was noted that mental health is commonly operationalised using symptoms of psychopathology rather than mental health per se. This is at odds with the World Health Organisation’s (2014) definition of mental health, which emphasises positive functioning and wellbeing not just symptoms and pathology. It was hypothesised that operationalising mental health with measures of both dimensions might provide further insight into mental health that differs from what is found when only symptoms of psychopathology are analysed.

In addition, it was noted that the vast majority of mental health and related research employs regression-based techniques. It was argued that these techniques, which are based on group means and assume homogeneity, lead to potentially important individual differences being averaged out and lost. Therefore, an alternative way of analysing data is needed. It was posited that a person-centred approach could be beneficial as latent class techniques are able to identify (unobserved) patterns and
subgroups within the data.

To investigate these two hypotheses, a series of latent profile analyses were conducted with data from a non-clinical sample of Australian adults. Five distinct subgroups were found, each with unique patterns of positive and negative mental health, which supports the argument that the assumption of homogeneity is not appropriate for mental health research.

To gauge how much this issue affects statistical modelling and theory development, a series of structural equations models (SEM) were conducted. Results from traditional SEM (based on a full sample) were compared to results from multigroup and mixture SEM. This revealed that a model with strong support (based on the full sample) was actually only valid and accurate for 40% of the sample.

Although the study was exploratory, the results clearly demonstrate the need to assume heterogeneity, not homogeneity, when analysing mental health and related data. The findings also highlight the importance of conceptualising and operationalising mental health in accordance with the international standard definition (WHO, 2004, 2014), which captures positive and negative dimensions of mental health. Taken together, the findings of this research have notable implications for theory, practice, and policy, and they underscore the need for more rigorous and advanced model testing and program evaluation if effectiveness and efficiency in the mental health sector is to be substantially improved.
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Declaration

I, Jennifer Nicholls, declare that this thesis entitled:
“Effectiveness in Mental Health: A review and rethink
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Glossary and Acronyms

ADHD: Attention deficit/hyperactivity disorder
AIHW: Australian Institute of Health and Welfare
APA: American Psychiatric Association
APS: Australian Psychological Society
ATAPS: Access to Allied Psychological Services
CANMAT: Canadian Network for Mood and Anxiety Treatment
CBT: Cognitive behavioural therapy
CEDA: Centre for Economic Development of Australia
CMO: Community-managed organisation
DoHA: Department of Health and Ageing (Australian Government)
DSM: Diagnostic and Statistical Manual of Mental Disorders
Effectiveness: The ability of an intervention to achieve the planned outcomes under normal conditions (such as in field studies and routine practice)
Efficacy: The ability of an intervention to achieve the planned outcomes under controlled conditions
Efficiency: The level of resources needed to produce the benefit
GDP: Gross domestic product
ICD: International Classification of Diseases
IPT: Interpersonal therapy
LPA: Latent profile analysis
LVMM: Latent variable mixture modelling
MBS: Medicare Benefits Schedule
MCS: Mental Health Component Summary from the SF-36
MDD: Major depressive disorder
NHMRC: National Health and Medical Research Council (Australia)
NICE: National Institute of Health and Clinical Excellence (UK)
NIMH: National Institute of Mental Health (USA)
NMHC: National Mental Health Commission (Australia)
NNT: Number needed to treat
NSPP: National Suicide Prevention Program
OECD: Organisation for the Economic Cooperation and Development
RCT: Randomised controlled trial
QOL: Quality of life
SEM  Structural equation modelling
WHO  World Health Organisation
YLD  Years lived with disability
Chapter 1

Mental health problems are extremely common and can have devastating effects on the functioning and wellbeing of individuals, their families and their communities. Around a third of the global population experience mental illness at some point in their lifetime, with one in five people affected at any particular point in time (Steel et al., 2014). The World Health Organisation (WHO) and the World Organization of Family Doctors (Wonca; 2008) notes that the need for treatment greatly exceeds capacity in many developed and developing countries, with current costs to governments estimated to be upwards of $60 billion each year (about 4% of national gross domestic product (GDP) in developed countries (Organisation for Economic Cooperation and Development, 2014). If prevalence rates and the associated personal, social and economic costs of mental health are to be reduced, then sustained and focussed attention on this issue is needed.

The WHO (1946, 2006) defines health as “a state of complete, physical, mental and social well-being and not merely the absence of disease or infirmity” and mental health as “a state of well-being in which an individual realises his or her own abilities, can cope with the normal stresses of life, can work productively and is able to make a contribution to his or her community” (2014, p.1). This implies that mental health is more than just the absence of symptoms; it encompasses positive dimensions of wellbeing and functioning, and it is inherently linked to the process of stress and coping. Conceptualised this way, mental health is an integral part of the human experience.

Attempts to understand and improve mental health have persisted across the centuries with philosophical, religious and scientific explanations peppering the ages. Ancient scrolls, proverbs, and Aristotle’s theories make reference to mood and wellbeing, while modern-day genetic mapping and functioning imaging investigations seek to uncover the biological origins and mechanisms underpinning mental disorders. Today, it is understood that a broad range of biological, psychological, and developmental processes underpin mental health and functioning. Dysfunction in these processes often leads to mental illness, which is characterised by significant disturbance in an individual’s thoughts, perceptions, emotional regulation, behaviour or relationships with others (American Psychiatric Association, 2013; WHO, 2016).

The difference between mental illness (clinically diagnosable disorders) and mental health problems is generally based on the severity and duration of symptoms. Mental disorders may be diagnosed when symptoms meet the criteria for psychiatric
disorders spelt out in the WHO’s International Classification of Diseases (ICD-10; 1992-2016) or the American Psychiatric Association’s (APA) Diagnostic and Statistical Manual for Mental Disorders (DSM-5; 2013). Such disorders vary in severity and duration, and can be episodic (such as following a particularly stressful event) or persistent in nature. Globally, the most common mental disorders include anxiety disorders (such as social anxiety disorder), affective (mood) disorders (such as major depressive disorder) and substance use disorders (such as alcohol dependence; WHO, 2014). Less common, but often more severe disorders include neurodevelopmental disorders, bipolar disorder, severe personality disorders, and psychotic disorders like schizophrenia and schizoaffective disorder (Australian Institute of Health and Welfare, 2014b).

Recent estimates indicate that mental illness accounts for 21.2% of the global burden of disease (Vos et al., 2015). Burden of disease refers to a combination of premature death and the number of years lived with significant and severe disability (WHO, 2017). While anxiety disorders frequently feature in the top 10 leading causes of disability, major depressive disorder (MDD) is currently the leading cause of years lived with disability (YLD) in 56 countries around the world and the second or third leading cause in a further 90 countries. It accounts for 7.51% of YLD globally and is a major contributor to suicide deaths (WHO, 2017). Research indicates that between 50-80% of individuals diagnosed with one major depressive disorder (MDD) go on to have another, typically within about four years (Kessler et al., 2005). In such cases, the frequency and severity of episodes tends to increase with age, and the greater the number of episodes, the more likely a suicide attempt will be made (Fava, Park, & Sonino, 2006). After three episodes, the recovery between episodes is frequently lost, so that the individual appears to be in a continuous depressive state (Lam et al., 2016).

It is widely understood that individuals living with a mental illness experience significant cognitive, emotional and/or social impairment, which can detrimentally impacts their personal wellbeing, their relationships with family and friends, their capacity to learn at school, their workforce participation and productivity, and their ability to get involved and contribute to the wider community (Australian Government Department of Health and Aging (DoHA), 2013). People with persistent mental illness have been identified as being among the most excluded in society (Committee for Economic Development of Australia, 2015) with many people experiencing stigma or discrimination because of their disorder as well as economic disadvantage associated
with unemployment or under-employment and inadequate income. They often “suffer with poor health, premature mortality, have low self-confidence and feel powerless” (AIHW, 2014a, p.1). The combined effects of mental, emotional and behavioural symptoms, and their social and economic consequences, perpetuate cycles of disadvantage, exacerbate inequality, and increase the risk of mental illness in the next generation (VicHealth, 2015; Victoria Institute Of Strategic Economic Studies, 2016).

To break the cycle and begin to reduce the burden of mental illness on individuals, families and their communities, a multifaceted strategic approach is needed - one that seeks to reduce the need and demand for treatment on the one hand and improve the effectiveness and efficiency of programs and interventions on the other. This may sound simple enough on paper but the complexity of mental health, the sheer scale of the problem, and operating within the context of finite resources (in governments and organisations) makes this a worthy challenge for researchers, practitioners, and policy makers.

Public health organisations and scholars increasingly argue that if we are to begin to reduce the prevalence and burden of mental health problems, then greater emphasis needs to be placed on prevention (e.g., Fazel, 2016; Ginsburg, 2009; M. Greenberg et al., 2015; Jacka, Mykletun, & Berk, 2012; Jacka & Reavley, 2014; Jorm, 2014; Jorm, Patten, Brugha, & Mojtabai, 2017; Kazdin & Blase, 2011; National Institute of Mental Health, 2016; Nazareth & Kendrick, 2014; Petersen, Bhana, Lund, & Herrman, 2014; Rosen & Byrne, 2014; Shiers & Lester, 2014; VicHealth, 2015; WHO, 2014). This entails reducing risk factors, such as social determinants of health, and by identifying people at-risk of developing mental disorders and investing effort and resources into them before they exhibit significant levels of impairment and dysfunction, rather than afterwards. Although this has the potential to reduce the need and demand for treatment over the long-term, it means that the resources allocated to prevention are not available to treat people who are already experiencing symptoms, dysfunction and impairment (Kazdin & Blase, 2011).

Other national research bodies contend that substantial gains in mental health will be made when interventions can be better targeted to individuals and ‘personalised medicine’ becomes a reality (e.g., National Institute of Mental Health, 2013). Although ‘personalised medicine’ remains some distance off, the basic principle underpinning it could be applied to existing interventions. That is, accurately identifying what biopsychosocial variables and/or mechanisms are dysfunctional and then targeting them
selectively with an intervention. It is anticipated that tailoring interventions in this way will increase efficacy and effectiveness rates, which in turn could improve efficiency. In the context of mental health: \textit{efficacy} refers to the degree to which an intervention or program is successful in producing the desired results or outcomes under controlled conditions (such as in a laboratory or other setting with strict protocols and procedures); \textit{effectiveness} refers to the ability of an intervention to achieve the planned outcomes under normal conditions (such as in field studies and routine practice); and, \textit{efficiency} refers to what level of resources are needed to produce the benefit (Andrews, 1999). Efficiency is usually calculated as a function of the programs’ effectiveness and the overall costs of the program, hence improving the effectiveness of interventions can help improve efficiency.

It stands to reason that both strategies are needed if the high and stable prevalence rates of mental disorders are to change, such that greater emphasis and resources will need to be put into preventing the development and onset of mental disorders, and the effectiveness of current programs will need to be improved.

**Focus of the Thesis**

The impetus for this program of research stems from two broad questions: first, how well are we doing in the mental health sector, and, second, how can we do it better? These questions lay at the heart of quality improvement programs and, although they are more commonly applied to specific programs or services, it seems prudent to ask them of the sector more broadly. Indicators that can help monitor and evaluate performance and progress in the sector include: prevalence rates, burden of disease (for mental disorders), rates of access to treatment, effectiveness rates (e.g., portion of clients reporting significant improvement post-treatment; 12-month re-admission rates), efficiency ratios (e.g., cost per treatment day, cost per episode of care), and consumer and carer satisfaction ratings (AIHW, 2016a). Monitoring these indicators over time helps provide a picture of how well mental health needs are being addressed overall and highlight areas for improvement. In many countries, the first two indicators are routinely assessed and monitored; there is less consistency and availability of data for the others. However, if the prevalence and burden of mental disorders are to be significantly reduced, then effectiveness and efficiency in mental health merits review and sustained attention.

Accordingly, this thesis focuses on effectiveness in mental health. It first examines effectiveness at the national level in terms of the performance indicators just
mentioned. Then the effectiveness of national programs for improving mental health is reviewed. According to Frieden (2013), national health programs succeed and are effective when there is:

1. an evidence base for action;
2. a technical package of a limited number of high-priority evidence-based interventions that together will have a major impact;
3. effective performance management, especially through rigorous, real-time monitoring, evaluation, and program improvement;
4. partnerships and coalitions with public- and private-sector organizations;
5. communication of accurate and timely information to the health care community, decision makers, and the public to effect behaviour change and engage civil society; and
6. political commitment to obtain resources and support for effective action.

(p.17)

As will be seen, there is strong evidence and progress in areas one (establishing an evidence base for action) and six (political commitment to resourcing mental health care) at the national level in Australia but further work is needed in each of the remaining areas. A range of issues and gaps that potentially undermine program effectiveness are identified and discussed following the review of national programs.

The remainder of the thesis focuses more specifically on the evidence base for interventions in mental health. It stands to reason that if the actual interventions delivered through a national program are not particularly effective or efficient, then the overall program is likely to have limited success and impact. Effectiveness at the intervention level relies on: an accurate definition and understanding of the problem, knowledge of evidence-based strategies that rectify (or at least manage) the problem, and the capacity and resources to successfully implement those strategies. Ideally, progress should be easily and reliably measured and the improvement shown should be clinically and statistically better than due to ineffective treatment, placebo effect, or no treatment at all. The placebo effect refers to “changes in symptoms, disability and risk factors that are due to spontaneous remission, regression to the mean, and the effect of being in treatment” (Andrews, 1999, p.316). Andrews (1999) argued that, when widely applied, effective interventions should have an effect on the prevalence of a disorder, not just by preventing recurrence but by shortening the duration and severity of illness in those who are ill. In the context of prevention, effective interventions should have an effect on the prevalence of a disorder by averting the initial onset of clinical disorders in those who are at risk.
Accordingly, the evidence base for mental health interventions is reviewed with a particular focus on: how mental health is defined and understood according to the different psychological perspectives; how improvement is thought to occur; and, the status of interventions designed to prevent and treat depressive and anxiety-related disorders when symptoms are moderate to severe (National Institute for Health and Care Excellence, 2016), which are the two most common mental disorders (WHO, 2017). Note that whilst psychopharmacological interventions play an important role in the treatment of these disorders, the focus of this review is on psychological interventions and, therefore, pharmacological findings are not reviewed in detail. The aim of the current review is to clarify the different ways that mental health is commonly conceptualised, how those conceptualisations shape the development of interventions, and how effective they are in research and practice.

Following the review of key psychological perspectives of mental health and intervention models, recent bio-medical findings are synthesised and integrated with well-established psychosocial factors in a stress-diathesis model of mental health. This was done because it was initially anticipated that one of the keys to improving effectiveness and efficiency in mental health might lay in identifying a more accurate and comprehensive model of mental health – ideally, one that is broad enough to apply to everyone but specific enough to guide meaningful interventions. However, while conducting the psychological and bio-medical literature reviews for this project, a consistent pattern emerged: most interventions help some people, some of the time, but not others – even though they may have the same presenting problem or diagnosis.

This pattern prompted a change in thinking. Rather than seeking to develop a single theoretical model of mental health that fits everyone, a better strategy could be to firstly clarify who fits what models (and who does not), and then work towards accurately predicting who will benefit from what interventions and under what circumstances. Potentially, this can be achieved through statistical modelling.

Therefore, the remainder of the thesis focuses on the process of model testing and data analyses. It specifically examines some common practices in data analysis and it questions some basic assumptions that have underpinned mental health and related research over the past century. The importance of these assumptions and practices is considered and then their capacity to compromise the development of effective and efficient interventions and programs is examined through an exploratory study, which was conducted as part of this research program.
The aim of the study was to explore an alternate way of looking at the data, both in terms of how mental health is conceptualised and operationalised, and how mental health and related data is analysed. Using the WHO’s (2014) definition of mental health to guide how it was operationalised, data from a non-clinical sample was examined using latent variable analysis (LVMM). LVMM differs from the usual regression-based techniques used in mental health and related research because, rather than calculating how much of a particular factor is explained by the model specified by the researcher, it looks for patterns in the data. The response patterns help identify latent classes or subgroups of individuals in the sample that are not readily observed or apparent to researchers and clinicians.

It was hypothesised that differences between these subgroups may help explain why some interventions help some people and not others – because some theoretical models accurately apply to some subgroups but not others. This hypothesis was tested in a series of structural equation and mixture models. The analyses illustrate how common regression-based analyses can yield misleading results, which in turn lead to misguided recommendations for interventions. The results of these analyses illustrate how important it is for scientists and practitioners to examine who a model fits and who it does not.

Taken together, the findings from this program of research have clear implications for theory, model development and testing, targeting interventions, program evaluation, and screening and prevention, all of which dominate the ensuing discussion.

Scope of the Thesis

This thesis reviews effectiveness in mental health at different levels and examines numerous areas, issues, and perspectives to better understand what might be underpinning the high and stable prevalence rates of common mental disorders, like anxiety and depression. The examination begins at the national level, moves down to the intervention level, and then focuses on how some common research practices and basic statistical assumptions may be contributing to the current problem. The study conducted as part of this research focuses on these assumptions and practices; it demonstrates their potential impact and illustrates a potential solution.

The initial review of effectiveness focuses on national mental health programs in Australia, where the prevalence rates for mental illness are higher than average for a developed country (lifetime prevalence rate 45% vs. 33%; ABS, 2014; WHO, 2008).
Rates have remained high and stable for two decades (Australian Bureau of Statistics, 1998; ABS, 2008; WHO, 2017) despite substantial government spending and numerous health plans and policies that prioritise prevention and early intervention (DoHA, 2016; Australian Health Ministers, 1992, 1998; Commonwealth of Australia, 2009b). Recent findings indicate that this is not simply an artefact of increased reporting of symptoms because of greater public awareness and reduced stigma, or due to increases in risk factors, but is likely to be because “much of the treatment provided does not meet the minimal standards of clinical practice guidelines and is not targeted optimally to those in greatest need” (Jorm et al., 2017, p.90). The Australian government has recently responded to a national review of programs and services by the National Mental Health Commission and initiated major system reform to address a raft of practical and structural issues (Commonwealth of Australia, 2015). Although there is much more to be done in that area, this thesis intentionally focusses on more theoretical-based issues that may be contributing to the lack of progress being made at the national level.

Given the breadth of this topic, there are many directions and avenues this thesis could pursue, such as what are the critical success factors that make national programs or specific interventions more or less effective. Although such avenues are certainly worthy of research and discussion, this thesis maintains a strategic (big-picture) focus. That is, it reflects on current practices and focusses on principles, processes and outcomes of whole programs rather than specific diagnoses or manualised interventions. Moreover, it considers how theory informs practice and, importantly, it reflects on current practice to inform and refine theory.

Although there are many ways mental health can be operationalised, the current research draws on measures that are commonly used in epidemiology or hospital settings. This decision to do this was based on the desire to use measures that are widely used in the literature and would be readily meaningful to mental health clinicians. Although the selection of measures was guided by core facets of mental health and common mental health problems (i.e., negative affect, anxiety and depression), the suite of measures is not definitive. It was anticipated from the outset that further research would be needed to identify an optimal suite (or suites) of measures for use in future research and practice.

Similarly, a single sample is used for all of the statistical analyses conducted in this study. Ordinarily this is ill-advised because samples can be biased and results can be spurious. This limits external validity. However, given the exploratory nature of this
study and its focus on the actual process of model testing not the content per se, the
decision was made to use the same sample to help illustrate how the same data can lead
to very different conclusions, depending on the type and quality of the statistics used.
As will be seen, this is a crucial point because statistical choices impact the results of
studies, which in turn guide conclusions, theory development, interventions, future
research, and funding recommendations.

**Thesis Contribution**

This thesis seeks to contribute to the current international discussion about why
prevalence rates in mental health remain high and steady and what are some of the
practical steps that can be taken to help improve effectiveness and efficiency in mental
health. It does this by:

- Reviewing the effectiveness and efficiency of current mental health programs,
  both at the national level and interventions based on different psychological
  theories
- Reflecting on some common practices and basic assumptions that potentially
  undermine and limit effectiveness
- Examining an alternate way to operationalise common mental health problems
  that incorporates dimensions of positive health and wellbeing as well as
dysfunction
- Exploring unobserved heterogeneity (patterns in individual differences) and the
  potential impact of it on statistical modelling of mental health
- Challenging the assumption of homogeneity, which underpins common
  regression-based analyses, and demonstrating that heterogeneity should be
  assumed and analysed in mental health and related data in research and in practice
- Employing an advanced statistical technique that can help clarify who fits what
  model of mental health
- Discussing the implications of these findings for theory and program evaluation
to help optimise effectiveness and efficiency, and
- Offering specific policy recommendations.

Whilst specific facts, figures and national programs may vary across countries, it
is anticipated that the principles and processes elucidated throughout this thesis and the
subsequent recommendations will apply across settings, in Australia and abroad.
Structure of the Thesis

In this chapter, the focus, context, and significance of the thesis have been outlined. Specifically, it has been posited that if we are to begin to reduce the incidence and burden of common mental health problems, such as anxiety and depression, then a strategic approach is needed that puts greater emphasis on preventing mental disorders on the one hand and more effective and efficient intervention programs on the other.

In light of this, Chapter 2 reviews national mental health programs in Australia and examines the evidence for their effectiveness and efficiency. Evidence is drawn from the academic and grey literature, including government reports, annual reports, clinical trial and program evaluation outcomes. Findings indicate that there are considerable effort and resources going into mental health prevention and treatment but with minimal impact on the medium to long-term mental health outcomes of the community. A range of issues and gaps are outlined, which are likely to be contributing to the current predicament, including the ways mental health is routinely conceptualised and analysed.

Chapter 3 begins to investigate the first of these issues by focussing on the different ways that mental health and illness are conceptualised within psychology. Key psychological perspectives of mental health and disorder are reviewed with four questions asked of each theory: (1) How is mental health, anxiety and depression conceptualised? (2) What screening, prevention, and model(s) of change arise from the theory? (3) What evidence is there of their effectiveness and efficiency? And, (4) how does the theory and its findings fit with recent research findings? Findings from the review indicate that interventions based on the different theories tend to demonstrate similar effect sizes, each approach helps some people but not others, and therapist-related factors demonstrate bigger effect sizes than the actual theoretical approach used.

To gain a better understanding of what might be underpinning this phenomenon, recent scientific findings and the developmental aetiology of common mental health problems are reviewed in Chapter 4. A stress-diathesis framework is used to synthesise recent findings from longitudinal epidemiology, epigenetics, and neuroendocrinology. It is noted that some biological processes and mechanisms occur in some people and not others, even though they may have the same diagnosis. This is similar to the pattern observed with the psychology interventions. Hence, the challenge is how to identify what models fit who and what interventions are most likely to benefit particular individuals. The ability to predict these things could help practitioners to better tailor
interventions and, presumably, improve effectiveness and efficiency.

With this in mind, Chapter 5 discusses the role that statistics may play in perpetuating the disparity between current theoretical models, recent research findings, and the fairly modest intervention effects seen in practice. It is argued that some of the basic assumptions that underpin common regression-based analyses (e.g., reflective measurement models, the assumption of homogeneity) may not be appropriate for mental health. Therefore, an alternate way of looking at the data is needed. One option posited is mixture modelling, which looks at patterns across variables rather than variation within variables. It is hypothesised that this type of “person centred” approach could help overcome the issue of heterogeneity and help identify groups of individuals that differ in potentially important ways for mental health and prevention and treatment interventions.

Chapter 6 describes the design and conduct of the study, which explored the potential usefulness of this type of approach for mental health prevention and model testing. Information about the methodology is provided, including design, participants, data collection, and instruments used in the study. The chapter also discusses the various statistical procedures used to investigate the research questions.

Chapter 7 reports the results from the study. The chapter is divided into four parts. In Part 1, the psychometric properties of the measures are examined and issues are resolved to ensure that the measures can be used confidently in subsequent analyses. In Part 2, latent profile analysis (LPA; Lazarsfeld & Henry, 1968) is used to find clusters of individuals who are similar in terms of their risk for common mental health problems. The LPA model is then extended (with the addition of covariates) to generate profiles for each of the subgroups based on people’s endorsement of a range of demographic, cognitive and coping-related measures. In Part 3, mediational analysis with structural equation modelling (SEM) is employed to test a novel model of stress and mental health, which posits that the fulfilment of basic psychological needs mediates the relationship between stress and mental health. (While the model may have some intrinsic interest of its own, its primary purpose in this research is to facilitate a comparison of results from different statistical techniques, so it is not elaborated on in enormous detail.) After establishing support for the model with the full sample, subgroup analyses are employed to test if the model applies across the subgroups found in Part 2. The final part of the chapter reports the results of mixture SEM, which is an advanced hybrid technique that tests the structural equation model and looks for latent
subgroups at the same time. Results from the different analyses are compared and discussed.

Chapter 8 provides an overview of the results and discusses them in relation to the research questions and specific objectives, in particular, how can we conceptualise, operationalise, and analyse mental health and related data in a way that improves our ability to screen for mental health problems and target interventions? Theoretical, practical and policy implications of these findings are discussed. The chapter concludes by documenting the limitations of the current study, outlining important issues for future research, and summarising the contributions of the current research.

Supporting the main body of the thesis are the appendices. A copy of the ethics’ approval form is provided in Appendix A and select results from the preliminary analyses (i.e., psychometric testing of the measures) are presented in Appendix B.
Part One: Effectiveness of the Mental Health Sector
Chapter 2  Effectiveness at a National Level

Mental health problems are highly prevalent around the world and are associated with significant costs to governments, communities, and the individuals who experience them. Prevalence rates for the most common mental health problems, namely anxiety and depressive disorders, have remained high and steady for several decades in Australia, Canada, the United Kingdom, and the United States of America, despite significant government spending and investment. The pressing question is: why, and what can be done about it?

Given the complexity of mental health and all the factors that affect it, it is helpful to have a clear framework for thinking about mental health, its context, and the programs and policies designed to support it. Bronfenbrenner’s (1979, 2005) bioecological model of human development can assist with this. Figure 1 illustrates the model in which the individual is situated and develops within the context of their environment. The model highlights the multiple levels (e.g., individual, groups, organisations, communities), the multiple dimensions (e.g., physical, social and cultural environments), and the complexity of human systems and situations. Individuals are influenced by, and influence, their relationships and environments. The inner circles reflect the most direct interaction with parents and family, friends, objects and technology. Next are the systems and environments in which the family live and operate. The outer circles reflect the cultural norms and values at that time in history, which permeate through and indirectly influence the other levels of the system. The arrows indicate the mesosystem, which are the connection between the systems and microsystems, and highlight the interdependence and reciprocal nature of the connections across levels.

From this bioecological perspective, it is not surprising that determinants of mental health include individual attributes, such as genetics and the ability to manage one’s emotions, thoughts and behaviours, but also social, economic, and environmental conditions and processes, including gender and inequality, violence and abuse, education, employment and income, and community support (WHO, 2014).
The WHO (2014) recognises this and asserts that national mental health policies need to recognise and address the broader issues that promote mental health, not just focus on the treatment of mental disorders. This includes inter-sectorial (cross-sector) strategies such as: early childhood interventions (e.g., psychosocial screening and home visits for pregnant women, psycho-social activities in pre-schools, additional psycho-social and nutritional help for disadvantaged populations); support to children (e.g., psychosocial skills training, youth development programs, mental health promotional activities in schools); socio-economic empowerment of women (e.g., improving access to microcredit schemes, reducing gender pay inequality); social support for elderly
populations (e.g., befriending initiatives, community and day centres for the aged); programs targeted at vulnerable groups, including indigenous people, refugees and migrants, minorities, and people affected by conflicts and disasters; violence prevention programs (e.g., reducing the availability of alcohol and access to weapons); housing and community development programs; poverty reduction and social protection for the poor; anti-discrimination laws and campaigns; and advocacy for the rights and care of people with a mental illness (WHO, 2014).

A comprehensive mental health strategy needs to consider and balance factors within and across each level of the ecological model. Strategic planning and decisions must be made by governments around what factors to target, at what level, through what policies and programs to make the biggest difference for the community. These decisions guide policy content and implementation. The impact of mental health strategies and policies can be gauged through indicators such as: prevalence rates, burden of disease (for mental disorders), access to treatment rates, effectiveness rates (e.g., portion of clients reporting significant improvement post-treatment; 12-month re-admission rates), efficiency ratios (e.g., cost per treatment day, cost per episode of care), and consumer and carer satisfaction ratings (e.g., AIHW, 2014b). Favourable change in these indicators over time provides support to policies and programs implemented in the preceding period. These indicators also attest to how well mental health needs are being addressed overall and can highlight areas for improvement.

With this strategic, bioecological perspective in mind, this chapter begins to investigate why prevalence rates for anxiety and depressive disorders may have remained high and steady for several decades, despite significant government spending and investment. Using Australia as a case study, the extent of mental health problems at the national level is examined first and then the government’s response is considered. This entails a brief overview of the national policies and programs that target mental health/illness and then a review of the effectiveness and efficiency of the national mental health programs.

After reviewing the extent of the problem in Australia and the effectiveness of the national programs designed to address it, the second part of the chapter outlines some of the gaps and issues that could be compromising program effectiveness. Note that a range of structural issues (which pertain to how the mental healthcare system is set-up, governed and funded) has been identified in a recent national review of programs and services conducted by the National Mental Health Commission (NMHC,
in Australia, so this thesis does not discuss those in detail. Instead, this thesis focusses on common practices and basic assumptions in research and practice that may be (inadvertently) undermining effectiveness in mental health. The chapter concludes with a summary statement and outlines the next chapter.

**The Current Problem in Australia**

In Australia, the estimated lifetime prevalence rate of mental disorders is 45% (ABS, 2008), which means that almost half the population will experience some form of diagnosable mental disorder in their lifetime. This is 12% higher than the average rate for other developed countries, according to figures from the Organisation for Economic Cooperation and Development (OECD; 2014).

According to the most recent available National Mental Health Report (AIHW, 2014a), 9 - 12% of Australians (around 2 million people) have a mild disorder, 4 - 6% of the population (about 1 million people) have a moderate disorder, and 3% of Australians have a severe mental illness, as determined by diagnosis, intensity and duration of symptoms, and degree of disability caused (DoHA, 2013).

Mental illness is the second leading cause of disability (healthy years of life lost) in Australia, accounting for nearly a quarter (24%) of the total years lived with disability and 13% of the total health burden (NMHC, 2014c). It is the leading cause of death and disability for people aged 16 to 24 years (AIHW, 2014a) and accounts for more deaths than the national road toll each year (i.e., road fatalities; ABS, 2015a).

Recent health economic estimates in Australia put the overall cost to government of supporting people with a mental illness at more than $28.6 billion per annum (Medibank and Nous Group, 2013). This includes more than $13.8 billion per annum in direct health expenditure and more than $14.8 billion per annum in direct non-health expenditure, such as government welfare payments, crime rates and suicide rates. Other financial modelling suggests that lost productivity due to mental illness costs Australian businesses around $48.9 billion per annum (CEDA, 2015; NMHC, 2014a). This includes costs associated with absences ($4.7 billion), job turnover, unemployment, reduced labour income, and time off to care for someone else with a mental illness. At the same time, more than 30% of people receiving the Disability Support Pension have a “psychological/psychiatric” condition listed as their primary medical condition (Australian Government Department of Social Services, 2014). It is worth noting that none of these figures and estimates take into account the cost of homelessness associated with mental illness, even though mental illness is known to be
a key driver in homelessness (Costello, Thomson, & Jones, 2013; NMHC, 2014c). Taken together, these statistics reflect massive human suffering and lost opportunities for those who experience mental illness, for their families, communities and the broader society (NMHC, 2014c).

In addition, it is important to acknowledge that diagnosable mental disorders only represent the extreme end of continuums. Many more people experience symptoms but do not meet all the duration, frequency and/or severity criteria for a clinical diagnosis. Perhaps a more telling indication of how wide-spread mental health problems are in Australia is that one in every three Australians report moderate to very high levels of psychological distress at any particular point in time (ABS, 2013a). Psychological distress is also associated with poorer physical health (symptoms, physical functioning), increased health service usage, reduced productivity and personal wellbeing (ABS, 2008, 2013a, 2015b). Clearly, mental illness is a significant health and social issue in Australia (DoHA, 2016).

**Mental illness across the lifespan and high risk groups.**

Epidemiological research suggests that around 50% of all lifetime mental disorders start by the time people are in their mid-teens; 75% have begun by the age of 24 (Kessler et al., 2007). Around one in seven (13.9%) Australian children and adolescents aged 4 - 17 years experience a mental disorder each year (Lawrence et al., 2015), which means that more than half a million young people live with a mental disorder each year. The most common childhood disorders include attention deficit/hyperactivity disorder (ADHD; 7.4%), anxiety disorders (6.9%), major depressive disorder (2.8%) and conduct disorder (2.1%). Almost a third of those young people have two or more comorbid (concurrent) mental disorders (i.e., 4.2% of all four to 17 year olds; Lawrence et al., 2015), which typically increases impairment and makes them harder to treat.

According to Australia’s national health and wellbeing surveys, one in five (17.6%) people aged between 16 and 64 years experience a mental disorder in any given year (i.e., 4.3 million individuals; 2008; NMHC, 2014a). The most common mental disorders throughout adulthood include anxiety disorders (affecting 14% of the population), depressive disorders (6%) and substance use disorders (5%). The three disorders often occur in combination. Psychotic disorders (such as schizophrenia), eating disorders and severe personality disorders afflict an estimated 0.45% of the population and are considered to be low prevalence conditions (DoHA, 2013).
In people aged over 64 years, an estimated 10-15% experience anxiety or depressive disorders (AIHW, 2015a), with certain subgroups at significantly higher risk of experiencing poor mental health. These include permanent aged care residents (52% report significant symptoms of depression), individuals with dementia, elderly folk in hospital and/or with physical comorbidities, and individuals who are carers (Rickwood, 2005).

In additions to age and stage-based variations in mental disorders, there are clear gender differences. Prevalence rates by age and gender from the most recent National Mental Health and Wellbeing Survey are shown in Figure 2. Note the clear difference in prevalence rates across the life span for males and females: males are more likely than females to experience mental disorders each year between the ages of 4-17 years of age (16.3% compared with 11.5%; Lawrence et al., 2015) but less likely than females to experience a disorder between the ages of 16 and 85 years of age (ABS, 2013b). For both genders, there is a rapid increase in prevalence during early adolescence and the high levels of mental illness are sustained across early to mid-adulthood.

![Figure 2](image)

*Figure 2. Mental illness prevalence rates by age and gender in Australia. Adapted from Access Economics (2009), based on Begg, Vos, Barker, Stevenson, Stanely and Lopez (2007) and ABS (2009) data.*

Tables 1 and 2 display the overall 12-month prevalence rates for each of the major common disorder groups based upon the most recent Child and Adolescent Mental Health Survey (Lawrence et al., 2015) and the National Survey of Mental Health and Wellbeing (ABS, 2008). This data suggests that the gender differences observed in
Figure 2 are primarily due to the higher rates of ADHD in child and adolescent males and anxiety disorders in adult women. Although considerably more boys experience ADHD than girls, girls experience more depressive disorders than boys. Women are much more likely to experience anxiety disorders than men, whilst more men experience substance use disorders than women. These differences indicate that gender moderates the prevalence of some disorders. This is important to note because it means that overall trends and data, which combine data from males and females, can hide significant differences that may exist across genders and age groups.

Table 1

<table>
<thead>
<tr>
<th>Type of disorder</th>
<th>Females</th>
<th>Males</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Attention Deficit/Hyperactivity Disorder</td>
<td>4.3%</td>
<td>10.4%</td>
<td>7.4%</td>
</tr>
<tr>
<td>Anxiety disorders</td>
<td>6.8%</td>
<td>7.0%</td>
<td>6.9%</td>
</tr>
<tr>
<td>Depressive disorders</td>
<td>3.1%</td>
<td>2.5%</td>
<td>2.8%</td>
</tr>
<tr>
<td>Conduct disorders</td>
<td>1.6%</td>
<td>2.5%</td>
<td>2.1%</td>
</tr>
<tr>
<td>Any common mental disorder</td>
<td>11.5%</td>
<td>16.3%</td>
<td>13.9%</td>
</tr>
</tbody>
</table>

Source: Child and Adolescent Mental Health Survey (Lawrence et al., 2015)

Table 2

<table>
<thead>
<tr>
<th>Type of disorder</th>
<th>Females</th>
<th>Males</th>
<th>Total Adults</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anxiety disorders</td>
<td>17.9%</td>
<td>10.8%</td>
<td>14.4%</td>
</tr>
<tr>
<td>Depressive disorders</td>
<td>7.1%</td>
<td>5.3%</td>
<td>6.2%</td>
</tr>
<tr>
<td>Substance use disorders</td>
<td>3.3%</td>
<td>7.0%</td>
<td>5.1%</td>
</tr>
<tr>
<td>Any common mental disorder</td>
<td>22.3%</td>
<td>17.6%</td>
<td>20.0%</td>
</tr>
</tbody>
</table>

Source: National Survey of Mental Health and Wellbeing (ABS, 2008)

Many of the peaks in the prevalence rates for both genders (see Figure 2) coincide with key developmental stages and transition points, at least in the first half of life. For example, during the ages of 16-19 years, many people complete school, enter the workforce, move into tertiary education, and/or move out of home. Each of these life events require significant change and can be incredibly stressful. Likewise, individuals in their early thirties are often building careers, buying houses, and
frequently have young families, which can be physically demanding and associated with substantial relational and financial pressure (e.g., parental leave dramatically reduces income at a time when household costs are increasing, and stay-at-home parents can feel socially isolated). Coping with such transitions and pressures requires considerable mental and emotional resources, and can play a role in the onset of mental disorders (Bilszta, Ericksen, Buist, & Milgrom, 2010; Buist, Westle, & Hill, 1999; Salleh, 2008).

According to Figure 2, mental disorders are most prevalent in women aged 30-40 years, when one in every three women is likely to experience a mental illness. This period in life coincides with peak fertility rates in Australia, meaning that many women have their first child during this period (median age = 31 years; ABS, 2016). Australian-based research focussed on perinatal and infant mental health estimates that the risk of developing depression in the perinatal period (i.e., from conception to one year postpartum) increases to 14% for women (and up to 11% for fathers; beyondblue, 2011). As well as being very challenging for women (and fathers) experiencing mental health problems, the perinatal period is a particularly critical time for the developing infant. Longitudinal epigenetic research has shown that parent mental illness can significantly impact the neurophysiology of the developing child and affect their long-term (physical and mental) health trajectory (Beardslee, Gladstone, & O'Connor, 2011; Beardslee, Versage, & Gladstone, 1998; Slominski, 2010). Unfortunately the perinatal period is also a time of high risk for the onset or worsening of domestic (family) violence (AIHW, 2015b). Figures suggest that one in five women and one in twenty men (ABS, 2013c) experience domestic violence, which detrimentally impacts the mental (and physical) health of victims (Rees et al., 2011) and the children who experience and witness it (Dehon & Weems, 2010).

Certain other subgroups are also at higher risk of experiencing poor mental health. This includes people who differ in terms of their sexuality and gender identity (such as lesbian, gay, bisexual, transgender, and intersex people; LGBTI) and those with mental health problems who face compounding disadvantage, including: indigenous Australians, those from culturally and linguistically diverse backgrounds, those who have experienced childhood trauma or abuse, those who have fled from persecution as refugees, people living in rural and remote regions, and people living with an intellectual disability (NMHC, 2014a). The mental health needs of these people groups are significantly higher than those of other Australians. For example, the suicide rate for young indigenous men is the highest in the world at present (Commonwealth
Youth Programme, 2016) and the prevalence of major depression in LGBTI Australians has been found to be between double (for gay men) and more than four times the rate (for trans women – male to female) of heterosexual people, in addition to being at increased risk for anxiety disorders, self-harm and suicide (Leonard et al., 2012). Although each of these groups of people may represent relatively small proportions of the community overall, their higher mental health needs mean that they merit special attention and targeted programming.

**Government Response in Australia**

In response to the substantial personal, societal and economic costs of mental illness, the Australian government increasingly prioritises mental health and wellbeing. An extensive range of policies and programs have evolved over the past 20 years to help address the mental health needs of the nation. National mental health strategies are developed by the federal government every 10 years; national mental health plans are developed every five years and national action plans on mental health are developed every four years by COAG (Council of Australian Governments). These strategic, high-level documents are designed to complement the National Standards for Mental Health Services, the Australian Framework for Safety and Quality, the suicide prevention strategy, and the e-health strategy. Together, they are intended to guide state and regional policy development, budgetary spending, and the selection and implementation of initiatives and programs.

Since implementation of the first National Mental Health Plan (1993-1998), there has been a tremendous increase in the amount of money spent, the size of the mental health workforce, and the provision of psychological and pharmacological treatments (NMHC, 2014a, 2014c). This has led to reductions in the level of unmet needs of people with mental illness (i.e., the number of people with a mental illness who access treatment went up from 38% in 1997 to 48.6% in 2007, Whiteford et al., 2013). However, despite the $10 billion the Commonwealth government currently spends each year on mental health-related programs (NMHC, 2014a), prevalence rates remain steady and less than half of the people with a mental illness actually access treatment. This has important implications because untreated mental illness can become more severe, harder to treat, and lead to the development of co-occurring mental illnesses (NMHC, 2014b).

A closer look at Commonwealth expenditure on mental health reveals that 87.5% of it is spent on five programs: Disability Support Pension ($4.7 billion), National Health Reform Agreement ($1 billion, which includes $280 million for
standalone psychiatric institutions), Carer Payment and Allowance ($1 million), Medicare Benefits Schedule ($900 million, which includes the Better Access program), and the Pharmaceutical Benefits Scheme ($800 million; NMHC, 2014). Based on these figures, just 17% of total spending goes to providing direct interventions (9% on focused psychological strategies provided by GPs, psychiatrists, allied health professionals or psychologists, and 8% on psychotropic medication). Conversely, the greatest level of funding goes into high cost, non-health areas such as disability support, carer benefits, and the justice system. A recent review by the NMHC (2014) described these as downstream costs “that show that the system has failed to prevent avoidable complications in people’s lives” (p.11). To avoid further blowout of these costs and to enable people to live meaningful and “contributing lives”, the NMHC strongly recommended that upstream factors be prioritised, including health promotion, prevention, early intervention, self-help, self-care and participation (i.e., an education, job, and meaningful relationships).

**Promotion and prevention versus treatment interventions.**

To put this into context, interventions for mental health can be conceptualised as existing on a spectrum that ranges from mental health promotion and prevention at one end, to early intervention, treatment, and relapse prevention at the other end (Mrazek & Haggerty, 1994). *Mental health promotion* “aims to increase positive mental health by increasing psychological wellbeing, competence and resilience, reducing inequalities, and creating supportive living conditions and environments” (WHO, 2004, p.17). *Prevention* interventions aim to prevent the initial onset (or recurrence) of a clinically diagnosable disorder(s) by modifying vulnerability factors and reducing symptoms. In contrast, *early intervention* targets people already in the early phases of a disorder to facilitate faster recovery and better long-term outcomes by modifying risk factors and increasing their protective factors. *Risk factors* refer to conditions that increase the probability of onset of a mental disorder and/or greater severity and duration of the disorder. *Protective factors* are biopsychosocial resources that help improve an individual’s resilience to risk factors by altering or mediating conditions and promoting more adaptive responses to environmental stressors (Petersen et al., 2014). The main goal of *treatment* interventions is to alleviate suffering by reducing impairment and dysfunction, whilst *relapse prevention* seeks to stop the occurrence of subsequent episodes of the disorder.

Whilst each of these activities play a vital role in helping to address mental
health needs at the population level, if the prevalence of depression and anxiety-related disorders is to be reduced, then the initial onset of the disorders must be prevented. Therefore, greater emphasis and resources need to be directed to prevention programs and services.

In practice, prevention interventions often have aims and/or methods that overlap with mental health promotion and/or early intervention activities. This is particularly true for interventions that are universal or targeted by design.

**Levels of intervention.**

Similar to the classification framework for the prevention of physical illness, mental health interventions consist of three levels: universal, selective, and indicated interventions. *Universal* interventions target a whole population group regardless of individual risk or symptom level. *Selective* prevention targets subgroups of populations whose risk of developing a mental disorder is significantly higher than average as evidenced by particular biological, psychological or social factors. *Indicated* prevention interventions target high-risk individuals who either already have some symptoms foreshadowing mental disorder or they have biological markers indicating a pre-disposition for a particular mental disorder but who do not meet diagnostic criteria for the disorder at that time (Mrazek & Haggerty, 1994; Petersen et al., 2014).

One of the ongoing tensions in this area is where to focus effort and resources to optimise effectiveness and efficiency in mental health. In the past, it has been argued that universal interventions have the potential to prevent more mental illness by reducing a risk factor by a small amount in the general population than by selectively reducing it by a large amount in high-risk individuals (e.g., Huppert, 2004; Zulman, Vijan, Omenn, & Hayward, 2008). However, selective and indicated intervention programs typically yield greater effect sizes than universal interventions (Cuijpers, Straten, Smit, Mihalopoulos, & Beekman, 2008). This is principally because there is greater scope for improvement in individuals who are already at high risk or have sub-threshold symptoms. However, it stands to reason that optimal effectiveness and efficiency at the population level may be best achieved by a combination of prevention interventions that target each of the three levels.

**National prevention programs.**

In Australia, 64 programs for mental health and suicide prevention are run by three Commonwealth departments (Department of Health, Department of Social Services, and Department of the Prime Minister and Cabinet, 2016). These span the
spectrum from mental health promotion to treatment and relapse prevention. At the time of this review, key mental health promotion, prevention and early intervention programs for mental health include: the National Perinatal Depression Initiative, KidsMatter, *headspace* and hYEPP (headspace Youth Early Psychosis Programme), National Suicide Prevention Program, eMental Health (e.g., MindSpot), Access to Allied Psychological Services (ATAPS; which is part of the Better Outcomes program), and the Better Access to Psychiatrists, Psychologists and General Practitioner for Mental Health (Better Access) program. Figure 3 shows how these maps across the life span. Tables 3 to 5 provides a summary of these programs and outlines the evidence of their effectiveness and efficiency. Effectiveness is defined as the extent to which an intervention or program produces intended outcomes and desired benefits (Mathison, 2005). Efficiency is defined as the extent to which the intervention or program produces outputs and outcomes without wastage of resources, including time, effort, money, or other resources (Mathison, 2005). This information is important because it helps answer questions about whether the cost of a program is reasonable in relation to the magnitude of the benefits or whether alternative approaches could yield equivalent benefits at less cost.
### Current national mental health programs by developmental phase

**Perinatal**
- Prenatal care
- Psychosocial screening for MH
- Maternal & child health care
- Home visits
- First-time parent groups
- What Were We Thinking (help line)

**Early childhood**
- Early childhood interventions
- Parenting skills training
- KidsMatter - Social and emotional skills training
- Parenting support and education

**Childhood**
- Kids Helpline

**Adolescence**
- MindMatters – prevention of suicide, substance abuse, aggressive behaviour or risky sex
- headspace, eheadspace, hYEPP (early psychosis program)
- eHealth: ReachOut, BiteBack
- Teleweb: LifeLine, Suicide Call Back service, Mensline, Adults Surviving Sexual Abuse, This Way Up Clinic, MindSpot

**Young adulthood**

**Middle adulthood**

**Older adulthood**

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*Figure 3.* Current national mental health programs by developmental phase. ATAPS = Access to Allied Psychological Services
**Table 3**

*Effectiveness and Efficiency of the National Mental Health and Suicide Prevention Programs in Australia*

<table>
<thead>
<tr>
<th>Focus</th>
<th>Level of intervention</th>
<th>Program</th>
<th>Description</th>
<th>Evidence of effectiveness and efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prevention &amp; Early Intervention</td>
<td>Universal</td>
<td>National Perinatal Depression Initiative (NPDI)</td>
<td>Aims to raise awareness of perinatal depression in the community and improve prevention and early detection of antenatal and postnatal depression through the development of training materials and support for health professionals</td>
<td>Limited evaluation conducted. A high level of acceptance has been reported (NMHC, 2014) but limited uptake (e.g., Reilly et al., 2014). Although without objective and detailed measures, the effectiveness and efficiency of the program as a whole cannot be adequately assessed.</td>
</tr>
<tr>
<td>Promotion, Prevention &amp; Early Intervention</td>
<td>Universal</td>
<td>KidsMatter(^a)</td>
<td>Supports mental health promotion, prevention and EI for all children through universal, evidence-based primary school and early childhood programs, which seek to build a positive (school) community, enhance social and emotional learning, offer parenting support and education, and support early intervention for children at risk of developing mental health problems, or who are showing early signs or symptoms of mental health problems</td>
<td>Evaluation of the pilot primary school program reported significant improvements in student social and emotional competence, coping strategies and behaviour. Some improvement in student wellbeing were found together with a decrease in mental health difficulties: Medium to large effect sizes for symptom reduction in students with baseline scores in the borderline and abnormal ranges on a standardised measure of MH difficulties, and medium effect sizes for improvements in mental health strengths for students in the abnormal range (Slee et al., 2009). Evaluation of the pilot program in early childhood centres found medium and large effect sizes (according to staff) and small and large effect sizes (according to parents) for the small groups of children with scores in the borderline and abnormal range respectively on a standardised measure of MH difficulties. Over the two year period, no significant change in MH difficulties found for children in the normal range (Slee et al., 2012). Inadequate data to assess cost efficiency.</td>
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</tbody>
</table>
### Table 4

*Effectiveness and Efficiency of the National Mental Health and Suicide Prevention Programs in Australia continued…*

<table>
<thead>
<tr>
<th>Focus</th>
<th>Level of intervention</th>
<th>Program</th>
<th>Description</th>
<th>Evidence of effectiveness and efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Promotion &amp; Prevention</td>
<td>Universal</td>
<td>MindMatters</td>
<td>A national mental health promotion program for secondary schools that addressed some of the risk and protective factors for mental health and suicide prevention</td>
<td>High level of uptake and acceptance but no evaluation of effectiveness or efficiency (NMHC, 2014).</td>
</tr>
<tr>
<td>Prevention &amp; Early Intervention</td>
<td>Universal</td>
<td>headspace</td>
<td>Provides integrated early intervention services for mental health, general health, and vocational issues to 12-25 year olds either face-to-face at “shop fronts” or online via eheadspace. Also provides support to schools for suicide prevention and recovery and an early psychosis program (hYEPP) is available at some sites.</td>
<td>A 2015 evaluation found that the centres had helped increase access to services but raised questions about the lack of treatment effect, adequacy of treatment provided for mental health (i.e., median = 3 sessions), the lack of reach to people from diverse groups at many centres, and a lack of local planning and integration with existing services (Rickwood et al., 2015).</td>
</tr>
<tr>
<td>Prevention</td>
<td>Targeted &amp; Indicated</td>
<td>National Suicide Prevention Program (NSPP)</td>
<td>A multi-component program based on the Living is for Everyone framework that includes Taking Action to Tackle Suicide (TATS) and funding to existing programs, such as MindMatters, ATAPS, Social Emotional Wellbeing program, and Teleweb services. Teleweb involves a range of telephone counselling, self-help and web-based support programs and virtual clinics to supplement or substitute for existing services (e.g., Kids Helpline, Mensline, Lifeline, Suicide Call Back service, BiteBack, This Way Up Clinic, QLife, What Were We Thinking, Adults Surviving Sexual Abuse; MindSpot)</td>
<td>Most projects report having achieved their objectives but a lack of outcome data makes it difficult for projects to demonstrate their impact on mental health problems, their effectiveness or efficiency. Average cost per hour of service provision varies by program.</td>
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<td>A 2014 evaluation of the NSPP noted that there have been no targets set to reduce the suicide rate nor have there been coordinated efforts to roll out evidence-based interventions in a coordinated and targeted way (Australian Healthcare Associates, 2014).</td>
</tr>
</tbody>
</table>
Table 5
Effectiveness and Efficiency of the National Mental Health and Suicide Prevention Programs in Australia continued...

<table>
<thead>
<tr>
<th>Focus</th>
<th>Level of intervention</th>
<th>Program</th>
<th>Description</th>
<th>Evidence of effectiveness and efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Early Intervention &amp;</td>
<td>Indicated</td>
<td>Access To Allied Psychological Services</td>
<td>A two-tiered program that targets disadvantaged groups who miss out on Medicare-subsidised services by funding short-term focused psychological strategies services (mostly CBT) for common mental health problems (e.g., anxiety and depression; tier 1). It also provides telephone-based CBT (T-CBT) and targets: women with perinatal depression; individuals who attempt suicide or self-harm, people at risk or who are homeless with a mental illness; people in remote locations; Aboriginal and Torres Strait Islander people; children who have or are at risk of a mental illness; and, people impacted by the Victorian bushfires, 2011 floods and cyclone Yasi</td>
<td>Improved outcomes for consumers have been demonstrated across all 13 services as evidenced by reductions in standardised outcome measures and consumer feedback. Positive consumer satisfaction ratings have been consistently achieved with respect to the availability of the service and quality of service provider (Bassilios et al., 2011).</td>
</tr>
<tr>
<td>Treatment</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Early Intervention &amp;</td>
<td>Indicated</td>
<td>Better Access</td>
<td>Facilitates access to short-term psychological interventions) for common mental health problems in the primary care setting through the Medicare Benefits Schedule</td>
<td>Good evidence that it has improved access to mental health care in the community, even among relatively disadvantaged groups, and provides an effective and cost-efficient model of service delivery (J Pirkis, Harris, Hall, &amp; Ftanou, 2011). Positive outcomes for clients have been demonstrated as evidenced by reductions in standardised measures of distress, depression, anxiety, and stress but questions raised about the efficacy of the GP MH Care Plan required to access treatment, the need to ensure that the program targets those most in need, and the limited number of sessions (max. 10 per year), which does not meet the needs of people with more moderate to severe symptoms or complex disorders (NMHC, 2014a).</td>
</tr>
<tr>
<td>Treatment</td>
<td></td>
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</table>

*Note.* a Results only available for the pilot programs.
Overall, most of these national programs reported achieving their objectives, in terms of increasing access to psychological treatment and support but evidence to support their effectiveness at improving client outcomes is surprisingly thin and short-term. Positive outcomes for clients were reported for the ATAPS and Better Access programs, as evidenced by reductions in standardised measures of distress, depression, anxiety, and stress immediately post-treatment, but questions have been raised about the lack of effect and adequacy of treatment provided through headspace (Rickwood et al., 2015). Moderate to large effect sizes were initially reported in the pilot studies for KidsMatter and T-CBT but there has been very little (or no) evidence to support their effectiveness at improving client outcomes or preventing disorders since the programs have been rolled out nationally.

Without data on the effectiveness of programs, cost efficiency cannot be modelled. This makes it very hard for decision makers to plan and select effective and efficient mental health interventions that can help reduce the prevalence and burden of mental illness.

A noticeable absence from the national programs is routine screening and prevention, especially for subgroups whose risk of developing mental illness is significantly higher than average due to biological, psychological or social risk factors. Routine screening was supposed to form part of the National Perinatal Depression Initiative, and there is strong evidence to support the benefits of psychosocial screening and referral in terms of better outcomes for parents and their infants (Reilly et al., 2014). However, uptake has been limited (e.g., Reilly et al., 2013). Other subgroups known to have much higher rates of mental illness than the general population include Aboriginal and Torres Strait Islander people, LGBTI (lesbian, gay, bisexual, transgender, and intersex) people, refugees, and even young university students (Bayram & Bilgel, 2008; Castillo, 2013; Commonwealth of Australia, 2015; Macaskill, 2013; Stallman, 2010). As previously stated, although each of these groups of people may represent relatively small proportions of the community overall, their higher mental health needs mean they merit special attention and targeted programming. Given that effective and efficient prevention (and early intervention) first require accurate and timely recognition of individuals at-risk, the lack of routine screening and referral pathways in the national plan appears to be a significant gap.
In sum, the Australian government has made significant policy and funding commitments since the 1990s and introduced a range of reforms across sectors to benefit mental health. Yet despite significant investment every year, the prevalence of mental illness remains high and stable, and mental health outcomes in Australia continue to be suboptimal (i.e., direct mental health expenditure increased by 178% in real terms between 1992-93 and 2010-11 while the 12-month prevalence rate of mental disorders increased from 17.7% in 1997 to 20.0% in 2007; DoHA, 2013; NMHC, 2014; Medibank & Novac Group, 2013). National spending on mental health is already above the average for OECD countries and demand for mental health services currently exceeds supply. Current projections suggest that even a modest increase in the proportion of people seeking help for mental health problems, combined with projected Australian population growth, will lead to an increase in the use of mental health services of between 135% to 160% over 15 years, at a cost of around $9 billion in salaries alone (Hosie, Vogl, Carden, Hoddinott, & Lim, 2015). This is simply not sustainable without substantial budgetary cuts elsewhere in the economy, which adversely impacts other parts of the community.

To combat the growing economic, social and personal cost of mental disorders, system-wide reforms are urgently needed with increased focus on prevention and early intervention. The NMHC’s recommendation to reallocate funding and resources “from downstream to upstream services, including prevention and early intervention” (NMHC, 2014a, p.5) has been somewhat controversial (Jorm, 2014, 2015) as clinical services often claim they need more resources to meet the current demand. However, this shift seems essential if we are to reduce the prevalence of mental disorders and the associated burden and cost.

The current findings echo calls from population health experts who seek to draw attention to the high and stable prevalence rates in high income countries, including Australia, the U.K., U.S.A. and Canada (e.g., Jorm, 2014; WHO, 2004). In a recent analysis by Jorm and his colleagues (Jorm et al., 2017), Australia was found to have relatively high access rates compared to the other three countries - yet the trend of high and stable prevalence rates persists. The authors concluded that greater attention and investment needs to be placed on prevention (through risk modification) and improving the quality of treatment provided, not just increasing the availability of treatment. The
current findings support those conclusions and recommendations.

It does need to be said, however, that a lot of the data on “current” prevalence rates is more than five years old. Many of the national epidemiological studies were conducted prior to 2010 (e.g., AIHW’s 2007 National Survey of Mental Health Wellbeing; the British National Psychiatric Morbidity Survey, 2007; the U.S. National Health and Nutrition Survey, 2005-2010) and are due to be repeated soon. It will be interesting to see if there has been any change in prevalence rates over the past couple of years or whether they continue to be high and steady.

Even with this proviso, this review found that current policies and programs in Australia are conceptualised within a bio-ecological framework and take a life course perspective of mental health. This is in line with WHO recommendations and best-practice population health models, which seek to reduce risk factors and enhance protective factors. However, this review has also shown that there is very limited evidence of effectiveness and cost-efficiency for the current suite of national mental health and suicide prevention programs. Clearly, more needs to be done to: firstly, improve the evidence base for the current suite of programs and, secondly, improve the effectiveness and efficiency of prevention programs if we are to achieve the aim of reducing the incidence of common mental health problems and improve mental health and wellbeing across the community.

Implications of Limited Effectiveness

The WHO (2000) asserts that programs that lack at least moderate evidence of effectiveness, can impair the ability of the health care system to achieve the nation’s population health goals. This occurs as a direct result of the resources (time, effort, money, and goodwill) that are invested into the program, which might otherwise be spent elsewhere, and failing to successfully treat individuals with a mental illness. Research has shown that unsuccessfully treated mental illness can lead to: poorer health outcomes and increased health care costs in the long-term (WHO, 2000); an exacerbation of existing conditions and lower quality of life; increased problems with family, peers, employment, and academic performance; lower productivity and increased absenteeism; increased risk taking behaviour; and increased risk of substance use/abuse, delinquency, physical and sexual partner violence, and suicide (Agency for Healthcare Research and Quality, 2015; Boston Consulting Group, 2006; WHO, 2014).
In sum, low efficacy and effectiveness in mental health represent important missed opportunities to lower the burden of mental illness for individuals, families, and communities.

Possible Explanations for Lack of Effect

This review found limited evidence to support the effectiveness of five out of seven of the national mental health programs reviewed. To be clear, that does not mean that those five programs are ineffective, it just means that there is no robust evidence in the public domain demonstrating that they are effective. Without evidence of improved outcomes for consumers and significant benefits to the community, one is left to wonders how the programs’ ongoing funding is substantiated.

To provide a broader context for this discussion around evidence of effectiveness, it is useful to consider the lifecycle of biomedical research. This can be conceptualised as a five-phase process: (1) epidemiology research on the target problem; (2) research on the aetiology of the problem, including the risk and protective factors that may be modifiable through intervention; (3) intervention design, pilot testing, and efficacy trials - to assess whether the intervention program works when implemented under ideal conditions; (4) effectiveness studies - to assess whether the intervention works when delivered under real-world conditions; and, (5) dissemination (Mrazek & Haggerty, 1994). Two further steps are recommended to successfully translate intervention research into effective and efficient practice but, in practice, they are rarely undertaken. These include implementation trials, to determine what implementation processes work best, and efficiency studies to assess whether the benefits of the intervention program are worth the costs. These two steps are vital for assessing and improving effectiveness and efficiency, so it is odd that so little attention is paid to them. Furthermore, each phase of the research process has its own set of opportunities and challenges, which can impact whether or not an intervention is ultimately effective in large scale roll-outs.

In Australia, phases one and three are being routinely carried out, with national health and wellbeing surveys conducted every 10 years and numerous pilot tests and (single) efficacy studies conducted each year. However, as discovered in the current review, effectiveness studies for prevention interventions are rare and implementation trials and efficiency studies are practically non-existent. These areas represent important
gaps in the evidence base, which will need to be addressed if we are to improve the effectiveness and efficiency of the mental health sector. There seems to be substantive issues in research and practice linked to the other phases of the research process also. These can be grouped into three broad categories: practical issues, conceptual issues, and statistical issues.

**Practical issues.**

The recent review of programs and services by the NMHC (2014a) highlighted a number of key issues and gaps including: difficulties translating research into practice; lack of local planning, coordination and integration of programs with existing services; workforce issues (i.e., availability and retention of appropriately trained staff); ongoing barriers to access, such as social stigma relating to mental health, which results in a reluctance to talk about mental health problems and/or seek help; and, difficulties engaging with some target groups due to competing priorities (e.g., in schools and workplaces) or cultural and language barriers.

At the health service and program level, some additional gaps and issues include: the lack of program logic underpinning programs and services; a lack of program fidelity; poor adherence to treatment; and, a lack of routine monitoring and evaluation embedded into practice. For example, evidence-based programs are frequently adapted to fit in with service constraints, clinician preferences, or client needs and preferences. However, in practice, it seems that there is little or no monitoring and evaluation to determine whether the modifications are beneficial, harmful, or benign.

The lack of routine monitoring and evaluation raises questions about quality and safety, and transparency and accountability. It is at odds with other health services (and other industries and sectors that receive government funding) where regulatory reporting exists and quality assurance forms part of standard business operating procedure. It also potentially limits program improvement as it misses vital opportunities for organisational learning and for practice-based research to feedback and inform theory by clarifying what interventions work for whom and under what circumstances.

Stephan and colleagues (2015) highlight the importance of this point in their commentary on treatment efficacy and how it impacts effectiveness. They note that
“Without tests to predict efficacy and guide individual treatment, psychiatrists undertake a prolonged process of trial and error to find an effective therapy” (p.1). They argue that the most effective and efficient intervention will depend on what is causing the symptoms for each individual. This might mean determining what neurochemicals are out of balance or which schemas are being automatically activated and produce the symptoms of concern. Whilst a comprehensive assessment can help to narrow down probable predisposing, precipitating and perpetuating factors (both physical and psychological), the science and technology are not sufficiently advanced for us to routinely detect pathophysiological processes and/or intervene with accuracy and specificity.

Furthermore, the aetiology of psychiatric disorders remains largely unknown. Decades of research has shown that current mental disorders cannot be traced to a single, homogeneous condition (with the exception of Down’s syndrome, which is linked to having all or part of an extra 21st chromosome; D. Borsboom, S. Epskamp, R. Kievit, A. Cramer, & V. D. Schmittmann, 2011). Rather, a variety of biological (genetic and neurological), psychological, social and environmental factors interact and contribute to the onset and progression of mental illness. As mentioned earlier, these factors interact in complex ways and vary depending on the particular disorder and the individual. Insel (2014) summed up this issue and the current state of knowledge in his writing about the pursuit of personalised medicine in psychiatry: “Genetic findings are statistical associations of risk, not diagnostic of disease; neuroimaging findings report mean group changes, not individual differences; and metabolic findings are not specific” (p.395). Without a clear understanding of the aetiology of mental health problems, it is extremely difficult to identify the key variables that interventions should be targeting to effectively and efficiently address underlying causes or even who should be targeted for prevention and early intervention.

Large mental health and wellbeing surveys typically focus on the prevalence of mental disorders and psychological distress, with a minor focus on the positive elements of mental health and wellbeing (e.g., social engagement and satisfaction with life). This bias is consistent with medical disease-based or deficit models and perspectives of the past but it does not enrich our knowledge or enhance our focus on protective factors and mechanisms that help prevent the onset (or relapse) of mental disorders. This too
suggests a gap in current research and practice. If we are to develop and deliver effective prevention interventions, then these practical issues and gaps need to be addressed.

**Conceptual issues.**

Another set of issues that may undermine intervention effectiveness pertains to how mental health and disorders are conceptualised. The WHO’s definition of mental health is fairly standard around the world, but the current taxonomies (classification systems) for mental disorders, namely the ICD-10 and the DSM-5 are plagued with problems of excessive comorbidity, arbitrary cut-offs, and temporal instability (Wright, 2011). Consequently, the empirical validity of these classification systems has been called into question over the past decade. These taxonomies are based on a categorical approach to classification, which conceptualises disorders as discrete entities that are qualitatively distinct from each other and from normality (Eaton, 2015; Murray, 2013). They also assume that individuals with each disorder form relatively homogenous populations that display similar symptoms and attributes of a disorder (Jones, 2012).

In reality, this is not the case: clients frequently meet the criteria for multiple diagnoses and diagnostic populations are highly heterogeneous. Disorders such as major depressive disorder (MDD) and generalised anxiety disorder (GAD) overlap much more frequently than expected by chance alone (Eaton et al., 2013; Krueger, Millon, & Simonsen, 2010) and around 45% of people with a mental disorder have comorbid disorders (i.e., more than one diagnosable mental disorder; Eaton, 2015; Kessler et al., 2005). Furthermore, two individuals can be diagnosed with the same disorder but experience very different symptoms. For example, one person with MDD may experience depressed mood, hypersomnia, significant weight gain, fatigue, feelings of worthlessness, and recurrent thoughts of suicide. Another person with MDD may present with a diminished interest in things, insomnia, significant weight loss, psychomotor agitation, and difficulties concentrating. Both meet the criteria for MDD but have very different presentations. In an attempt to address such issues of high comorbidity and heterogeneity, each edition of the DSM has added more diagnoses, subtypes, or specifiers (e.g., MDD - With anxious distress or With mixed features).

On the one hand, these categorical-based classification systems are helpful because: they guide clinical observation and interpretation, helping to put order to
otherwise complex, diverse and (often) ambiguous symptoms and phenomena in psychopathology (Jones, 2012); they improve reliability for most diagnoses (inter-rater reliabilities of around 0.8 are common; Murray, 2013); and, they can facilitate communication between clinicians and researchers. On the other hand, these taxonomies lack structural validity and their capacity to help clinicians select the most effective intervention, predict course and prognosis, and facilitate research is increasingly questionable (Cramer, Waldorp, van der Maas, & Borsboom, 2010; Jorm, 2014). Therefore, the way mental health problems are conceptualised needs to be reconsidered (Insel & Wang, 2010; National Institute of Mental Health, 2013).

**Statistical issues.**

In addition to the way mental health is conceptualised, there are some issues with how mental health data is often modelled. Current taxonomies conceptualise mental disorders as discrete clusters of symptoms that are manifestations of some common underlying condition or disorder (Borsboom, Cramer, Schmittmann, Epskamp, & Waldorp, 2011). For instance, MDD causes symptoms of low mood, loss of interest or pleasure, insomnia or hypersomnia, and so on. When this is modelled statistically, MDD becomes a latent (unobserved) factor and the symptoms are modelled as indicator variables that reflect the degree to which MDD is present. This type of modelling is consistent with classical test theory, which assumes that the observed variables (e.g., symptoms or items on a scale) reflect the construct thought to underlie them (Bollen & Lennox, 1991). Common statistical techniques (such as factor analysis, regression, analysis of variance, and structural equation modelling) are based on this theory.

However in reality, symptoms can cause other symptoms; they do not have to be caused by a change in the latent factor. Borsboom and colleagues (2011) give the example of sleep deprivation: sleep deprivation can lead to fatigue (a symptom of MDD), which in turn can lead to concentration problems (symptom of MDD and GAD), which in turn can lead to irritability (symptoms of GAD). These types of direct relationships exist between symptoms but they are not captured or depicted in the way that disorders are typically modelled. Furthermore, it could be the combination of symptoms give rise to the mental disorder, rather than the other way around. In either case, these relationships are not well accounted for by the general linear model in classical test theory, nor are they captured when composite measures (e.g., total scores
on checklists) are used to operationalise mental disorders in statistical analyses. Cramer and her colleagues (2010) highlight this issue and assert that it may underpin the limited success of traditional research designs with the current categorical-based taxonomies. This is a bold claim but it merits further consideration and investigation. It will be discussed further in Chapter 5.

Another statistical issue and information gap relates to subgroup analysis. Subgroup analysis typically involves splitting all the participants’ data into smaller subgroups often on the basis sex or gender (male or female), age group, or geographical location (Deeks, Higgins, & Altman, 2011). This is usually done to examine particular client groups or, in the case of clinical trials, the subgroups are generally formed on the basis of which intervention the participants received, which enables researchers to compare results from the different arms of the trial. However, subgroup analysis could be taken further, it could be used to analyse who significantly improves with each intervention, who significantly deteriorates, and who fails to respond to the intervention.

This is not a new concept. In medical research, it is often discussed in the context of predicting prognosis and treatment completion. However, in mental health research and practice, this is not common practice (McMahon, 2014). When it has been done (e.g., Berman & Hegel, 2014; Cipriani & Geddes, 2016), it is usually during efficacy trials. Rarely are such analyses undertaken in field studies or when the intervention is implemented in practice. Yet one might anticipate that analysing subgroups for whom interventions do not work could lead to greater clarity and advance our understanding of why some interventions work for some people some of the time but not for others. In turn, this could improve our capacity to better target interventions and predict intervention outcomes.

Although analysing subgroups sounds fairly simple and straightforward, there are several reasons why it is not routinely conducted in research and practice. These include: difficulties modelling dynamic, complex data; a lack of technical know-how; and, insufficient statistical power. In practical terms, statistical power refers to the ability to detect an effect (or change) when there actually is one. (This ability is chiefly affected by the size of the effect and the size of the sample used to detect it (Ellis, 2010). To analyse the effects of interventions on various subgroups, large samples are needed to ensure that there are sufficient individuals within each subgroup to
confidently detect a change. Small sample sizes (which are the norm in intervention studies) make it extremely hard to show a meaningful difference between groups and subgroup analyses further compound the problem by splitting small samples into even smaller subgroups. As a result, intervention research often lacks the power to detect a change or difference between subgroups, if one is present.

Whilst the simplest solution to this might be to increase sample sizes to enable meaningful subgroup analyses to be conducted, this comes at a cost: more time effort, money and other resources are needed to accommodate larger samples, which in turn acts as a significant barrier for such projects to get off the ground and be seen through to completion. Nevertheless, despite this obstacle, subgroup analyses make sense as a potential strategy that could help clarify what interventions work for whom.

Chapter Summary

In sum, there are numerous practical, conceptual, and statistical issues that are likely to contribute to the modest intervention effect sizes seen across the literature and lack of effect on national prevalence rates. Clearly, there is much to be done in terms of (a) clarifying the causal structures and mechanisms that underpin mental health problems, (b) developing more targeted prevention and treatment interventions, (c) ensuring that they are effective and efficient in practice, and then (d) developing the capacity to accurately predict treatment outcomes and prognosis to help clinicians determine which intervention is most likely to work for whom, and under what circumstances. As discussed in this chapter, there are some fundamental barriers to achieving these goals, not the least of which may be the way mental health and illness are conceptualised and analysed. These two issues will be examined further in the following chapters, starting with the different ways that mental health and illness are conceptualised within psychological practice, what impact that has on modelling mental health, and what impact it has on intervention effectiveness.
Chapter 3  Effectiveness at the Intervention Level

The bedrock of an efficient mental healthcare system is the delivery of effective prevention and treatment interventions. If the interventions delivered by programs and services are not effective, then the outcomes and long-term impact of the programs, services and system as a whole will be limited. Accordingly, this chapter examines effectiveness at the intervention level.

Effective interventions are those that achieve the intended outcomes and desired benefits (Mathison, 2005) with minimal or nil undesired side effects. The development of effective interventions ideally stems from an accurate understanding of the problem and then rigorous development, trialling, and refining processes, which are characteristic of the biomedical research process. Today there are a variety of interventions deemed to be effective for common mental health problems, such as anxiety and depression, including a diverse range of psychological and pharmacological therapies. Each of them stems from a different theory about how mental health problems arise, what perpetuates them, and how best to intervene to resolve the problem, reduce symptoms, and restore wellbeing and functioning.

This chapter considers how the different psychological theories and interventions impact the overall effectiveness of the mental healthcare system. Key psychological theories about mental health and disorder are reviewed with a particular focus on the two most common mental health problems, namely anxiety and depression. These two groups of disorders are often referred to as internalising or emotional disorders and recent evidence suggests that the epigenetic and neurological processes underlying them are very similar (e.g., Cross-Disorder Group of the Psychiatric Genomics Consortium, 2013; Goldberg, Krueger, Andrews, & Hobbs, 2009; P. Sullivan, Daly, & O'Donovan, 2012; Vaidyanathan, Nelson, & Patrick, 2012). Key psychological theories reviewed include psychodynamic, behavioural, cognitive, mindfulness, interpersonal, and humanistic perspectives. Four questions are asked of each approach: How is mental health, anxiety and depression conceptualised? What model(s) of change arises from the theory (i.e., treatment effect mechanisms)? What evidence is there of their effectiveness and efficiency in prevention and treatment? And, given that most of the theories were developed decades ago, the final question asked of each approach is how do the theory and past findings fit with recent research findings?
Given the plethora of individual intervention studies published over the past few decades, the review of effectiveness for each theoretical approach will be limited to more recent meta-analyses of randomised controlled trials targeting depression and anxiety-related concerns and reported pre- and post-intervention measures of the same. The chapter concludes with a summary of key findings, discusses the limitations and implications of the findings, and then outlines the next chapter.

**Psychological Perspectives of Mental Health**

**Psychodynamic perspective.**

Sigmund Freud’s (1894, 1933) theories, which formed the basis of the psychodynamic approach, posit that people’s thoughts, feelings and behaviour are determined by the unconscious mind and childhood experiences. According to Freud, the unconscious mind consists of three components: the id, the ego, and the superego. The ego (the “I”) sits at the centre of three powerful forces: biology, as represented by the id; society, as represented by the superego; and reality. Freud posited that the id and the superego are in constant conflict with each other, and the ego works to resolve the discord and bring about harmony among the forces. When the ego struggles to balance these conflicting demands, individuals may feel threatened and overwhelmed. This feeling is anxiety. It signals to the ego that its survival, and the survival of the whole individual, is in jeopardy (Freud, 1933).

When one feels threatened because the id or superego becomes too demanding, the ego employs defence mechanisms in order to protect one’s self from feelings of anxiety or guilt (Freud, 1894, 1896). Defence mechanisms are believed to operate at an unconscious level to reduce the unpleasant feelings or increase pleasurable feelings. For example, repression keeps disturbing or threatening thoughts from becoming conscious and denial involves blocking external events from awareness, if it is just too much for the person to handle. Although ego-defence mechanisms are considered natural and normal, psychodynamic theorists argue that neuroses develop when they are used excessively. Neuroses may include anxiety states (e.g., hysteria), phobias, or obsessions, as well as somatoform and dissociative disorders (Nydegger, 2011).

With respect to depression, Freud (1917) argued that whilst many cases are due to biological factors, some can be linked to loss or rejection by a parent. In such cases, depression can be understood as a grief reaction to the actual loss of a loved one or a
symbolic loss (e.g., loss of a job) whereby the loss causes the person to re-experience childhood events when he or she experienced loss of affection from a significant person, such as a parent. Freud (1917) argued that in order to avoid loss turning into depression, the person needs to engage in a period of grief work, during which she or he recalls memories of the lost one. This allows the person to separate her/himself from the lost person and reduce inwardly directed anger. Sometime later Freud (1933) modified his theory asserting that the tendency to internalize loss objects was normal and depression was caused by a severe super-ego (i.e., the moral functions of the person), which results in excessive guilt and shame.

Other psychodynamic theorists (such as Alfred Adler, Erik Erikson, Carl Jung, Erich Fromm, Karen Horney, Otto Rank, Melanie Klein, and Harry Stack Sullivan) have focussed more on the conscious mind and less on the id’s instinctual forces. Amongst these theorists and their followers, depression has been understood in terms of deprivation in the mother-infant relationship during the first year (M. Klein, 1935, 1975), unresolved psychosocial developmental tasks (Erikson, 1950), narcissistic vulnerability (i.e., preoccupation with self; Chodoff, 1972), and loss of self-esteem (Bibring, 1953).

**Model of change for treatment and prevention.**

The contemporary short-term psychodynamic psychotherapies (STPP) approach to treatment focuses on unconscious processes as they are manifested in the client's present symptoms and behaviour. Clinicians work to identify and explore recurring themes and patterns in the client’s feelings, thoughts, self-concept, relationships and life experiences with the goal of helping the client to recognise them and then understand them in the context of past and recent trauma. In general, STPP aims to improve long- and short-term problems with emotion processing, behaviour, and communication and relationships with others (Abbass et al., 2014).

**Efficacy and effectiveness in treatment and prevention.**

Recent meta-analyses support the efficacy of STPP for treating common mental disorders such as anxiety and depressive-related disorders with moderate to large effect sizes reported (Abbass et al., 2014; Gaskin, 2012). While the Australian Psychological Society (APS; 2010) guide to evidence-based treatments reports evidence supporting the use of psychodynamic therapy for depressive and anxiety-related disorder, STPP is
notably absent from the treatment recommendations set out by the National Institute of Mental Health (NIMH) in the United States. There are likely to be several reasons for its exclusion, but the main one undoubtedly relates to the standards of evidence used to judge the effectiveness of treatment approaches. The NIMH standards deem systematic reviews and meta-analyses of RCTs with multiple replications as the best evidence of how well a treatment works (i.e., efficacy). Evidence of comparable clinical impact when the treatment is delivered in regular clinical settings (i.e., effectiveness studies) generally provides the essential support for it to be recommended for routine clinical use (Hunsley, Elliott, & Therrien, 2013). For interventions to be included in RCTs, typically they need to be able to be standardised and manualised (to ensure consistency across practitioners and settings) and outcomes need to be quantifiable. Given the intrapsychic and highly individualised nature of STPP, it is not easily standardised and manualised, and unconscious processes are notoriously difficult to measure. Without supporting evidence from multiple RCTs, meta-analyses and comparative analyses, the NIMH appears reluctant to recommend STPP.

STPP is recommended by the National Institute of Health and Clinical Excellence (NICE; 2011) in the United Kingdom as one of four treatment options for social anxiety disorder. However, the recommended “25 – 30 session of 50 minutes’ duration over 6 – 8 months” is double the number of sessions and time period required for the other psychological interventions. This implies that it is likely to be more expensive and less efficient than the other intervention models (based on CBT), which are factors that need to be taken into account by clinicians and clients when choosing between treatment options.

In terms of preventing mental disorders, a review of the prevention literature reveals only one program directly associated with psychodynamic theory. Shen (2002) implemented a randomised controlled trial (RCT) with a play therapy-based depression prevention program for primary school aged children ($n = 65$) who had experienced the 921 earthquake in Taiwan. The targeted group program ran for four weeks and included 10 (40 minute) sessions with three students per group. Although positive effects were reported post-intervention, attrition was not reported, intention-to-treat analyses were not included, and the control group received no intervention. Hence, the results need to be interpreted with caution because it is unclear whether the reported effects were real
or just a placebo effect.

**Fit with recent findings.**

Over the past several decades, it has become clear that all mental processes derive from mechanisms of the brain (Kandel, 1998). There is also clear evidence that our subjective experiences affect the brain (Gabbard, 2005). Therefore, any change in psychological processes is likely to be reflected by changes in the neurophysiology and neurochemistry activity in the brain. Multidisciplinary studies in neuroscience have been looking at the effects of psychotherapy on the brain since the early 1990s, however, very few have examined the effects of psychodynamic therapy. Those that have generally have been small, single studies. For example, in a study by Buchheim and colleagues that examined the neurophysiological correlates of long-term attachment therapy for depressed patients, preliminary findings from functional magnetic resonance imaging (fMRI) and electroencephalography experiments (EEG) included changes in the amygdala- anterior hippocampus region and changes in prefrontal areas such as the subgenual cingulate cortex (Buchheim, Labek, Walter, & Viviani, 2013; Buchheim et al., 2012). However, these changes are merely correlational and have yet to be replicated. In another study by Karlsson and colleagues (Karlsson et al., 2010), which investigated the molecular mechanisms mediating the effects of psychotherapy for MDD, increased serotonin 5-HT1A receptor binding in multiple cortical regions was found following STPP but not in patients receiving fluoxetine medication. Although this study was heralded as one of the first direct demonstrations of a specific neurotransmitter mechanism involved in the neurobiology of psychotherapy, the small sample size set inherent limitations and the clinical implications of these findings are unknown.

Over the years Freud’s theories have been strongly criticised for being so “abstract that they cannot be correlated with clinical material… [and] so remote from any observables in clinical data that it defies systematic validation” (Beck, 1964, p.253). His theories were based on what his patients told him during therapy and so were considered to be clinically-derived. However, this type of case-study approach, with subjective interpretations and a biased sample (i.e., largely middle-aged women from Vienna), limits the external validity and generalisability of the results (Sulloway, 1991). Other critics argue that psychoanalytic theory is markedly deterministic and it ignores
important mediational processes such as thinking, memory, and personal agency (McLeod, 2007).

Despite the critics, some of Freud’s concepts continue to influence thinking and practice today. There is now extensive empirical support for the integral role of early childhood experiences in determining one’s developmental trajectory in terms of health (Barker, 2004; Burdge & Lillycrop, 2010) and vulnerability to mental illness (A. Lewis & Olsson, 2011; M. Lewis & Rudolph, 2014). In fact, this premise underpins current prevention policy and programs, which seek to prioritise perinatal, child and adolescent health and wellbeing.

The aims of STPP (which include improving emotional regulation, behaviours, communication, and relationships with others) directly correspond to the core processes targeted in transdiagnostic prevention interventions (Musiat et al., 2014) and treatment programs (Bolton et al., 2014; Newby, McKinnon, Kuyken, Gilbody, & Dalgleish, 2015). This is a testament to the fact that these elements have stood up to rigorous empirical investigation over the past century, even though other elements of Freud’s theories (e.g., the Oedipus complex) now tend to be dismissed as inappropriate, irrelevant, and/or unsubstantiated.

Finally, research in the areas of cognitive and social psychology has shown support for Freud’s notion of unconscious processes by uncovering cognitive processes such as automatic processing (Bargh & Chartrand, 1999; Heflin et al., 2011) and procedural memory (Tulving, 2002), and demonstrating the importance of implicit processing in interpersonal relationships (Greenwald & Banaji, 1995). Such empirical findings support the role of unconscious processes in human behaviour (McLeod, 2007) and reflect the important contribution that Freud and his followers have made to our current understanding of mental health and illness, even though traditional psychoanalysis is no longer recommended as an effective and efficient treatment for common mental health problems.

**Behaviourist perspective.**

In contrast to psychodynamic theories that focus on intrapsychic and interpersonal processes, behaviourism emphasises the importance of the environment in shaping behaviour. More specifically, behaviourism focuses on observable behaviour and the conditions through which individuals learn behaviour. Four pathways have been
identified through which people are said to acquire complex behaviours, including dysfunctional behaviour and emotional responses. These pathways or processes include classical conditioning, operant conditioning, observational (vicarious) learning, and transmission via information and instructions (Rachman, 2013).

Classical conditioning has been implicated in the development of many phobias. It involves learning a new behaviour or response via the process of association. This occurs when a biologically potent stimulus (such as a loud noise) is paired with a previously neutral stimulus (such as a white rabbit). When these co-occur, the previously neutral stimulus (white rabbit) can start to elicit a similar response to the potent stimulus (i.e., fear response). Through this process, fear can become a conditioned emotional response. Watson and Raynor (1920) demonstrated the role of classical conditioning in phobias in their classic experiment with “Little Albert” who learnt to be afraid of white furry things through this process.

In contrast to phobias, which involves intense fear of specific stimuli, anxiety is conceptualised as a particular form of fear that occurs when the source of the fear is vague (Mowrer, 1953). Anxious responses are generally believed to be learned through the process of conditioning as a result of a single traumatic event or a series of sub-traumatic events that involve strong nervous system reactions (Rachman, 2013). However, a prominent behaviourist, Albert Bandura, demonstrated that people can also acquire anxiety responses and other complex behaviours by simply observing another person’s behaviour (modelling) or by watching another person learn and noting the consequences of that behaviour (vicarious learning; Nydegger, 2011). These types of observational learning occur cognitively and do not require individuals to personally perform the behaviour in order to learn. This helps explain how phobias and anxiety responses arise even though the person may not have been directly exposed to the feared object or situation.

Avoidant behaviours are also implicated in the onset and maintenance of anxiety disorders. Avoidant behaviours refer to attempts to prevent, escape, or reduce contact with aversive (or minimally rewarding) stimuli (Carvalho, 2011). Such stimuli may include thoughts and memories, behaviours, emotions, and social interactions. For example, this could include situations where a person avoids being face-to-face with his or her boss following a reprimand, or finds excuses to isolate herself or himself from
being with friends after being slighted, or even abandons responsibilities at work, school or home after feeling overwhelmed by the various demands of life. Cognitions and behaviours that serve an avoidant function are believed to perpetuate anxiety because the affected person does not confront their fear, learn that they can cope with it, and begin to extinguish the fear-response. Rather, the fear-generated behaviour persists because it is typically followed by a significant reduction in fear or anxiety, which reinforces the avoidant behaviour (Rachman, 2013).

Avoidance is also implicated in the onset and maintenance of depressive disorders, although it plays a slightly different role. Cognitions and behaviours that serve an avoidant function are thought to be critical precursors to reductions in rewards and positive reinforcement, which in turn predispose people to depression (Carvalho, 2011; Ferster, 1973). This taps into the notion of operant conditioning. Operant conditioning (also known as instrumental conditioning) involves changing behaviour through the use of reinforcement. Reinforcement is something that occurs after a desired response (Skinner, 1938): positive reinforcement occurs through events that increase the frequency of behaviour, whereas negative reinforcement refers to the removal of an aversive stimulus (e.g., discomfort or fear) when a particular behaviour is exhibited. This latter process is thought to lead to an increased frequency of avoidance behaviours.

According to Ferster (1973), feelings of dysphoria in a depressive person result in diminished reinforcement. This is because characteristic behaviours of depression (e.g., excessive crying, fatigue, irritability, self-criticism) are associated with the loss of other types of activities that ordinarily provide positive reinforcement (e.g., relating to friends or feeling productive at work).

Lewinsohn (1974) expanded on Ferster’s behavioural model of depression and argued that depression is caused by a combination of stressors in a person’s environment and a general lack of social skills. He asserted that environmental stressors become significant because they often include the loss of a major source of reinforcement, for example, the loss of a partner through divorce, death of a family member, or loss of a job, among others. Such stressors lead to reduced opportunities and availability of social reinforcement and/or the increased presence of aversive experiences (Lewinsohn, Clarke, & Hoberman, 1989). A person’s capacity to elicit positive reinforcement from the environment or cope with aversive events is also central
to the amount of positive reinforcement they experience. Hence, individuals lacking effective social skills may experience a low rate of response-contingent positive reinforcement also, which can lead to and exacerbate the passivity and dysphoria characteristic of depression.

**Model of change for treatment and prevention.**

According to the principles of behaviourism, conditioned responses that are not reinforced begin to be extinguished; those that are reinforced can become motivating and reinforce subsequent behaviour (Strongman, 1995). Thus, traditional behaviour therapy models are based on operant conditioning principles and aim to change the person’s fear response or depressive mood by changing his or her patterns of behaviour (Shinohara et al., 2013). Behavioural interventions for anxiety disorders mainly involve increasing pleasant activities to increase exposure to positive reinforcements (Manicavasagar, 2014); relaxation training (Kangas, 2014), and graded exposure for specific phobias, social anxiety, and panic with agoraphobia.

A number of behavioural therapy models have been developed for depression based on Lewinsohn's (1974) model. These largely focus on increasing pleasant activities to help individuals to re-engage with their lives and increase the likelihood of positive reinforcement. Typical strategies include behavioural activation (to offset patterns of inactivity and withdrawal), social skills/assertiveness training, and relaxation therapy.

**Efficacy and effectiveness in treatment and prevention.**

In terms of treatment, recent meta-analyses evaluating the efficacy of behavioural therapies for treating acute depression report moderate to large effect sizes, which are at least as good as, if not slightly better than, most other evidence-based psychological treatments (e.g., Samad, Brealey, & Gilbody, 2011; Shinohara et al., 2013). There is strong consistent evidence to support the use of graduated exposure therapy for specific phobias and it is recognised accordingly in clinical guidelines and treatment recommendations (Australian Psychological Society, 2010; Hunsley et al., 2013; National Institute for Health and Care Excellence, 2008).

In terms of prevention, there is also some clear and reliable evidence supporting the use of behavioural interventions as a component of universal and targeted prevention programs, particularly with young people (e.g., Callaly, 2014; Merry et al.,
Core interventions in this domain include education and training in social skills, problem-solving skills, and relaxation techniques. The importance of these skills in promoting mental health and wellbeing, and protecting people against mental health problems, is now widely recognised and has led to them being taught in primary schools (e.g., in the Social and Emotional Learning component of the Victorian and Queensland curriculums for primary school students; Department of Education, 2016). However, as discussed in the previous chapter, the long-term effectiveness and impact of such interventions have yet to be rigorously investigated and reported.

**Fit with recent findings.**

Classical behaviourism, which focussed almost exclusively on observable behaviour and viewed thinking as mere reflex chains, was largely discounted by developments in cognitive neuroscience over 30 years ago (R. Thompson, 1994). This occurred because neuroimaging studies demonstrated direct links between cognitive processes, neural substrates, and behaviour such as the brain reward circuitry, which forms the neuroanatomical basis for operant conditioning. (For a detailed description of the neuro-process involved in this circuitry, see Winger, Woods, Galuska, & Wade-Galuska, 2005). Although it is highly likely that this circuitry would be implicated in successful behavioural interventions for anxiety and depressive disorders, behaviour therapy techniques have not been widely studied on their own, rather they are combined with cognitive techniques as part of cognitive behaviour therapy.

Behavioural models of mental health have been criticised over the years because they do not adequately explain the full range of cognitive and emotional (affect) factors related to anxiety and depression. For instance, in support of his model, Lewinsohn (1974) explicitly stated that the cognitive features of depression (e.g., low self-esteem, pessimism, and guilt) are merely secondary to the feelings of dysphoria caused by a low rate of response-contingent positive reinforcement. However, many scientist-practitioners disagreed with this and considered cognitive processes to be central in depression, which lead to the development of cognitive models of mental health.

**Cognitive perspective.**

Instead of focussing on external conditions, cognitive theorists focus upon attention, perception, and thinking, and how these processes effect the development and/or maintenance of mental health problems (Nydegger, 2011). Aaron Beck (1964,
1976), the father of cognitive therapy, asserted that a person’s conceptions (or misconceptions) of events are the key to his or her emotional upset rather than the events themselves. Beck conceptualised anxiety and depression as overgeneralised responses that are triggered by a specific stimulus or event (D. A. Clark, Beck, & Alford, 1999). The stimulus may include thoughts and memories, behaviours, emotions, and social interactions that trigger fear (in the case of anxiety) or loss of interests and pleasure in a range of activities (in the case of depression).

More specifically, Beck and other cognitive theorists argue that anxiety disorders are characterised by distorted beliefs about the dangerousness of certain situations and/or internal stimuli (D. M. Clark, 1999).

…a precipitating event (or series of events) elicits or magnifies an underlying attitude of fear. These events may impinge on the patient’s specific vulnerabilities to elicit such danger related ideation. Subsequently, the patient is overly vigilant of danger. He scans internal and external stimuli for ‘dangerous’ properties. When new situations with possibilities of unpleasant outcomes are encountered, they are construed as dangerous. That is, the patient magnifies the possibility and intensity of unpleasant outcomes in his cognition of the situation. (Beck & Rush, 1985, p.365). Hence, anxiety reactions are thought to persist primarily as a result of the persisting maladaptive cognitions (Rachman, 2013).

Similarly, Beck (1976) argued that in the absence of a biological cause, depressive symptoms are typically caused by negative automatic thoughts and judgements, generated by dysfunctional beliefs. Three main dysfunctional belief themes (or schemas) dominate depressed people’s thinking, including negative views about (a) oneself (e.g., “I am deficient, helpless and/or unlovable”), (b) the world (e.g., “Everyone is against me”), and (c) the future (e.g., “Things will never get better”). These are known as the cognitive triad. Beck asserted that these beliefs are perpetuated by errors in logic and negative information processing bias. Errors in logic include cognitive distortions such as overgeneralising, catastrophising, personalisation, and interpretational biases (e.g., “If I fail at something, it means I’m a total failure”). These errors and biases in information processing over time leads “to selective attention to negative aspects of experiences, negative interpretations, and blocking of positive events and memories” (Beck, 2008, p.970).
In his cognitive vulnerability model, Beck (2008) posits that “early adverse events foster negative attitudes and biases about the self, which are integrated into the cognitive organization in the form of schemas; the schemas become activated by later adverse events impinging on the specific cognitive vulnerability and lead to the systematic negative bias at the core of depression” (p.970). He goes on to say that “the salience (or energy) of the schemas depend on the intensity of a negative experience and the threshold for activation at a given time (successive stressful experiences, for example, can lower the threshold)” (Beck, 2008, p.970).

**Model of change for treatment and prevention.**

According to Beck (1979), the formula for treatment is “the therapist helps a patient to unravel his distortions in thinking to learn alternative, more realistic ways to formulate his experiences” (p.3). It is argued that the most effective and most lasting way to reduce or remove anxiety and depressive symptoms is to identify and modify or remove the responsible cognitions (D. A. Clark et al., 1999; D. M. Clark, 1999; Rachman, 2013). However, this is often easier said than done.

The basic premise of combined cognitive-behavioural therapy (CBT) is that cognitions, behaviours, and affect are intimately connected and change in any one of those can lead to change in the others. In this way, CBT recognises that changing behaviour is a powerful way of modifying maladaptive cognitions and can inhibit self-defeating patterns of avoidance. Accordingly, CBT-based prevention and treatment programs use a combination of cognitive and behavioural interventions.

**Efficacy and effectiveness in treatment and prevention.**

Without doubt, CBT has the largest evidence base for treating anxiety and depressive disorders in terms of the number of academic papers published about it. Recent meta-analyses continue to demonstrate that CBT is significantly more effective than no therapy in reducing symptoms of anxiety and depression in children and young people (e.g., James, James, Cowdrey, Soler, & Choke, 2013), in adults (e.g., Twomey, O'Reilly, & Byrne, 2015), and in older adults (e.g., Orgeta, Qazi, Spector, & Orrell, 2014). However, when compared to a placebo or other psychological therapies (e.g., STPP, interpersonal therapy, self-help books), clinically significant differences are not typically found in terms of the amount of change produced.

Compared to medication, mounting evidence indicates that CBT is comparable
to pharmacotherapy for treating MDD in the short term (i.e., immediately after treatment) but CBT is superior in the medium to long term (e.g., 12-months posttreatment) due to reduced rates of relapse (APS, 2010; NICE, 2016). These findings support the inclusion of CBT in clinical guidelines and treatment recommendations for anxiety and depressive disorders, and suggest that CBT is on par with other psychological therapies but is not necessarily superior to them.

In the area of mental health promotion and prevention, CBT principles have been successfully applied to the prevention of major depression. Van Zoonen and colleagues (van Zoonen et al., 2014) reviewed a large number of recent studies of prevention programs aimed at strengthening protective factors (such as social skills, problem-solving skills, and stress management skills) using cognitive and behavioural methods. The majority of the studies included in the meta-analysis were conducted with young people in schools or targeted at adolescents whose parents have a history of mental illness. Others studies targeted pregnant women in order to prevent postnatal depression and anxiety (e.g., Milgrom, Schembri, Ericksen, Ross, & Gemmill; Munoz et al., 2007), whilst a few studies targeted the prevention of anxiety and depression in later life (e.g., Konnert, Dobson, & Stelmach, 2009; Spek et al., 2008). Van Zoonen et al.’s (2014) findings from the meta-analysis indicate that CBT-based programs can reduce the risk of subthreshold symptoms developing into full MDD, and that such interventions could be cost-effective.

Several reviews have also been conducted that exclusively focus on prevention and early intervention with higher education students, who are renowned for having higher rates of psychological distress and mental disorders that the general population (e.g., Buchanan, 2012; Christensen, Pallister, Smale, Hickie, & Calear, 2010; Miller & Chung, 2009; Reavley & Jorm, 2010). Overall, promising results have been shown for prevention of MDD using CBT principles in this population, although serious questions remain about the effectiveness, scalability, and cost-efficiency of such programs given that most of the empirical research involves single efficacy studies, which have been designed for research purposes and have limited longitudinal follow-up. Consequently, the medium to long-term effectiveness and efficiency of such programs remain unknown.
Fit with recent findings.

Interdisciplinary research in the field of neuroscience has demonstrated neurobiological correlates of mental processes and changes occurring in the brain due to CBT. The studies, largely based on brain imaging techniques such as positron emission tomography (PET) and functional magnetic resonance imaging (fMRI), have shown that (a) cognitive activity contributes to dysfunctional behaviour and emotional experience through focusing, selective perception, memory and recall, and characteristic cognitive distortion (D. A. Clark & Beck, 2010); (b) functional and non-functional behaviour and experiences may be learned through lifelong learning, due to brain neuroplasticity that continues across the entire lifespan (Kleim & Jones, 2008); and (c) neurological changes have been found following successful CBT in patients with depression (e.g., Goldapple et al., 2004), specific phobias (for a review, see McNally, 2007), and panic disorder (e.g., Prasko et al., 2004). These changes have been attributed to changes in meta-cognition resulting from successful completion of CBT (Jokić-Begić, 2010).

Studies indicate that symptom improvement in anxiety or depression after CBT is associated with decreased neurophysiological and neurochemical activity in the brain regions involved in emotion processing, including the amygdalo-hippocampal subcortical, orbitofronatl cortex (OFC), medial prefrontal cortex (mPFC), and the ventral and dorsal anterior cingulate cortex (ACC; Linden, 2006). See Jokić-Begić (2010) for an in-depth review. However, without comparative studies that compare neurophysiological changes associated with different treatment techniques, it is unclear whether the observed changes are unique to CBT, are common across therapeutic approaches, or merely reflect a return to normal functioning.

There are some other issues with CBT that seem to persist also. First, intervention research has been unable to demonstrate a significant additive advantage of including cognitive strategies in therapy over and above the effect of "purely" behavioural interventions (D. A. Clark & Taylor, 2009). This raises questions about how pertinent cognitive elements are within CBT. Second, it has been difficult for researchers to demonstrate that clinical improvement from CBT is due to change in dysfunctional cognitive content and process (i.e., establish cognitive mediation) even though this is the basic premise of CBT. Without clear and reliable evidence of this, we cannot be sure exactly how or why CBT works – is it due to changes in cognitions or
could it be due to other factors, such as behavioural strategies, therapist-related factors (e.g., unconditional regard), or other factors common across treatment techniques (e.g., social support and a sense of connectedness)?

**Mindfulness perspective.**

In contrast to the Western perspectives discussed so far, mindfulness is an ancient practice found in a range of Eastern philosophies, including Buddhism, Taoism, and Yoga. Jon Kabat-Zinn (2005), who is credited as introducing mindfulness into western psychology, describes it as “Paying attention in a particular way: on purpose, in the present moment, and non-judgementally” (p.4). Mental health problems are believed to arise when individuals are not paying attention to the present moment and perceive stressors in their imagination, which do not really exist (McKenzie & Hassed, 2012). The stressor need not be real; it could be something experienced in the past or imagined in the future. Either way the thought of it triggers a sympathetic nervous system (flight-fight) response in the body and is experienced as anxiety.

It is believed that excessive orientation toward the past or future in this way is linked to problems with anxiety and depression (e.g., Kabat-Zinn, 2003) because people employ avoidance strategies to alleviate the intensity and/or frequency of the perceived stress and unwanted internal experiences (Hayes, Luoma, Bond, Masuda, & Lillis, 2006). These avoidance strategies are considered to be maladaptive and are thought to contribute to the maintenance of many, if not all emotional disorders (Bishop et al., 2004; Hayes, Linehan, & Follette, 2004).

**Model of change for prevention and treatment.**

According to the mindfulness tradition, experiencing the present moment openly and nonjudgmentally can effectively counter the effects of stressors (Kabat-Zinn, 2003). Focussing attention on the present helps people to see which stressors are actually real and which ones are not. This is said to lead to a profound shift in one’s relationship to thoughts and emotions, which enables individuals to better regulate emotions and respond in more adaptive ways (i.e., with better control and less avoidance; Hayes et al., 2006). Hayes and colleagues (Hayes, Strosahl, & Wilson, 2012) refer to this process as cognitive diffusion. The emphasis is on changing one’s relationship to thought rather than attempting to alter the content of thought itself (c.f. CBT). This is similar to Shapiro and colleagues’ concept of reperceiving (Shapiro, Carlson, Astin, & Freedman,
Reperceiving, which is the capacity to be objective about one’s own internal experience, is construed as the overarching mechanism of action that leads to change and positive outcomes in prevention and treatment.

Shapiro and colleagues contend that there are four complementary processes implicated in positive mental health and treatment gains resulting from mindfulness practice: self-regulation; values clarification; cognitive, emotional, and behavioural flexibility; and exposure (rather than avoidance). It is argued that these processes function as both potential mechanisms for other outcomes (e.g., helping to reduce psychological symptoms) and as worthwhile outcomes in and of themselves (Shapiro & Carlson, 2009; Shapiro et al., 2006). McKenzie and Hassed (2012) assert that, with regular practice of mindfulness, these processes help people deal with stress skilfully, prevent small issues from escalating into anxiety and depressive disorders, and lead to greater mental wellbeing.

**Efficacy and effectiveness in treatment and prevention.**

There is moderately strong evidence to support the effectiveness of mindfulness meditation programs as a means of promoting psychological health and wellbeing, reducing psychological symptoms, and improving behavioural regulation (e.g., Creswell, 2017; Keng, Smoski, & Robins, 2011; Khoury, Sharma, Rush, & Fournier, 2015). A meta-analysis of 209 studies concluded that mindfulness-based interventions (MBI) showed large, clinically significant effects in treating anxiety and depression, which were maintained through follow-up (Khoury et al., 2013). More specifically, the results indicate that MBI (which include mindfulness-based stress-reduction therapy (MBSR) and dialectical behaviour therapy (DBT) amongst others) are moderately effective in pre-post comparisons, waitlist comparisons, and when compared to other active treatments. However, MBI did not differ significantly from CBT, behavioural therapies or pharmacological treatments in terms of amount of change produced.

Other systematic reviews and meta-analyses have found mixed effects when looking at specific population groups, such as perinatal populations (Lever Taylor, Cavanagh, & Strauss, 2016) and older adults (Geiger et al., 2016), as well as across technology platforms (e.g., internet-based interventions; Fish, Brimson, & Lynch, 2016). However in each of these analyses, the authors assert that the lack of significant between-group effects was most likely an artefact of differences in the study design, the
implemented protocols, attrition, and the assessed outcomes in the studies included in the analyses.

According to the MBSR Standards of Practice, mindfulness is contra-indicated for “suicidality, psychosis (not treatable with medication), PTSD, depression (clinical) or other major psychiatric diagnosis (if it interferes with participation in the [stress reduction program]), and social anxiety (difficulty being in a classroom situation)” (Centre for Mindfulness in Medicine, 2014, p.7).

There are promising findings for the efficacy of mindfulness programs in reducing common mental health problems according to recent meta-analyses, (e.g., Greeson, Juberg, Maytan, James, & Rogers, 2014; Lever Taylor, Strauss, Cavanagh, & Jones, 2014; Song & Lindquist, 2015). ‘Third-wave’ behavioural therapies that include mindfulness components have also demonstrated promising effects, with several studies showing mindfulness-based cognitive therapy (MBCT) is efficacious in the prevention of MDD (e.g., N. Thompson et al., 2015) and the reduction of anxiety, panic disorder and stress (McKenzie & Hassed, 2012). MBCT combines the problem-solving approach of CBT with mindfulness techniques to help individuals become less reactive to their unhelpful negative thoughts, and thus prevent and ameliorate anxiety and distress (Troy, Shallcross, Davis, & Mauss, 2013). Although these findings are promising, to-date the overall quality of the prevention studies based on mindfulness (with or without CBT) has been fairly low, with few randomised controlled trials conducted, no active control groups, and limited longitudinal follow-up. Therefore, more high-calibre prevention research is needed to determine whether mindfulness-based programs can significantly reduce the incidence of anxiety and depressive disorders.

Fit with recent findings.

Recent efforts to understand how and why mindfulness improves mental health have shown that there is a neurological basis for mindfulness. Regular practice has been shown to modify and strengthen neural pathways over time (Tang, Holzel, & Posner, 2015; Taren et al., 2015), improves concentration (e.g., A. Moore & Malinowski, 2009), memory process (e.g., Jha, Stanley, Kiyonaga, Wong, & Gelfand, 2010), emotional reactivity and cognitive flexibility (Siegel, 2007) and reduces ruminative thinking, which is believed to contribute to high levels of stress and anxiety (Chambers, Gullone, & Allen, 2009). The slow and deep breathing involved in mindfulness meditation has
been shown to help alleviate bodily symptoms of distress also by balancing sympathetic and parasympathetic responses (Kabat-Zinn, 2003). (See Davis & Hayes, 2011, for a more extensive review of the benefits of mindfulness.) In sum, there is some support for mindfulness practice as a method of improving mental health, general wellbeing and alleviating symptoms of anxiety and depression in subclinical and mild cases, however, it is not recommended as a treatment for severe cases.

**Humanistic perspective.**

Emerging partly in reaction to the determinism implicit in both psychoanalysis and behaviourism, humanistic theorists assert that people are more than just a composite of unconscious instincts or learned behaviours (Maslow, 1968), they have free will. Building on existential philosophy, the humanistic approach emphasises choice and responsibility as well as people’s uniqueness, subjectivity, and capacity for psychological growth. It assumes that people are basically good and have an innate need and capacity to make themselves, and the world, better (Maslow, 1943, 1968). Within this perspective, psychopathology is seen as a failure to fulfil the natural potential for personal growth (Davies & Bhugra, 2004). Anything that blocks one striving to fulfil this need can be a cause of depression (McLeod, 2015).

According to Carl Rogers (1961), one of the founders of the humanistic tradition, anxiety arises as a result of increasing tension between our true self and the actions we take to please other people. The “self” is viewed as the fundamental structure of personality; it is the core of who we are and who we will become as a person. Experiences that are consistent with the self are viewed as good and healthy, whereas experiences that are inconsistent with the self are typically considered bad or uncomfortable. Inner conflict arises because people have the need to seek out experiences that are consistent with their true selves but they also need positive regard, which is the need to feel good about ourselves and have others feel good about us too. Consequently, people do things that they think will make other people value them. The conflict between wanting to stay consistent with the self and wanting to meet the expectations of others leads to tension (Davies & Bhugra, 2004). As the distance between the self and one’s experiences grows, the inconsistency produces feelings of anxiety. Hence, anxiety signals that there is a discrepancy between the self and our experience (Nydegger, 2011).
Model of change for prevention and treatment.

Rogers (1951) argued that behaviour is largely driven by self-concept and that the distress resulting from mental health problems can be ameliorated through the experience of positive relationships in which the person is given unconditional positive regard. He argued that through this experience, the person increasingly develops positive self-regard and self-acceptance. As a result, the tendency to self-actualise (i.e., to fulfil one’s natural potential) is promoted and, in turn, dysfunctional behaviour decreases (Davies & Bhugra, 2004).

A large number of therapeutic approaches draw on humanistic principles, some of the key ones include person-centred therapy (Rogers, 1951), Gestalt therapy (Perls, 1973), existential therapy (Deurzen, 2007), transactional analysis (Berne, 1961), and emotion-focused therapy (L. Greenberg, 2002). Whilst a detailed review of each of these therapies is beyond the scope of this thesis, in general, it is the therapist’s trust in the self-actualizing tendency of all individuals that differentiates the humanistic approach to interventions from other psychological approaches. Rather than selecting specific symptoms of psychopathology as the focus of concern in therapy, the humanistic approach focuses on the holistic person in its consideration of psychological distress and individualises therapy to fit with the personal goals, preferences and values (Churchill et al., 2010).

In a meta-synthesis of eight qualitative research studies addressing clients’ experiences of change in humanistic therapies, Timulak and Creaner (2010) identified 11 meta-categories of client-reported change: Healthier Emotional Experiencing, Experiences of Appreciating Vulnerability, Experiences of Self-Compassion, Resilience, Empowerment, Mastery of Symptoms, Enjoyment of Changed Life Circumstances, Feeling Supported, Enjoyment of Interpersonal Encounters, Self-insight/Self-awareness, and Changed View of Others. Changes in these areas are thought to underpin reductions in symptoms of mental illness and improved wellbeing and functioning (Angus, Watson, Elliott, Schneider, & Timulak, 2015).

Efficacy and effectiveness in treatment and prevention.

The humanistic approach does not lend itself well to manualised programs because it is typically non-directive and responds to client’s individual presenting problems, characteristics, values and goals. Accordingly, the evidence-base for
humanistic approaches in the treatment of anxiety and depressive disorders is less extensive than for CBT-oriented therapies. However, in the most recent meta-analysis of more than 191 studies, involving 199 samples and 14235 clients, Elliot and colleagues found that humanistic therapies are associated with large pre-post client gains, which are maintained over short and longer-term follow-ups (i.e., $\geq 12$ months; Elliott, Watson, Greenberg, Timulak, & Freire, 2013). Results indicated that person-centred therapy is as effective as CBT (based on 22 studies), and emotion-focused therapy might be more effective than CBT (based on 6 studies) for depression. The authors concluded that humanistic therapies meet criteria to be considered an evidence-based therapy for depression but noted that they appeared to be less effective than CBT for anxiety problems. Hence, for anxiety and related disorders “the use of traditional humanistic therapies can only be justified as second-line treatments for clients who have also tried or refused CBT” (Angus et al., 2015, p.334).

Humanistic principles are a cornerstone of self-help groups and wellness programs (Bastable, Gramet, Jacobs, & Sopczyk, 2010). The recent National Review of Mental Health Programmes and services in Australia (National Mental Health Commission, 2014b) identified that there is at least moderate evidence for the effectiveness and efficiency of such interventions and advocated for their widespread implementation as mental health promotion and prevention interventions for the general population (to enhance wellbeing and promote resiliency) and as targeted prevention and early intervention for those with low to moderate mental health needs and symptoms.

**Fit with recent findings.**

Humanistic models of psychopathology have been criticised for lacking a clearly defined theory that integrates biology and psychology (Rowan, 2001), and promoting an optimistic but often vague view of the mind with subjective, unscientific concepts such as self-actualization, which cannot be objectively measured. Nevertheless, there is now substantial evidence supporting the importance of a client-centred approach to therapy, which is characterised by therapists providing “core conditions” of empathy, genuineness, and unconditional positive regard (Churchill et al., 2010). These attributes play an integral role in effective health interventions and are now enshrined in clinical practice guidelines (beyondblue, 2011; NICE, 2016) and serve as the guiding principle.
for contemporary mental health system reform (NMHC, 2014b) and standards for mental health services (e.g., Mental Health Standing Committee, 2010).

**Interpersonal and other integrative perspectives.**

Integrative therapies are approaches that combine components of different psychological therapy models. Integrative therapy models include interpersonal therapy (IPT; Klerman, Dimascio, Weissman, Prusoff, & Paykel, 1974; Klerman & Paykel, 1969), cognitive analytic therapy (Ryle, 2005), and Hobson’s (1988) conversational model. IPT is widely regarded as an evidenced-based treatment for common mental health problems, having been originally developed to treat depression (APS, 2010; NICE, 2016). Inspired by the content of Harry Stack Sullivan’s (1968) psychodynamic interpersonal theory and the structured approach of CBT, IPT draws on attachment theory (Bowlby, 1969) and assumes that mental health problems are interrelated with interpersonal problems.

**Model of change for prevention and treatment.**

Accordingly, “the goal of IPT is to help people understand how [interpersonal] problems, operating in their current life situation, lead them to become distressed, and put them at risk of mental health problems” (APS, 2010, p.6). The interpersonal problems may include grief, role disputes, role transitions, and deficits in interpersonal skills (Markowitz, Svartberg, & Swartz, 1998). Interventions explore the individual’s perceptions and expectations of relationships, and aim to improve communication and interpersonal skills to facilitate the resolution of interpersonal problems and symptom remission.

**Efficacy and effectiveness in treatment and prevention.**

Recent meta-analyses support both the effectiveness of IPT as a treatment for depression, dysthymia and social anxiety (APS, 2010) and the efficacy of IPT in the prevention of common mental health problems (e.g., Cuijpers et al., 2008; van Zoonen et al., 2014). Overall, effect sizes are at least comparable to CBT, if not better, in both treatment and prevention contexts. In one of the few meta-analyses that controlled for attrition and sample size, van Zoonen and colleagues (2014) found that preventive interventions using IPT were vastly more effective than CBT-based preventive interventions: the average number of people needed to treat (NNT) to prevent depression in one person with a CBT program is ten times that of IPT programs (i.e.,
CBT: NNT = 71; IPT: NNT=7). This is a staggering difference. If it is replicated in further studies, then it could indicate that interventions that focus on interpersonal problems, and improve communication and interpersonal skills, are better at helping people reduce risk and subthreshold depressive symptoms than other intervention models. However, multiple replications are needed to ensure it was not spurious or an artefact of the analyses before such assertions and recommendations for routine use can be confidently made.
## Table 6

**Summary of Theoretical Approaches and their Model(s) of Change**

<table>
<thead>
<tr>
<th>Theoretical approach</th>
<th>Key constructs</th>
<th>Conceptualisation of anxiety and depression</th>
<th>Model of change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Psychodynamic</td>
<td>Unconscious drives and processes, Early life experiences, including attachment and object relations</td>
<td>Conflict between unconscious forces (id, ego and superego) and reality, Unresolved emotional and relational issues from childhood</td>
<td>Increase awareness of unconscious processes, Facilitate acceptance and resolution of past issues</td>
</tr>
<tr>
<td>Behavioural</td>
<td>Classical and operant conditioning, Social learning, Avoidance/exposure, Response-contingent positive reinforcement</td>
<td>Unhealthy behaviours reinforced (e.g., avoidance, withdrawal), Diminished reinforcement or punished for healthy behaviours, Increased presence of aversive experiences</td>
<td>Extinguish fear/phobic response via exposure to feared stimuli, Behavioural activation and pleasant event scheduling to reinforce healthy behaviours and increase positive reinforcements in social contexts, Improve skills to manage stressor(s)</td>
</tr>
<tr>
<td>Cognitive</td>
<td>Cognitive distortions, Negative automatic thoughts, Information processing biases, Maladaptive schemas</td>
<td>(Anxiety &amp; Phobias) Distorted beliefs about the dangerousness of certain situations and/or internal stimuli, (Depression) Caused by negative automatic thoughts and judgements generated by dysfunctional beliefs and schemas developed earlier in life</td>
<td>Identify and modify or remove maladaptive cognitions and patterns of avoidance</td>
</tr>
<tr>
<td>Mindfulness</td>
<td>Cognitive diffusion/Reperceiving, Self-regulation of attention, Exposure</td>
<td>Excessive orientation towards the past or future when dealing with stressors</td>
<td>Increase capacity to be objective about one’s own experiences, Clarify values, Increase self-regulation of attention, Psychological (mental, emotional &amp; behavioural) flexibility, Exposure</td>
</tr>
<tr>
<td>IPT</td>
<td>Interpersonal problems</td>
<td>Psychological distress and symptoms are interrelated with interpersonal problems (current and past)</td>
<td>Increase awareness of their perceptions and expectations of relationships, Improve communication and interpersonal skills to help resolve current issues</td>
</tr>
<tr>
<td>Humanistic</td>
<td>Needs hierarchy, Self-actualization, Unconditional positive regard, Conditions of worth, Basic psychological needs</td>
<td>Failure to fulfil the natural potential for personal growth, Conflict between inner self-actualizing tendency and positive regard received from others</td>
<td>Provision of unconditional positive regard, Increase self-regard and promote self-actualization, Increase satisfaction of basic psychological needs to improve wellbeing</td>
</tr>
</tbody>
</table>
Chapter Summary

In sum, there is a diverse range of ways that mental health, anxiety and depression are conceptualised within psychology practice (see Table 6 for a summary of the key concepts and models of change reviewed). Each perspective emphasises different elements of the human experience (e.g., intrapsychic processes, learning processes, interpersonal processes) and different ways to restore and improve mental health (e.g., gaining insight into unconscious processes, identifying and challenging core beliefs, fostering self-awareness and self-acceptance). This review found at least moderate empirical support in the literature for each of the theories, their model(s) of change, and treatment interventions.

Overall, based on the evidence reviewed, it appears that under ideal conditions (i.e., efficacy studies) psychological treatments successfully help around 40% of clients who commence treatment. [This calculation is based on reported effect sizes of between .53 and .87 (Cuijpers, Andersson, Donker, & Van Straten, 2011; Hunsley et al., 2013). Equivalent NNT values are 3.32 and 2.33 respectively (Kraemer & Kupfer, 2006), which convert to treatment success rates of 30.12% and 42.92%.] This means that, at best, only two in five individuals are likely to experience significant improvement; three out of five (60%) do not. This may be because the intervention is not beneficial for them and/or it could be because they withdraw from treatment prematurely. Either way, these figures are rather sobering, as they imply that current treatments are not effective for the majority of people seeking help. This represents a major source of inefficiency for mental health programs and the mental health system more broadly.

In addition to the fairly modest efficacy rates, this review found that effect sizes vary markedly between individual studies and meta-analytic reviews commonly report little (if any) difference in the effectiveness of one approach versus another (e.g., Hunot et al., 2013; van Zoonen et al., 2014). This strong trend towards negligible or no difference between treatment techniques in amount of change produced is counterbalanced by some strong evidence that shows some treatments are efficacious for particular disorders (e.g., graduated exposure therapy for specific phobias). This strong evidence supports the inclusion of such treatments in clinical guidelines and treatment recommendations for those conditions. At the same time, it is worth noting that whilst CBT may have the largest evidence base, it does not mean it is the most effective intervention approach for other conditions - merely that it has been the most
commonly used in published research to date. Other approaches, such as STPP and humanistic interventions, are more suited to qualitative research designs. Such designs can yield valid and valuable findings but tend to be much harder to synthesise and incorporate into the meta-analyses that underpin most clinical guidelines.

Given the diversity of the theories and models of change reviewed, it is curious that there is so little difference in their intervention efficacy rates. One explanation could be the potential confounds of cross-study comparisons (e.g., where psychodynamic treatment is examined in one study and compared to CBT treatment from another study). These include factors such as differences in samples studied, measurements, and investigator allegiance, which complicate the process of making general conclusions. However, in exemplar studies (generally meta-analyses) that control for these factors, the findings are consistently small or negligible (Lambert, 2013).

Another explanation for the relative equivalence of treatment approaches could be that each psychological theory and its model of change fits (or applies to) some people but not others and, consequently, the corresponding intervention helps those people but not the others. Given the complexity of the human mind and the bio-ecology that influences it, it is conceivable that different variables and processes could lead to similar symptoms, and different interventions could yield similar outcomes. In this way, each of the psychological approaches to mental health and intervention provides a different piece of the puzzle. The pressing question is: how can we determine who fits what model and how can we predict who will benefit from which treatment approach? This question lies at the heart of precision medicine and psychiatry, as the ability to predict treatment outcomes and prognosis would enable practitioners to better tailor interventions and treatments to each individual. To-date, there appears to have been limited research into this issue within psychological services, other than what disorder subtypes might be indicated or contra-indicated for a particular intervention (e.g., reactive vs. melancholic depression and dysthymia). As such, identifying and predicting who fits what model and who will benefit from which treatment approach represents a significant gap in the literature and contemporary practice.

An alternative explanation for why there is little difference between psychological approaches could be that there are some common factors responsible for client change, that operate irrespective of the theoretical approach taken. Common factors could include environmental factors, process-related factors, therapist/facilitator-
related factors, individual factors, or even some combination of these. For instance, Wampold (2001, 2007, 2011, 2015) argues that therapist-related factors demonstrate bigger effect sizes than the actual theoretical approach used in treatment. These include factors such as: sophisticated interpersonal skills; creates conditions of acceptance, empathy and genuineness; provides a treatment plan; and continuously monitors progress. (For more in-depth discussion, see Wampold, 2010). This makes intuitive sense and highlights the importance of the therapeutic process, rather than the content per se. In his earlier work, Wampold examined causative mechanisms in effective treatments by looking at studies that broke effective treatments down into their various components (i.e., subtracting treatment elements and thereby dismantling them) and studies that add elements to an existing treatment and then comparing the outcomes. Overall, the results from 18 years’ worth of comparative, dismantling, and constructive analysis studies indicated that adding or removing components of treatment did not change the effects of the core treatment (Ahn & Wampold, 2001). Wampold (2001) concluded that “there is little evidence that specific ingredients are necessary to produce psychotherapeutic change” (p.126).

Another trend observed in the current review was that meta-analyses frequently report little difference in the effectiveness of intervention programs for anxiety and depression compared to active control groups (e.g., Shinohara et al., 2013; van Zoonen et al., 2014), regardless of the therapeutic approach used. Given the significant variation across studies in terms of what active control groups do or receive (e.g., bibliotherapy, psychoeducation only, craft or activity groups), this suggests that there may be factors other than those specifically related to the therapist and therapy process going on that are helpful for clients/participants. For instance, perhaps therapists and interventions (including active controls) help meet individuals’ basic psychological needs for relatedness, autonomy, and/or competence. In turn this leads to improved wellbeing and functioning, and a reduction in symptoms.

This concept of basic psychological needs comes from Ryan and Deci’s (2008) self-determination theory (SDT). SDT is based on the premise that humans have a set of psychological needs, the fulfilment of which is vital for optimal human functioning, social development, and wellbeing (Richard M. Ryan & Deci, 2017). It is argued that the satisfaction of three basic psychological needs—autonomy, relatedness and competence— direct individuals to initiate actions that are essential for personal growth and development. The need for autonomy refers to the degree to which individuals feel
that their actions are volitional and self-governed. Competence refers to the extent to which individuals feel effective in their interactions with the social environment and underpin the need to engage in challenges, whereas relatedness refers to the need to belong and to feel connected to others (Deci & Ryan, 2000). Ryan and Deci (2001) argue that the satisfaction of these needs foster immediate wellbeing and strengthens inner resources, which contribute to subsequent resilience. Conversely, the frustration or thwarting of any of these needs is related to emotional and social dysfunction, and increased vulnerabilities for defensiveness and psychopathology (Vansteenkiste & Ryan, 2013). This is known as basic psychological needs theory (BPNT; a sub-theory of SDT) and it assumes that levels of wellbeing are directly proportional to the extent that such needs are adequately met.

The fulfilment of these basic needs could occur in two ways. One way is via the process of therapy, such as feeling connected and accepted by the therapist and other program participants, taps into the need for relatedness, and identifying treatment goals and collaborating on treatment plans reinforces a sense of volition and supports autonomy. Another way is via the content of interventions, for example, skills training can enhance competence. Hence, it is plausible that basic psychological needs mediate the relationship between individual and therapist factors, and mental health and wellbeing. This hypothesis will be explored a little later in the study. In the meantime, let us return to the conceptualising of common mental health problems and the various psychological theories.

In terms of intervention effectiveness, a number of key findings emerged from this review. First, based on the current evidence, IPT-based interventions appear to be the most effective and efficient option for preventing common mental health problems. However, high calibre studies are needed to confirm this before it can be recommended for routine use. Second, there is frequently negligible or no difference between treatment techniques used for anxiety and depressive disorders, despite them being based on very different psychological theories. (The main exception to this is exposure therapy, which is consistently found to be the most effective technique for treating phobias.) Third, there is often negligible difference between targeted treatment interventions and active control groups in the amount of change produced in trials for anxiety-related and/or depressive disorders. Fourth, even under ideal conditions, the best treatments successfully help between 40-60% of clients (Hunsley et al., 2013). Taken together these findings paint a picture of limited success. Essentially, prevention
efforts are still in their infancy and current treatments are effective for some people but not others.

Although somewhat disconcerting, these findings are consistent with the rather modest intervention effects seen in practice and they help explain why national prevalence rates for anxiety and depressive disorders continue to be high and stable. That is, if the effectiveness rate of psychological and pharmacotherapy treatments is 40% (at best) and around one half of all Australians with a mental illness seek currently treatment (as discussed in the previous chapter), then one could surmise that only 20% of individuals with a mental illness in Australia are being successfully treated. This has important implications for individuals, as mentioned in Chapter 2, as untreated (or unsuccessfully treated) mental illness often gets worse and each time someone relapses, symptoms severity and impairment tend to increase. Untreated (or unsuccessfully treated) mental illness also greatly impacts families, potentially compromising the mental health and wellbeing of other family members (especially children), and there are ripple effects on workplaces, local economies and communities.

It is interesting to note that none of the psychological theories discussed so far adequately account for the clear developmental and gender patterns seen in high prevalence disorders. Furthermore, none of them seem to readily accommodate recent findings from longitudinal, genetic, and neuro-endocrine research that show that anxiety and depressive disorders are heterogeneous clusters of symptoms, governed by a complex interplay of genetics, neurobiology, and a person’s environment (Beardslee et al., 2011). Whilst there has been some research with CBT and mindfulness-based interventions into the neurophysiological changes associated with therapy, and Beck (2008) has attempted to explain how the CBT paradigm fits in with some of the neurobiological findings, there is a strong sense of investigator allegiance throughout the studies. This potentially confounds the interpretation of results and associated conclusions. Nevertheless, if we are to clarify and enhance the way mental health is conceptualised, prevented and treated in research and practice, then findings from psychology need to be synthesised and integrated with the theories and findings from other scientific areas to form a more parsimonious, unified biopsychosocial model (Nydegger, 2011).

Therefore, the next chapter considers some of the key biological theories and findings in mental health and psychopathology and how these can be integrated with the observations and findings from psychology over the past century.
Part Two: Back to Basics
Chapter 4  Conceptualising Mental Health

If the effectiveness of mental health interventions is to be improved, then an accurate understanding of the phenomena is essential. The way that mental health and disorder are conceptualised and operationalised profoundly effects research findings, the evolution of theories, and the development and targeting of interventions. In Chapter 2, Bronfenbrenner’s (2005) bioecological model of human development was outlined, which serves as a framework for population mental health intervention models. The bioecological model highlights the integral role that environmental factors play in mental health by contextualising the individual within their micro and macro environment. As discussed, this framework helps guide interventions at the population level, including policies and programs that target different levels of the environment. In contrast to population health models, psychological models of mental health typically focus on the processes that occur within the individual and, sometimes, how they interact with particular elements in the microsystem (such as family, peers, schools and workplaces). The previous chapter reviewed key psychological perspectives of mental health and disorder, with a particular focus on how they actually conceptualised mental health and disorder, their models of change, and intervention effectiveness. Overall, negligible difference was found between the different models and intervention approaches in terms of treatment effectiveness. It was also noted that, with the exception of mindfulness and CBT, none of the psychological theories and models of change readily accommodate recent findings from longitudinal epidemiology and biomedical research, which show that anxiety and depressive disorders are heterogeneous clusters of symptoms, which arise from a complex interplay of genetics, neurobiology, and a person’s environment (Beardslee et al., 2011).

Accordingly, the goal of this chapter is to establish an overall framework for thinking about common mental health problems and disorders in a way that is consistent with the current evidence base and has the potential to accommodate new and emerging findings from bio-medical research. It begins by considering some of the key biological theories and findings in mental health and psychopathology, and then works to integrate these with the observations and findings from psychology over the past century using a diathesis (vulnerability)-stress model. The chapter concludes with a summary and outline of the next chapter.

Towards a More Unified Theoretical Framework for Mental Health

The traditional biological model of psychopathology (also known as the medical
or disease model) assumes that emotional and behavioural symptoms are outward signs of neurobiological processes. Within this model, anxiety and depressive disorders are conceptualised as disorders of brain circuits and functioning, likely caused by developmental processes and shaped by a complex interplay of genetics and negative or adverse experiences (Insel & Wang, 2010). This model underpins biomedical research and is the basis for pharmacotherapy research and treatments.

Whilst the medical model acknowledges the complex interplay of genetics, developmental and neurological processes, as well as environmental stressors, it does not integrate psychosocial variables and processes very well. To overcome this limitation, a helpful way to synthesise all of these factors could be with a diathesis-stress model.

**Diathesis-stress model.**

The diathesis-stress model, originally developed by Zubin and Speing (1977) to explain some of the causes of schizophrenia, posits that each person inherits certain biological vulnerabilities to mental health problems, which may or may not appear depending on what stresses occur in her or his life. The theory suggests that people have varying degrees of vulnerabilities or predispositions for developing mental disorders. However, having a propensity towards developing a disorder is not enough to trigger its onset; a person’s vulnerabilities (diathesis) must interact with environmental risk factors or stressful life events to trigger an episode or onset of the disorder (Borba & Druss, 2009; Ingram & Luxton, 2005). According to the model, the greater a person’s diathesis for a disorder, the less environmental stress is needed for the person to become ill. Someone with a low diathesis for a disorder will require greater levels of external risk factors and stress to develop a disorder.

This model could be extended to include psychosocial vulnerabilities and applied to other mental health problems and disorders. Figure 4 presents a schematic overview of a diathesis-stress model for internalizing symptoms and disorders, which includes anxiety and depression.

Each of the diathesis (vulnerability) factors will be considered in turn now, with the exception of avoidant coping style, which has already been discussed (see the Behaviourist section above).
**Biological vulnerability.**

*Genes.*

Genetic factors have been implicated in the development of mental health problems and disorders because there is considerable evidence indicating that the predisposition to develop depression and anxiety disorders is inherited. Family studies consistently show a four- to five-fold increase in the risk of anxiety and a three-fold increase in the risk of depression in the children of parents with anxiety and depression when compared to children of parents without those disorders (Colletti et al., 2009; Weissman et al., 2005). The greater proportion of genes that a person shares with an individual who has a depressive disorder, the higher the risk of developing the disorder (Lohoff, 2010). Meta-analyses of twin and adoption studies have established that genetics explain up to 51% of the variance in adolescent internalising symptoms (Burt,
2009). Shared environments (i.e., factors that are similar for family members, such as socio-economic status) explain approximately 15% to 20% of the variance and non-shared environment (i.e., factors that are unique to each individual, such as peer group influences) and error explain the remaining 30% of the variance (Beardslee et al., 2011; Drake et al., 2016).

A number of genes thought to effect anxiety and depressive disorders have been identified by molecular geneticists including: two S alleles in the serotonic transporter promoter region polymorphism (5HTTLPR), homogenous carriers of the T allele methylenetetrahydrofolate reductase (MTHFR), and carriers of the 9/10 genotype (SLC6A3 allele; López-León et al., 2008). However, support for these specific genes is inconsistent, with several meta-analyses unable to replicate the findings (e.g., Munafo, Durrant, Lewis, & Flint, 2009; Risch et al., 2009).

A large international genome study by the Cross-Disorder Group of the Psychiatric Genomics Consortium (2013) recently found nine specific genetic variations linked to five major disorders: schizophrenia, bipolar, ADHD, autism, and depression. The diversity of these five disorders is quite startling and fuels the debate about whether current diagnostic categories are merely an approximation of much deeper patterns (Stephan et al., 2015). It is important to remember that these genome findings are just statistical associations of risk, not indicative of causality.

Although it is typically assumed that genes are inherited from one’s parents, some genes are sensitive to the environment and can be widely influenced by a variety of environmental factors including heat, infections, toxins, nutritional deficiencies, and substance use. These genes are referred to as regulatory genes (Valba, Nechaev, Sterken, Kammenga, & Vasieva, 2015). Neuroscience researchers believe that these genes interact with the environment via epigenetic remodelling (Bagot & Meaney, 2010; Hochberg et al., 2011). Epigenetic remodelling posits that the environment modifies certain genomes to produce individual differences in the expression of certain traits. Traits most commonly implicated in the pathogenesis of internalizing disorders include inhibition, negative emotionality or neuroticism, and to a lesser extent, positive emotionality (Pahl, Barrett, & Gullo, 2012; van Veen et al., 2012).

Neurobiochemistry.

One way epigenetic remodelling occurs is through changes in neurophysiology. For instance, early life stress and trauma can trigger substantive changes in three major systems in the brain: (a) the hypothalamic-pituitary-adrenal (HPA) axis and the
corticotropin-releasing factor (CRF) system, (b) the hippocampus, and (c) the noradrenergic system. These systems are important because they support emotion processing, reward seeking, cognitive control, and regulation of emotion, all of which tend to be dysfunctional in common mental health problems, including anxiety and depressive disorders.

Under various stressful conditions (e.g., exercise, trauma, fear or sadness), cortisol enhances the body’s physiological response. It does this by stimulating the adrenergic system, which leads to a chain of events that ultimately provides immediate energy to the body and keeps the individual alert (i.e., the fight-flight response). In response to acute stress, CRF also mediates: the body’s endocrine (hormone) response via the HPA axis; emotional reactions via the amygdaloid neurons; cognitive and behavioural responses via the cortical CRF neurons; and autonomic responses (involuntary body functions like digestion) via the amygdaloid projections to brainstem nuclei (Nestler et al., 2002). Although this stress response serves an evolutionary function (i.e., it prepares individuals to react quickly to threats, thereby ensuring the survival of the species), prolonged exposure to cortisol can have detrimental physiological consequences (e.g., increased blood pressure, diabetes, osteoporosis, muscle atrophy; Nestler et al., 2002). If chronic activation of the CNS-CRF system occurs during early development (including pre- and postnatally via maternal cortisol and epinephrine/adrenaline), neuron development in the hippocampus and endocrine functioning (especially adrenocorticotropic hormone and norepinephrine) can be permanently altered, resulting in a persistently hypersensitive stress response system (e.g., de Abreu Feijó de Mello, Feijó de Mello, Carpenter, & Price, 2003). This represents a potent diathesis for hyperarousal, which is a defining characteristic of anxiety and related disorders.

On the other hand, depression tends to be characterised by low motivation and anhedonia, or lack of interest in pleasurable activities. Meta-analyses of neuroimaging studies implicate two complementary networks in the neural systems involved in depressive symptoms: (a) a medial prefrontal limbic network that is modulated by serotonin neurotransmission and includes the amygdala, anterior cingulate cortex, and medial prefrontal cortex; and (b) a reward network that is modulated by dopamine and is centred in ventral striatum and interconnected orbito-frontal and medial prefrontal cortices (Kupfer, Frank, & Phillips, 2012). Abnormalities in these two networks are consistently associated with depressive disorders. These networks also form the basis
for psychopharmacological treatments of depression. For example, the most recent class of monoamine antidepressants, triple reuptake inhibitors, work by blocking the reuptake of serotonin, norepinephrine and dopamine simultaneously (Marks, Pae, & Patkar, 2008).

Melatonin, which is related to serotonin, has also been implicated in internalising disorders. Melatonin is known to be important in regulating circadian rhythms (sleep), which are greatly disturbed in depression (de Bodinat et al., 2010). However, whether neurotransmitter abnormalities pre-date the onset of internalizing disorders or are concomitant has yet to be firmly established.

In terms of medical treatment for common mental health problems and disorders, psychotropic medications typically target neurotransmitters. Although neurotransmitters are not disorder specific, clinical trials demonstrate that psychotropic medications are: very effective for individuals with severe mental disorders; about as effective as psychological therapies (e.g., CBT, IPT) for mild to moderate cases of depression and anxiety during the acute phase (APS, 2010); and, less effective than CBT in preventing relapses over the longer-term (i.e., after medication is discontinued; NICE, 2016). The latter finding may be because psychotropic medication alone does not equip individuals with new insight, knowledge or skills that they can draw on to prevent and cope with future stressors. Nor does it directly address environmental factors, which can trigger or perpetuate symptoms.

Nevertheless, based on the current evidence, neurobiological changes constitute a vulnerable phenotype and are likely to underpin many of the cognitive deficits and behavioural symptoms that are characteristic of anxiety and depression. However, just as genetic findings are statistical associations of risk and not diagnostic of disease, neuroimaging findings are based on mean group changes, not individual differences, and metabolic findings are not disorder specific (Insel, 2014). This limits capacity for more accurate diagnosis and increased specificity of medical interventions. Nor does it offer a clear way to reconceptualise common mental health problems… at least not yet.

*Affective vulnerability.*

As noted above, one of the ways genes are thought to predispose an individual to anxiety and depression is through the expression of certain traits, including an inhibited temperament, negative emotionality, and poor emotional regulation.

*Temperament.*

Temperament refers to those early-emerging, stable individual differences in
emotional style and regulation that are biologically based (Bienvenu, Siegel, & Ginsburg, 2009; D. N. Klein, Kotov, & Bufferd, 2011). Developmental research has demonstrated that certain traits and temperament can be noticed even on the newborn baby and do not change much throughout the lifespan (Moehler et al., 2008). Together with character, which refers to individual differences due to socialization, temperament forms the basis for personality traits (Krueger & Johnson, 2008). It influences the way one behaves and reacts to other people and situations.

Although there are many classification schemes for temperament, one temperament style is consistently implicated in the early development of mental health problems and internalizing disorders, known as behavioural inhibition (Pahl et al., 2012). Behavioural inhibition (BI) is characterized by the consistent tendency to show marked behavioural restraint or fearfulness with unfamiliar people, things or situations (Moehler et al., 2008). Over the past 20 years, Jerome Kagan and his colleagues have tracked hundreds of people, beginning in infancy, to see what happens to those who start out inhibited or primed to fret. It appears that 15 to 20% of babies display those traits (Moehler et al., 2008) and are much more likely to grow up anxious. In a longitudinal study of 155 high-risk neonates Bosquet and Egeland (2006) extended this research and highlighted some of the mechanisms through which temperament influences mental health. They found that heightened neonatal bio-behavioural reactivity and poor regulation predicts emotion regulation difficulties in preschool. In turn, these difficulties predicted anxiety symptoms in childhood.

In Bosquet and Egelan’s (2006) study, anxiety symptoms showed moderate stability during childhood and adolescence. However, relations between temperament and anxiety and depression are far from static and often vary by study. Within epidemiology and prevention studies that find significant associations between temperament and internalizing disorders, the magnitude of associations range from negligible to moderate (D. N. Klein, Dyson, Kujawa, & Kotov, 2015). This means that a fair amount of discontinuity between temperament and psychopathology exists. Degnan and Fox (2007) argue that this discontinuity in childhood temperament, especially behavioural inhibition, “may be inherent to the child, may be influenced by environmental factors, or may be evidence of a resilience process that alters trajectories over time” (cited in Pahl et al., 2012, p.312). In sum, current evidence suggests that temperament and personality are not a fixed, static set of characteristics but rather dynamic constructs that develop over the lifespan and change in response to maturation.
Negative Emotionality.

Affective vulnerability can also reflect elevated negative emotionality or attenuated positive emotionality (Grafton, Watkins, & MacLeod, 2012). Negative emotionality is related to the personality construct neuroticism and a difficult or dysregulated temperament. It has been described as a proneness to sadness, frustration, anger, fear or worry (Morgan, Shaw, & Olino, 2012). Children characterised as having high negative emotionality tend to display more intense emotional reactions in challenging situations, and cry and fuss more overall compared to those with low negative emotionality (Rothbart & Bates, 2007). Intense sadness and worry, and strong attempts to suppress negative emotionality are frequently associated with internalising problems (Eggum et al., 2012; Zahn-Waxler, Klimes-Dougan, & Slattery, 2000).

Watson and Clark (L. A. Clark & Watson, 1991; D. Watson & Clark, 1984) suggested that negative emotionality, or the predisposition to experience negative affective states, makes one vulnerable to depression and anxiety. In their tripartite model of anxiety and depression, Clark and Watson’s (1991) posited that general emotional distress (negative affectivity) is common to both anxiety and depressive symptoms. This explains some of the overlap and high co-morbidity between the disorders. Watson and Clark (1984) argued that anxiety and depression could be differentiated on the basis of physiological hyperarousal (which is anxiety specific) and anhedonia (which is depression specific; see Figure 5).
Although empirical research has largely supported the validity of the three factors (e.g., Fox, Halpern, Ryan, & Lowe, 2010; Sorg, Vögele, Furka, & Meyer, 2012), there has been inconsistent support for the specificity of the factors. Systematic research has demonstrated that anhedonia (low positive affect) confers risk for depression (e.g., De Bolle & De Fruyt, 2010) but is a factor in some forms of anxiety also, such as social phobia (Shankman & Klein, 2003). Additionally, there is some evidence to suggest that somatic hyperarousal is only specific to panic disorder and some phobias, rather than the whole range of anxiety disorders (Rachman, 2013).

Watson (2005) subsequently proposed a reconfiguration of depressive and anxiety disorders into a hierarchical structure based upon “distress” and “fear” factors, which together form a higher-order internalizing factor (T. Slade & Watson, 2006). Using data from 4457 Australian adults participating in the National Survey of Mental Health and Wellbeing, Watson (2005) found that GAD, MDD, dysthymic disorder and posttraumatic stress disorder cluster on the distress factor, whereas panic disorder and social phobias cluster on the fear factor. Garber and Weersing (2010) replicated these findings and argued that these distinctions may have important implications for conceptualising and treating common mental health problems because of the likelihood that fear and distress-based disorders have different aetiologies and are likely to respond differently to interventions.

In sum, temperament and affect play an important role in the makeup of mental disorders and are linked to how emotions are perceived and regulated. There also appears to be important similarities and differences between mental disorders in terms of primary affect (i.e., distress vs. fear) that are not well represented in the current classification system for mental disorders.
Emotion regulation.

Emotions occur when an individual attends to a situation and sees it as relevant to his or her goals (Gross & Thompson, 2013). Situations that elicit emotions may be external events (e.g., suddenly seeing a venomous spider) or internal mental representations (i.e., interpretations, beliefs, memories, imagined situations or predictions of the future; J. M. Williams, 2010). Goals may be either immediate (e.g., avoid being bitten by the spider) or long-term (e.g., fulfilling family and career aspirations; Nolen-Hoeksema & Watkins, 2011). They may be central to one’s sense of self (e.g., being a good worker) or peripheral (e.g., opening a jar), conscious or unconscious. Whatever the goal, it is the meaning an individual associates with the situation that gives rise to emotion (Gross & Thompson, 2013). Emotions are believed to play an important role as they prime the body for behavioural responses, inform decision making, facilitate interpersonal interactions, and increase memories of important events. However, emotional reactions can be detrimental when they occur at the wrong time or at the wrong intensity level (Gross & Thompson, 2013).

Emotional responses can be modulated in a large number of ways. The term emotion regulation refers to a range of cognitive and behavioural processes that influence the occurrence, intensity, duration, and expressions of emotion, in order to accomplish one’s goals and respond appropriately to environmental demands (Campbell-Sills & Barlow, 2007; Johnson, Carver, & Fulford, 2010). Successful emotion regulation relies on the ability to down-regulate acute negative emotions (e.g., sadness, fear, guilt), through strategies such as problem solving (active attempts to overcome or prevent a problem to reduce distress), reappraisal (finding benign or positive attributions or interpretations of an event to prevent or reduce negative mood about the event), acceptance (acknowledging one’s emotions without judging them), and attentional redeployment (diverting one’s attention to positive or benign stimuli to change one’s mood; for a full review see Aldao, Nolen-Hoeksema, & Schweizer, 2010).

Emotion regulation models of psychopathology posit that an inability to downregulate acute affective episodes using such strategies leads to more severe, uncontrollable, and chronic unwanted emotions, which can lead to persistent negative mood and psychopathology (Nolen-Hoeksema, 2012; Sheppes, Suri, & Gross, 2015). Many of the clinical features of anxiety and depressive disorders can be considered as maladaptive attempts to regulate unwanted emotion (Farchione et al., 2012; Gross & Thompson, 2013). Depressed individuals report difficulties supporting themselves when
experiencing negative emotions (Gilbert, Baldwin, Irons, Baccus, & Palmer, 2006), accepting and tolerating negative emotions (Campbell-Sills & Barlow, 2007), and adaptively modifying emotions (Ehring, Fischer, Schnuelle, Boesterling, & Tuschen-Caffier, 2008). They also report greater engagement with processes that exacerbate and prolong these emotions, such as rumination (J. M. Smith & Alloy, 2009). Dysfunction can also result from excessive attempts to down-regulate negative emotions through strategies such as suppression (conscious or unconscious attempts to exclude unacceptable thoughts and feelings from the mind; Campbell-Sills et al., 2007). Research confirms that people who chronically suppress or avoid their emotions are at increased risk for depressive disorders (e.g., Wenzlaff & Wegner, 2000) and anxiety disorders, including panic disorder (e.g., Lissek et al., 2009) and social phobia (e.g., Kashdan & Breen, 2008).

In a meta-analysis examining the relationships of emotion regulation strategies to psychopathology, Aldo and colleagues (2010) found that depression and anxiety were consistently related to emotional regulation deficits in both community and clinical samples. In particular, they found a large effect size for rumination; medium to large for avoidance, suppression, and problem solving; and, small to medium for acceptance and reappraisal. The evidence suggests that the tendencies to use rumination, avoidance or suppression and failures to use problem solving are strongly associated with internalizing disorders. Although implicated in the phenomenology of these disorders, whether maladaptive emotion regulation is part of the causal chain that leads to the development of anxiety and depressive disorders or is a consequence of the disorder(s) remains unknown.

**Cognitive vulnerability.**

As discussed earlier in the chapter, cognitive models of mental health posit that vulnerability to mental health problems arises from maladaptive schemas and attitudes, and certain thinking patterns that selectively favour the processing of emotionally negative information (Beck, 1976; Everaert, Koster, & Derakshan, 2012). Cognitive vulnerabilities remain latent until they are activated by the occurrence of relevant stressors, resulting in elevated anxiety and depression. Although the various cognitive models of depression and anxiety differ in what element(s) of the cognitive process they emphasize (e.g., attribution, inferences or explanatory style), there is substantial support for the role of maladaptive schemas and negative cognitive styles in the predisposition to internalizing disorders. For instance, according to the hopelessness theory of
depression (Abramson, Metalsky, & Alloy, 1989), individuals with maladaptive cognitive styles are vulnerable to depression when they encounter negative life events because they assign a negative meaning or consequence to the negative event. Specifically, individuals who (a) make global and stable attributions, (b) make negative self-inferences, and (c) expect negative consequences following the occurrence of a negative life event are more likely to become depressed (Kleiman, Liu, & Riskind, 2013; Liu, Kleiman, Nestor, & Cheek, 2015).

Similarly, the looming vulnerability model posits that individuals who are cognitively vulnerable to anxiety disorders generally overestimate threat and imagine threats as intensifying and approaching faster than they can respond and cope (Kleiman et al., 2013). Although the specific nature of the imagined threat varies across anxiety disorders, the dynamic perceptions of threat increase anxiety levels and can prompt the use of maladaptive coping responses, such as avoidance (Riskind, Rector, & Cassin, 2011). This looming cognitive style (Riskind, Williams, Gessner, Chrosniak, & Cortina, 2000) is thought to function as a danger schema and has been found to prospectively predict general anxiety symptoms (Strunk & Adler, 2009) as well as symptoms of specific anxiety disorder symptoms such as social anxiety and GAD (Kleiman & Riskind, 2014).

Other thinking patterns also appear to be important to the aetiology of internalizing disorders, for example, rumination and anxious worry have been shown to be linked to depression and anxiety symptoms respectively (Ehring & Watkins, 2008). Rumination has been defined as a repetitive focus on one’s negative emotions, and the causes and consequences of them, without trying to problem solve (Conway, Csank, Holm, & Blake, 2000). This interferes with effective emotion regulation and has been shown to predict onset, severity, duration and recurrent depressive episodes as well as suicidal ideation (McLaughlin & Nolen-Hoeksema, 2011; Sorg et al., 2012).

**Section summary.**

In sum, no single biological, psychological or social causal pathway has been identified that leads to the onset of mental health problems and disorders, rather they have heterogeneous aetiologies (equifinality) whereby various biological, affective, cognitive and behavioural characteristics interact with each other and stressful experiences resulting in the development of symptoms and disorders. Although broad vulnerability factors are implicated in more than one disorder (multifinality; e.g., negative emotionality, poor emotional regulation, high use of avoidance), some specific
content or nuances within those factors can be mapped to specific disorders (e.g., social threat is associated with social phobia and GAD; distress is strongly associated with GAD and MDD whilst fear is predominant in phobias and panic disorder).

**The transdiagnostic approach.**

In response to these findings, there has been a move away from the single-diagnosis approach towards a transdiagnostic conceptualisation and treatment of anxiety and depressive disorders. The transdiagnostic approach focuses on the shared pathology across disorders, including core temperamental, cognitive-affective, interpersonal, behavioural, and biological processes that underpin a broad array of diagnostic presentations (D. Barlow, Allen, & Choate, 2004). Transdiagnostic interventions (also known as unified treatments) “apply the same underlying treatment principles across mental disorders, without tailoring the protocol to specific diagnoses” (McEvoy, Nathan, & Norton, 2009, p.21). As such, this approach operates outside the traditional diagnostic boundaries of the DSM and ICD (Craske, 2012) and allows for treatment of transdiagnostic constructs that don’t fall into neat categories (e.g., self-regulation, perfectionism). Common components of transdiagnostic treatment protocols include motivation enhancement (to increase readiness for change and foster treatment engagement), psychoeducation regarding emotions and learned responses, cognitive restructuring, graded exposure to difficult emotions, and regulating arousal (D. Barlow, 2010; Newby et al., 2015).

A recent systematic review of transdiagnostic psychological treatments for anxiety and depression in adulthood concluded that they are efficacious (Newby et al., 2015). Of the 50 intervention studies included in the meta-analysis, CBT techniques were most commonly employed to address the core transdiagnostic processes, followed by mindfulness/acceptance protocols. In a comparison of the two approaches, CBT was found to be more effective than mindfulness for anxiety but not depression. However, it is unclear whether differences in sample sizes were controlled for during the statistical analyses, which might otherwise skew the results. Overall, the transdiagnostic interventions demonstrated large mean effects for anxiety and depression and medium effects on quality of life post-intervention and these effects were stable at follow-up. Medium to large comparative group differences between transdiagnostic interventions and control conditions were found but only small differences in effect size were found when compared to treatment as usual (Newby et al., 2015). Based on evidence from four comparisons with disorder-specific treatments, Newby and colleagues concluded
that “transdiagnostic treatments are as effective for reducing anxiety, and may be superior for reducing depression” (p.91) compared to disorder-specific intervention programs.

In terms of prevention, many of the social and emotional development interventions delivered in schools target transdiagnostic processes (e.g., emotional regulation, problem solving and coping skills) as do workplace wellness programs (e.g., stress management and relaxation training). As previously discussed (see Chapter 1), there is moderate evidence supporting the efficacy of such interventions, particularly with people at heightened risk of developing mental illness. Although much of the evidence to-date comes from single intervention studies that lack active control groups, a recent double-blind RCT by McDermott (2015) investigated the efficacy of three web-based prevention programs with undergraduate students at risk of emotional disorders: a CBT intervention (MoodGYM), a transdiagnostic attentional bias modification program (by Dandeneau & Baldwin, 2004), and an active attentional control. McDermott found that individuals in the CBT condition showed more rapid and continuous depressive symptom improvement between baseline and follow-up than did participants in the other two conditions, and fewer participants met the criteria for MDD than in the other conditions at follow-up. The three conditions yielded similar and significant changes in anxiety over time and were equivalent in the frequency of anxiety disorders at the six-week and four-month follow-up time points. Whilst the disorder-specific intervention was more efficacious for treating depression than the transdiagnostic intervention (targeting attentional bias), these results suggests that the treatment effect mechanism(s) for anxiety symptoms may be more to do with attentional, interpersonal, and contextual factors than the actual theoretical approach used. This brings us back to the idea of common factors and the general equivalence of psychological treatments, which was discussed at the end of the previous chapter and the need for more rigorous intervention research to isolate and identify key treatment effect mechanisms - be they related to the specific content of programs or the process of therapy. Furthermore, the transdiagnostic approach to mental health and the relative success of such interventions reignites questions about the validity of current diagnostic categories and whether there may be better ways to conceptualise mental health problems and the biopsychosocial processes that underpin them.
Chapter Summary

Despite the deluge of research in genetics, neuroscience, cognitive science, and behavioural science over the past 15 years, clear etiological pathways to common mental health problems and disorders have not been found. Numerous theories and models have been proposed over the last century that emphasise interpersonal factors, biological factors, cognitive factors, and/or affective factors. Whilst there is empirical support for elements of each of these, perhaps the best explanation currently centres around a diathesis-stress model, which integrates and accommodates these diverse elements.

In the past decade, it was hoped that advances in biotechnology would help identify specific genomes and/or biochemical imbalances that underpinned each psychiatric disorder. Once the precise cause of the disorder was identified, nosologies could be reorganised and targeted treatments could be developed and delivered, thereby ushering in the age of precision medicine in psychiatry (Insel, 2014). However, findings such as the nine molecular structures and mechanisms that are common across five diverse, major mental disorders (Cross-Disorder Group of the Psychiatric Genomics Consortium, 2013) seem to further complicate the picture rather than bringing clarity, at least at this point in time.

Different conceptualisations, different methodologies, different samples, different measures, and different analytic techniques are often touted as key reasons for divergent findings across studies. For that reason, this review drew on the results of systematic and meta-analyses, which are designed to overcome such differences by using the effect sizes reported from individual studies. This serves as a common metric and allows for comparisons across treatments and studies, without the complications that might occur due to variability in measures and methods. Yet despite controlling for the variability across studies in this way, models and interventions were found to be roughly equivalent to each other (and active control groups) in terms of effectiveness.

So, where to from here?

Perhaps the current state of knowledge could be likened to when humanity thought the earth was the centre of the universe. At that point, the planets’ orbits seemed fairly random. However, when the sun was recognised as the centre of the solar system, the orbiting pattern of each planet became clear and predictable. In the same way, perhaps we need to look at mental health in a different way.

Different conceptualisations, different methodologies, different samples,
different measures, and different analytic techniques undoubtedly contribute to the divergent findings across studies. However, some of the discrepancies could also stem from faulty assumptions. Perhaps it is time to revisit some of the basic assumptions underpinning psychological measurement and mental health research to examine what (if any) role they may be playing in all of this.

To that end, the next chapter reviews alternative approaches to mental health data and considers the role that common data analysis techniques may play in perpetuating diverse (and sometimes divergent) theoretical models of mental health and the modest intervention effects seen in practice. It then outlines the empirical study undertaken as part of this program of research.
Chapter 5  Operationalising and Analysing Mental Health

Despite the diverse fields of research reviewed and the numerous theoretical models examined in this thesis so far, no single model has stood out or proved to be superior to the others. The diathesis-stress model was posited as a potential framework for integrating different theoretical models and findings but it does not readily account for the finding that each of the psychological models and interventions seem to suit some people but not others, even when people share the same diagnosis. This raises questions about the current classification systems but, at the same time, it is plausible that some of the varying responses to intervention could be related to individual differences in people’s diathesis and predisposing factors, and/or the combination of stressors they experience. This leads to the question: how can we better operationalise and analyse mental health and related data in a way that improves our ability to target interventions and improves effectiveness in mental health?

While reviewing the literature for the early chapters, two trends were observed that proliferated across research, practice and policy. First, although scientists, practitioners, and politicians talk about mental health, they tend to operationalise it in terms of mental illness, disorders, and dysfunction – not health per se. Second, the analyses underpinning mental health research and program evaluations are typically based on classical test theory and the general linear model, which assumes homogeneity. However, research and experience attest to how heterogeneous (diverse) people and disorders can be. Therefore, the validity of this assumption is questionable and merits review. There may be other assumptions underpinning the way constructs are typically modelled and analysed that merit closer examination also.

Accordingly, this chapter is split into several sections. The first section discusses the operationalisation of mental health. It begins by considering the World Health Organisation’s (WHO; 2004) standard definition of mental health and its emphasis on wellbeing and functioning, not just symptoms and dysfunction. The second part of this chapter considers how mental health and related constructs are typically modelled and analysed, and how these could be contributing to disparities in the current evidence base.

Common statistical techniques, such as multiple regression, factor analysis, analysis of variance, and structural equation modelling are known as variable-centred techniques, as they focus on how much variance (difference) in variables can be explained by a particular model. In contrast, person-centred techniques, such as latent
variable mixture modelling (LVMM; e.g., latent class analysis, growth mixture modelling) look for clusters of individuals who share similar patterns of responding across variables. It is proposed that applying a person-centred approach to mental health and related data could help identify subgroups of individuals that differ in ways that are important for mental health, which are not based on current diagnostic categories. It is further hypothesised that these latent (unobserved) subgroups may help explain why current models of mental health seem to fit some people but not others.

Undoubtedly, there are many other aspects of psychological measurement and analyses that impact research and conclusions that could be discussed here. These range from the historical over-reliance on cross-sectional data and correlations to support hypotheses that infer causation, to whether disorders are treated as categorical or dimensional variables, to the lack of discriminant validity between many mental health and related measures. However, these issues are covered in depth elsewhere in the literature. For the purposes of this thesis, the focus of this chapter is limited to the operationalisation and modelling of mental health because they are two fairly fundamental psychometric issues that underpin mental health research and evaluation.

The final part of this chapter outlines an exploratory study designed to test the above hypotheses. To facilitate some of this testing and to explore whether mechanisms underlying mental health and wellbeing differ across latent subgroups, the study tests a novel model of stress and mental health. The model, which posits that transdiagnostic processes, such as coping and basic psychological needs, mediate the relationship between stress and mental health. Note that whilst the model may have some intrinsic interest of its own, its primary purpose in this study is to facilitate a comparison between latent subgroups, so it is not elaborated on in enormous detail. This chapter concludes with a description of the study’s empirical framework and the specific aims and hypotheses.

**Operationalising Mental Health**

The WHO (1946) defines mental health as “a state of wellbeing in which an individual realises his or her own abilities, can cope with the normal stresses of life, can work productively and is able to make a contribution to his or her community” (WHO, 2014, p.1). This definition emphasises that mental health is more than just the absence of mental illness (Gilmour, 2014). It explicitly includes positive dimensions of wellbeing and functioning such as coping, participation, contribution and realising one’s potential. However, mental health research and initiatives often focus purely on mental
ill-health and dysfunction (Winzer, Lindblad, Sorjonen, & Lindberg, 2014) and success is evaluated in terms of the reduction of symptoms. However, according to the WHO’s definition, this is only one aspect of it.

In the past, the positive and negative dimensions of mental health were thought of as two poles of a continuum (Scheid & Brown, 2010). However, proponents of positive psychology have emphasized the discontinuity between positive mental health and mental ill-health, arguing that (positive) mental health constitutes a distinct entity (Diener & Emmons, 1984) and some of the processes that affect positive mental health are distinct from those effecting mental ill-health (Huppert & Whittington, 2003; Winzer et al., 2014). Corey Keyes (2002) termed this way of conceptualising mental health as “the dual continuum model”, stating that “mental health and mental illness belong to two separate but correlated dimensions among the population” (Keyes, Dhingra, & Simoes, 2010, p.2366). He argued that it takes a combination of emotional, psychological, and social well-being to be considered mentally healthy (Keyes, 2002). He also introduced the terms “languishing” and “flourishing” to reflect high and low levels respectively of feeling good about and functioning in life (Keyes et al., 2010). People who are not languishing or flourishing are considered to be moderately mentally healthy (Keyes, 2007; Westerhof & Keyes, 2010). It is argued that these states can exist in both the presence and absence of mental illness (Keyes, 2007), with languishing adults reporting the same degree of health-related limitations in daily living and levels of psychosocial functioning as mentally ill adults with moderate to high (positive) mental health (Keyes, 2005b).

The dual dimensions perspective of mental health has several implications for mental health research and interventions. First, it stresses the importance of positive mental health and functioning as a core component of complete mental health. Thus reducing mental illness does not necessarily lead to great mental health (Keyes et al., 2010), positive mental health and functioning (i.e., flourishing) also need to be promoted if the goal is to optimise mental health (Keyes, 2007; Winzer et al., 2014). Second, research and evaluation that look at subgroups based on symptom severity (e.g., mild, moderate, severe) may be overly restrictive because they only capture the negative dimension of mental illness and neglect positive mental health. This taps into the third point, which is that the current categorical approach to diagnosing and measuring mental disorders focuses almost exclusively on pathogenesis. This deficit approach almost certainly misses the dynamic nature of mental health, which results from
complex interplay between the two dimensions. If only one dimension is measured, then results can only show change in that area and only part of the picture is revealed. It could be that some of the heterogeneity seen within diagnostic categories and variation in treatment effectiveness across individuals and studies is due to variations in positive mental health. For example, individuals with a mental illness and moderate or high positive mental health may be more able to engage with and benefit from psychological interventions than individuals with a mental illness who are languishing. Therefore, mental health and intervention effectiveness may be best studied through the combined assessment of mental health with mental illness.

Support for the dual dimensions perspective of mental health has been found in many contexts with children (Antaramian, 2015; Greenspoon & Saklofske, 2001), adolescence (Lyons, Huebner, Hills, & Shinkareva, 2012; Suldo & Shaffer, 2008), and adults, with whom it has been found to predict college engagement and performance (Antaramian, 2015; Renshaw & Cohen, 2014), risk of cardiovascular disease in people experiencing MDD (Keyes, 2004), chronic physical conditions (Keyes, 2005a), and the prevalence and incidence of mental illness in midlife Americans (Keyes et al., 2010). However, in the majority of these studies, positive mental health was operationalised with a single measure, life satisfaction.

According to the WHO definition of mental health, a more complete model of mental health ought to include capacity to cope with everyday stress, wellbeing, and role and social functioning. If these elements were added to mental health analyses, it may be that alternative subgroups could be identified for whom interventions could be specifically tailored to more effectively and efficiently meet their needs.

The current study tests this hypothesis and attempts to identify specific vulnerabilities and profiles for each subgroup, so that future screening and interventions might be fine-tuned for more effective detection, risk reduction, and better mental health outcomes. However, before discussing the current study in more detail, there is one more issue that merits due consideration because of its potential to undermine analyses with mental health and related variables and lead to questionable research and evaluation findings. This issue affects statistical techniques that are based on classical test theory, such as factor analysis, regression, analysis of variance, and structural equation modelling.
Statistical Modelling

Throughout the behavioural and social science literature, constructs are typically modelled as reflective latent variables. Reflective measurement models are based on classical test theory whereby the observed variables (e.g., items on a scale, symptoms of a disorder) reflect the construct thought to underlie them (Bollen & Lennox, 1991). This relationship is illustrated in Figure 6a, with the direction of causality flowing from the latent variable to the reflective measurement items ($X_\xi$; Cadogan & Lee, 2013).

![Reflective and formative latent variable measurement models](image)

Figure 6. Reflective and formative latent variable measurement models. $X_\xi$ = observed variable. $\eta$ = latent variable. $\lambda_\xi$ = parameter estimate. $\zeta_\xi$ = error variation.

There are two issues with this model in the context of mental health. First, the “reflective” assumption is not always appropriate and, second, the model does not allow for direct relationships between the observed variables. Statisticians Kenneth Bollen and Rik Lennox (1991) argue that some theoretical constructs are formed by their indicators, which means that if you change the indicators, you change the meaning of the latent (unobserved) construct. This “formative” relationship is illustrated in Figure 6b in which the direction of causality flows from the measured items to the latent variable. A commonly cited example of a formative construct is socio-economic status (SES; Bollen & Lennox, 1991; Cadogan & Lee, 2013; Kline, 2010). SES is typically measured with three variables: education level, occupation (job prestige), and income. Adding or omitting a variable could alter the meaning of the construct and would violate one of the assumptions of reflective measurement.
Over the past 15 years, various authors have suggested criteria for determining whether a construct should be treated as reflective or formative (e.g., Bollen & Bauldry, 2011; Diamantopoulos, 2008; Edwards & Bagozzi, 2000; Franke, Preacher, & Rigdon, 2008; Jarvis, MacKenzie, & Podsakoff, 2003). Roberts and Thatcher (2009) developed a series of questions to assist with such differentiation, incorporating both theoretical and empirical considerations. These are presented in Table 7.

Table 7

<table>
<thead>
<tr>
<th>Questions</th>
<th>Model type</th>
<th>Reflective</th>
<th>Formative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Are the indicators defining characteristics of the construct?</td>
<td></td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Do changes in the indicators cause changes in the construct?</td>
<td></td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Do changes in the construct cause changes in the indicators?</td>
<td></td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Do the indicators necessarily share a common theme?</td>
<td></td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Does eliminating an indicator alter the conceptual domain of the construct?</td>
<td></td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Is a change in one indicator necessarily associated with a change in all other indicators?</td>
<td></td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Do the indicators have the same antecedents and consequences?</td>
<td></td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

*Note.* Adapted from Roberts and Thatcher (2009).

Per the criteria above, a large number of mental health and related constructs fit the criteria for formative measurement, including stress, anxiety, depression, coping responses, subjective wellbeing, and functioning. A distinguishing feature of these constructs is that a change in one indicator is not necessarily associated with a change in all other indicators. For instance, sleep difficulties are a common symptom of major depressive disorder (MDD) but they are not always accompanied by weight gain/loss, anhedonia, and suicidal thoughts. Yet according to the principles of reflective measurement models, a change in one indicator is associated with a change in other indicators, and all the indicators have the same antecedents and consequences. This is not necessarily the case for depressive symptoms, consequently MDD may be more appropriately modelled as a formative variable rather than a reflective latent variable.

This issue was raised in the statistical literature some time ago and debated for several years. For instance, Dawn Iacobucci (2010) admonished such formative
conceptualizations as “merely incomplete reflective measurement” (p.94). Using the SES example, Iacobucci argued that these indicators are merely single-item measures and, accordingly, ought to be modelled as a series of single indicator latent variables (see Figure 7). In this scenario, the indicator is essentially equated to the construct and the error is set to zero. Iacobucci contended that this is unrealistic because we rarely have zero measurement error. She argued that, as per classical test theory, each of these constructs would be better modelled with multiple measures to enable the substantive part of the factor to be separated from the noise (i.e., systematic and random error). For instance, in the case of SES, the education construct might be more comprehensively measured by mother’s education, father’s education, and oldest child’s education. Although Iacobucci acknowledged that “a single rough estimate” will often suffice for expediency purposes, she fervently states that this should not be grounds for “unsubstantiated modelling choices” (p.94), namely formative measurement.

![Figure 7. Single indicator latent variable measurement model.](image)

Iacobucci is not the only antagonist to formative measurement (Edwards, 2011; Howell, Breivik, & Wilcox, 2013). Even proponents of the approach acknowledge the paucity of theory and the numerous technical difficulties associated with modelling formative variables, concluding that formative measures are best incorporated within a reflective measurement model approach at present (e.g., Bagozzi, 2007; Bollen, 2007). The technical difficulties arise in conceptualization, model identification, and the validation and interpretation of formative measurement models (Diamantopoulos, Riefler, & Roth, 2008). Of these issues, model specification is especially problematic because formative constructs are unidentifiable in SEM if modelled by themselves (i.e. there are more parameters to be estimated than there are data points). Furthermore,
current SEM software based on maximum likelihood (ML) estimation cannot identify formative constructs when modelled as either ultimate dependent variables or mediating variables without at least two unique endogenous (dependent) variables. The two unique endogenous variables are needed to identify the residual variance (disturbance term). This imposes significant restrictions to model testing as theoretical models often include multiple formative constructs in, moderating, mediating, and/or ultimate outcome roles (e.g., coping is frequently hypothesised to moderate and/or mediate the relationship between stress and mental health and wellbeing).

An alternative statistical technique that could accommodate formative latent variables in any position is partial least squares (PLS). In contrast to SEM-ML, which is essentially a combination of factor analysis and path analysis, PLS is a combination of principal components and path analysis with estimates obtained via least squares (Lee & Cadogan, 2013). Principal components is a specific factor analytic technique that attempts to produce a smaller number of linear combination of the original variables (known as components or factors) in a way that captures most of the variability in the pattern of correlations, with all of the variance in the variables (Pallant, 2011). In contrast, factor analysis only analyses the shared variance (Tabachnick & Fidell, 2013).

PLS is particularly appealing because it can be used when the number of variables in the model exceeds the number of observations (Hair, Sarstedt, Ringle, & Mena, 2012) and, therefore, overcomes the technical difficulties associated with modelling formatively-measured constructs in the absence of two unique outcome variables (e.g., as an ultimate dependent variable). However, to achieve this the power of PLS to accurately estimate parameters is diminished, such that loadings tend to be overestimated and path coefficients underestimated (Bentler & Huang, 2014; Hair et al., 2012). This may not be problematic when the goal of analyses is to predict and capture the variance of the dependent variable but it is problematic for theoretical development and testing (Iacobucci, 2010; Wilcox, Howell, & Breivik, 2008).

In light of these issues and difficulties, current recommendations for modelling formative constructs in latent variable models include dropping the formative latent construct and modelling directly with the indicators (Cadogan & Lee, 2013) or constructing a composite index of the formative indicators (Kline, 2010; Treiblmaier, Bentler, & Mair, 2011). MacCallum and Browne (1993) demonstrated that modelling direct paths from the formative indicators to other latent variables in the model results in an equivalent structural equation model with the same overall fit to data but different
(and usually more complex) configuration of paths. Cadogan and Lee (2013) argue that this informs theory development and enriches our understanding because it can elucidate differences in the antecedents and consequences of each of the indicators, which might otherwise be hidden in a formative measurement model. Lee and Cadogan (2013) also caution that the weightings assigned to the indicator variables in composite variable models need to be reported and agreed upon in the field to ensure results are comparable across studies. Unfortunately international and country norms for mental health and related measures are not common, which results in researchers often using sample weights. These can vary substantially across studies and samples. The lack of agreement and consistency may well contribute to the variation (and sometimes contradictions) in mental health research and evaluation findings. To overcome these issues, it seems prudent for research and evaluation to use widely-used measures of mental health and related constructs and employs national norms to form weighted composites for the formative constructs whenever possible.

The second key issue with reflective models is that they do not allow for direct relationships between the indicators or symptoms, rather it is assumed that indicators are only related via the latent variable. Using the example of MDD, Angelique Cramer and colleagues (Cramer et al., 2010) point out that a latent variable model of MDD would indicate that symptoms of sleep disturbances, fatigue, difficulties concentrating and irritability are largely caused by the latent depression variable. However, in reality, it is possible that the sleep disturbances directly cause fatigue, difficulties concentrating, and irritability, which means that an unobserved variable is not needed to account for the relationships between symptoms (Cramer et al., 2010; Eaton, 2015).

If symptoms were modelled without latent variables, disorders could be conceptualised as networks of causally connected symptoms (Eaton, 2015). This makes intuitive sense and supports the idea that pathways to comorbidity arise from the symptoms of one disorder overlapping with another (e.g., sleep disturbances are a feature of both anxiety and depressive disorders) and some pathways are more likely than others (e.g., phobias to GAD and GAD to MDD rather than phobias to psychosis for instance).

Unfortunately, conceptualising and modelling symptoms and disorders in this way is not easily accommodated by the traditional statistical procedures used in psychology based on classical test theory (e.g., latent variable models such as regression, analysis of variance, and structural equation modelling). Instead, Cramer and
colleagues employ network analysis, which is a technique commonly used to analyse internet usage and social media. Network analysis enables symptoms to be mapped three-dimensionally without many of the assumptions required for latent variable models. For example, network models do not assume that a disorder is measured or indicated by its symptoms, which is the foundation of the reflective model. Nor is it assumed that comorbidity is caused by the presence of a higher-level latent (unobserved) comorbidity factor.

Results from network analysis studies have shown that half of the symptoms within the DSM are connected in a network fashion (Borsboom, Cramer, et al., 2011), “wherein particular symptoms cause one another dynamically, and where disorders are linked by symptoms that bridge their networks” (Eaton, 2015, p.846). As a result of these findings, Eaton (2015) argues that comorbid anxiety and depression is due to direct causal links among the symptoms rather than being manifestations of a latent internalizing variable.

This point is pivotal. It has profound ramifications for the way mental disorders are conceptualised, operationalised, and analysed. It also raises questions about the accuracy and reliability of past research that has operationalised mental health using reflective measurement models of categorically discrete mental disorders and specific diagnoses. How might the results and associated conclusions have been different if the analyses had included direct relationships between symptoms?

The National Institute of Mental Health (NIMH) in the United States recognised this and proposed a research framework known as the Research Domain Criteria (RDoC). Rather than promoting research into specific diagnoses, the RDoC focuses on “basic units of analysis”, which are the core concepts and systems believed to underpin behaviour (e.g., negative valence, which includes systems primarily responsible for responses to aversive situations or context, such as responses to fear, anxiety, frustration, and loss; for a detailed discussion, see NIMH, 2016). This framework, which was designed to “integrate many levels of information (including self-report, behaviour, genetics, brain imaging, and other types of psychophysiology) in order to better understand the relationship between biology and behaviour (symptoms) in mental illness, is helping to deconstruct processes and phenomena into basic units of analysis and tease out direct relationships between symptoms. At present, the RDoC matrix is too disaggregated to offer a clear alternate way of conceptualising common mental health problems and disorders but it does allow for direct relationships between systems.
and constructs without the assumption that symptoms are solely attributable to specific underlying mental disorder(s) or disease. It will be interesting to see how this revised approach to mental health and related research comes together over the coming years.

**Latent Class Perspective**

Another way of looking at the data is with a person-centred analytic approach known as latent variable mixture modelling (LVMM). In contrast to linear variable models, which are used to test theories of relationships between constructs, and network models, which are based on the frequency of item endorsement, LVMM seeks to uncover subgroups of people with similar profiles who differ from others in important qualitative or quantitative ways (Nylund-Gibson & Hart, 2014). This is done by looking at patterns in the data formed by particular combinations of responses to observed measures of interest. These patterns are not always readily apparent to researchers and clinicians because they are based on people’s responses to multiple measured items, not just a single item.

Rather than assuming that data comes from a single homogenous population and that everyone in a population can be described by a single probability distribution (as SEM does), LVMM describes the population using a mixture of distributions. Each distribution corresponds to a latent (unobserved) subgroup or class (McCrea, 2013). The joint distribution is a mixture (i.e., weighted sum) of the component distributions (G. Lubke & Muthén, 2005; G. H. Lubke & Miller, 2015):

\[ f(y) = \sum_{k=1}^{K} \pi_k f(y; \mu_k, \pi_k) \]

whereby \( \Sigma \) is diagonal (although this constraint can be locally relaxed), and \( \pi_k \) is the class proportion. Figure 8 illustrates this idea with a continuous outcome variable, \( y \). The three dashed curves represent the distribution for three subgroups. Note that each class has its own mean and parameters. When the full sample is analysed all together, these three distributions are not observed, only the mixture of the three, which is shown by the solid black curve.
Note how the overall joint distribution does not accurately reflect any of the subgroups. This means that it misses potentially important differences between groups of individuals that exist within the population or sample. For instance, the subgroup means for Class 1 in Figure 8 is much lower than Class 3, while the kurtosis is higher for Class 1 and 2 than Class 3. Translated into practice, these types of differences might reflect subgroups of individuals who have very different profiles and characteristics, and they may need or benefit from different interventions. However, if just the full sample’s means and joint distribution is used in analyses, these potentially important variations between individuals and subgroups are missed. This could explain why current prevention and treatment interventions help some people and not others – they are based on research that uses the joint distribution rather than identifying and analysing important differences between subgroups.

LVMM is flexible in terms of the type of data that can be analysed and the names of LVMM analyses vary according to the type of data used (i.e., cross-sectional or longitudinal), the scale of the observed and latent variables (i.e., continuous, categorical, or hybrid), and whether variability is allowed within the subgroups. Typically, latent class analysis (LCA) is used to describe LVMM based on cross-sectional categorical data and may include binary, nominal or ordinal observed variables for the class indicators. When the indicators are continuous, historically it has been referred to as latent profile analysis. Both LCA and LPA involve categorical latent variables (e.g., the latent class variable) and exclude continuous latent variables. Latent transitional analysis and latent class growth analysis extend these techniques for longitudinal data and model the change in people’s scores over time.
This approach is not new. It has been applied to lifestyle and chronic disease prevention programs (Hardie, Critchley, & Moore, 2015; Kuvaas, Dvorak, Pearson, Lamis, & Sargent, 2013; Larsen, Pedersen, Friis, Glümer, & Lasgaard, 2017; McCarthy, Ebssa, Witkiewitz, & Shiffman, 2015; B. Muthén, 2001), self-injury (Klonsky & Olino, 2008), anxiety subtypes (Lyons et al., 2012), and more recently in the areas of attachment and personality (Beeney et al., 2016), depression (Li et al., 2014), and dual diagnoses (Salom, Betts, Williams, Najman, & Alati, 2016). Within these contexts, LVMM has been used to identify subtypes or subgroups that are qualitatively different from one another, with distinct risk profiles and characteristics. This has enabled more tailored and specific intervention recommendations to be made for each subtype/group. It is anticipated that this approach will lead to more effective and efficient interventions than the usual one-size-fits-all approach (Hardie et al., 2015) but further research is needed to determine if this is true.

The Current Study - A Closer Look at Subgroups

To-date subtypes and subgroups in mental health research have largely been based on diagnostic categories with specifiers that describe prominent features (e.g., MDD - With melancholic features or - With anxious-distress) and/or severity (e.g., mild, moderate, severe). Such categories try to reflect an individual’s symptoms and dysfunction, and help guide clinicians towards appropriate treatment options. However, such categories often provide limited insight into people’s protective factors, quality of life and wellbeing. Perhaps different mental health subgroups can be identified if positive and negative dimensions of mental health are examined together.

Given the diversity of vulnerability factors (e.g., gender, socio-demographic disadvantage, significant negative life events) and protective factors (e.g., physically healthy, good coping skills, connected to family and community; National Research Council and Institute of Medicine, 2009) known to impact mental health, it is hypothesised that the mechanisms underlying mental health and wellbeing differ across the subgroups. If supported, this could help explain why models and interventions that are empirically supported, only apply or help a portion of the target population or client group.

The current study explores LVMM as an alternative way of looking at mental health data, including both positive and negative dimensions, and considers what it might add to the current state of knowledge, in terms of mental health subtypes, screening for mental health problems and targeting interventions. To investigate the
impact of these subgroups on traditional model testing (such as SEM with full samples), the study tests a mediated model of stress and mental health, first with the full sample, then in subgroup analyses, and then compares the results.

The model posits that coping and the satisfaction of basic psychological needs mediate the relationship between stress and mental health. The concept of basic psychological need satisfaction stems from Deci and Ryan’s (1985) humanistic work looking at the interplay between the extrinsic forces acting on people and the intrinsic motives and needs inherent in human nature. Their theoretical framework, known as self-determination theory (SDT), is based on the premise people have a set of psychological needs, the fulfilment of which is vital for optimal human functioning, social development, and wellbeing (Deci & Ryan, 2000; Richard M. Ryan & Deci, 2017). It is argued that the satisfaction of three basic psychological needs—autonomy, relatedness and competence—direct individuals to initiate actions that are essential for personal growth and development (Deci & Ryan, 2000). The need for autonomy refers to the degree to which individuals feel that their actions are volitional and self-governed. Competence refers to the extent to which individuals feel effective in their interactions with the social environment and underpin the need to engage in challenges, whereas relatedness refers to the need to belong and to feel connected to others (Deci & Ryan, 2000).

Ryan and Deci (2001) argue that the satisfaction of these needs foster immediate wellbeing and strengthens inner resources, which contribute to subsequent resilience. Conversely, the frustration or thwarting of any of these needs is related to emotional and social dysfunction, and increased vulnerabilities for defensiveness and psychopathology (Vansteenkiste & Ryan, 2013). This is known as basic psychological needs theory (BPNT; a subtheory of SDT) and it assumes that levels of wellbeing are directly proportional to the extent that such needs are adequately met.

Research testing the assumptions of BPNT have consistently found that the satisfaction of these needs in everyday life is positively associated with a variety of wellbeing outcomes, including emotional well-being, psychological adjustment and growth, self-esteem, and life satisfaction (Milyavskaya, Philippe, & Koestner, 2013; Sheldon, 2009; Şimşek & Koydemir, 2013), while a failure to satisfy these needs has a robust detrimental impact on psychological wellbeing and functioning, manifesting itself in common mental health problems, such as anxiety and depression (Richard M. Ryan & Deci, 2017; Vansteenkiste & Ryan, 2013). Research has also shown that these
needs mediate the relationships between many individual factors (e.g., personality traits: Şimşek & Koydemir, 2013) and environmental factors (e.g., socio-economic factors: Di Domenico, Fournier, Ayaz, & Ruocco, 2013) and mental health and wellbeing.

The mediational model tested in this study hypothesises that basic psychological need satisfaction (BPNS) mediates the relationship between stress and mental health. This is based on the supposition that interventions that increase BPNS lead to improved mental health and reduced symptoms of anxiety and depression, regardless of the theoretical approach used. Accordingly, it may be considered as a trans-theoretical model of mental health.

In sum, the current research draws on the WHO’s definition of mental health and proposes a novel way of operationalising it with non-clinical samples. Its operationalisation includes both positive and negative dimensions of mental health and draws on dimensional and transdiagnostic principles rather than the traditional, categorical diagnostic approach. This combination of measures will be empirically tested using person-centred data analytic techniques to determine whether meaningful latent (unobserved) subgroups can be identified. To explore whether mechanisms underlying mental health and wellbeing differ across these subgroups, the study also tests a mediated model of stress and mental health, and examines whether it is equally valid across the subgroups.

Two broad questions guide the study:

1. How can we conceptualise, operationalise and analyse mental health and related data in a way that improves our ability to screen for mental health problems and target interventions?

2. Can person-centred data analytic techniques improve the identification of subgroups that differ in important ways from the current diagnostic categories?
   a. If so, what can we learn from those latent (unobserved) groupings?
   b. How similar or different are they from groups based on symptom severity?
   c. Do mechanisms underlying mental health and wellbeing differ across the latent subgroups?

Given the exploratory nature of this study, a cross-sectional design with a community sample is appropriate for these questions to be examined. A non-clinical (community) sample is preferable to a clinical sample in this context because it
increases the likelihood that the full range of positive and negative dimensions of mental health will be present thereby enabling the identification of patterns and trends that might not be apparent if the sample was restricted to those who have a current mental illness. Moreover, if we are to begin to reduce the incidence and prevalence of mental disorders in the community, then we need to identify at-risk individuals prior to onset of the disorder(s), which necessarily requires a non-clinical population.

By addressing the above questions, this thesis seeks to contribute to the current international discussion about how best to reconceptualise the classification of mental health and illness, and improve intervention effectiveness by:

- Questioning some of the basic assumptions underpinning classical test theory and the general linear model in the context of mental health and related constructs
- Considering an alternative way to operationalise common mental health problems, which incorporates dimensions of mental health and wellbeing as well as dysfunction
- Investigating whether or not meaningful groups of at-risk adults can be identified and differentiated between based on self-reported measures of positive mental health and wellbeing, as well as symptoms of anxiety and depression
- Examining if psychological mechanisms underlying mental health and wellbeing differ across (latent) subgroups
- Discussing the implications of these findings for future screening and better targeting of intervention programs to help optimise effectiveness and efficiency.
Chapter 5    Method

The guiding questions for this program of research have been: how well are we doing in the field of mental health and how can we improve? Investigating these questions started with a brief overview of mental health needs at the global level and then a review of program effectiveness at a national level in Chapter 2. Limited evidence of effectiveness and efficiency at that level prompted a review of psychological models of mental health and their effectiveness in Chapter 3. The review found that despite the diverse models and approaches currently available for treating common mental health problems, intervention efficacy seems to hover around 40%, at best. Arguably there are many factors that contribute to these fairly modest efficacy and effectiveness rates; however this thesis has focussed on just two of them: how mental health is conceptualised and analysed.

These two issues form some of the fundamental building blocks for mental health research and evaluation because all research and evaluation projects need to consider them. Decisions about how mental health is conceptualised and analysed guide what measures are used and how results are interpreted, which in turn influences recommendations and the focus of future research, interventions and programs. Thus, it stands to reason that if there are inaccuracies and problems in the way mental health is conceptualised and analysed, then they could potentially affect research and evaluation outcomes and findings, including those related to intervention efficacy and effectiveness. In this way, intervention efficacy and effectiveness can be considered as downstream factors and this thesis is looking at some of the upstream factors that may be inadvertently limiting progress and performance in this area.

The previous chapter discussed the World Health Organisation’s (WHO, 2014) standard definition of mental health and the clear reference to positive wellbeing and functioning as core components of complete mental health. It was hypothesised that conceptualising mental health using a dual continuum model and operationalising it with measures of affect and wellbeing as well as symptoms of common mental health problems might enrich our understanding of individual differences in mental health. The previous chapter also discussed some of the issues with the way mental health is commonly modelled and statistically analysed with techniques that rely on classical test theory and the general linear model. Latent variable mixture modelling (LVMM) was posited as an alternative way of looking at mental health and related data that could potentially overcome some of the issues and assist with theory development (or
refinement) and better targeting of interventions. Several questions were raised for further exploration, including:

1. How can mental health be conceptualised, operationalised and analysed in a way that improves our ability to screen for mental health problems and target interventions?

2. Can LVMM techniques improve the identification of subgroups that differ in important ways, not just based on current diagnostic categories?
   a. If so, what can we learn from those latent (unobserved) groupings?
   b. How similar or different are they from groups based on symptom severity?
   c. Do mechanisms underlying mental health differ across the latent subgroups?

This chapter describes the research process that was employed to investigate these questions. This chapter provides details about the participants, materials and methods used, as well as the specific statistical analyses employed.

**Participants**

Data for this study were collected from 376 undergraduate students enrolled in first year psychology subjects at Swinburne University of Technology (one metropolitan campus and one outer-suburban campus) and Open Universities Australia (OUA). The combination of a metropolitan, an outer urban campus, and an online environment was planned to maximise the socio-demographic spread and heterogeneity in the sample.

Although studies with university student populations are often dismissed as being merely samples of convenience, epidemiology studies suggest that university students all over the world have higher rates of psychological morbidity, especially anxiety and depression, than the general population (e.g., in Australia: Stallman, 2010; in China: Kou, Meng, Xie, Chen, Yu, Shi et al., 2012; in Ireland: Macaskill, 2013; In Portugal: Sarmento, 2015; in Sri Lanka: Amarasuriya, Jorm, & Reavley, 2015; in the USA: Deasy, Coughlan, Pironom, Jourdan, & Mannix-Mcnamara, 2014). The UK Royal College of Psychiatrists (2011) advocates that the high rates of morbidity in undergraduate students represent a neglected public health concern and therefore merits ongoing research and interventions. From a purely pragmatic point of view, the increased prevalence rate is highly desirable in a study of common mental health problems because it improves the power of the analyses. Power, sample size and effect size calculations will be discussed further shortly.
Students were invited to participate in this study during a brief presentation about the project in a first-year lecture or via an online post. Consent information statements were distributed during the presentation and were available via a link in the online post. Consenting students completed the project survey on-line via Opinio at a time of their choosing.

**Response rate.**

Of the potential 592 OUA students and 865 on-campus students, 488 accessed the online survey. Of those, 376 completed the survey. This represents an overall response rate of 25.81% and a completion rate of 77.05%. The average time taken to complete the survey was 20 minutes.

**Sample profile.**

The final sample consisted of 306 females and 70 males who ranged in age from 18 to 79 years ($M = 30.54$, $SD = 11.53$). Whilst the majority of the participants who completed the survey were female (81.38%), a multivariate analysis of variance indicated that they did not differ significantly from their male counterparts on any of the mental health or related variables except for positive affect ($F(6, 314) = 2.92$, $p = .009$; Wilk's $\Lambda = 0.95$, partial $\eta^2 = .05$), such that male participants reported slightly less positive affect than females in the this sample ($M = 30.75$ and 33.72 respectively; $F(1, 319) = 6.06$, $p = .014$; partial $\eta^2 = .02$).

Forty eight percent were single (never married) and 41.12% were partnered or married. Nearly half of all participants had children. Just over a quarter of the sample lived with their parents, 21.28% lived with their partner/spouse and children, 14.89% lived with their partner/spouse only, and 9.57% were single parents.

Nearly a third of the sample reported that their main occupation was Household Duties (e.g., stay-at-home mum), 18.35% were intermediate clerical, sales or service workers and 11.97% were labourers or related workers. Fifty percent of the sample reported a personal income of less than $26,000 per annum. The majority of the participants (71.54%) reported gross household income of less than $78,000 per annum.

**Prevalence.**

Based on scores from the SF-36 Mental Health Component Summary (MCS), which measures emotional wellbeing and quality of life, 45.74% of the sample met the criteria for probable caseness (i.e., MCS score ≤ 42; Ware & Sherbourne, 1992). Caseness refers to symptoms that are specific and severe enough to merit a clinical diagnosis. This is substantially higher than the general Australian population (i.e., <
25% of the population have MCS scores ≤ 42; ABS, 2008) but more or less consistent with estimated prevalence rates for university students in Australia (e.g., Stallman, 2010) and around the world (e.g., Bayram & Bilgel, 2008; Eisenberg, Hunt, & Speer, 2013; Royal College of Psychiatrists (UK), 2011). Note that the SF-36 MCS mean in the current sample (M = 41.5, SD = 12.2) is almost a standard deviation lower than the mean for the Australian population (M = 50.1, SD = 10.0), which is significant (t(344) = -13.08, p < .001) and suggests that, overall, this sample has somewhat poorer mental health and wellbeing than the general population. This is consistent with the broader literature and previous research involving university students and community members who voluntarily participate in mental health and related research, who often have slightly better physical health than the general population (as a function of age) and significantly higher prevalence rates of mental health problems (e.g., Stallman, 2010).

Based on scores from the Hospital Anxiety and Depression Scale (HADS), half the sample (50.79%) reported anxiety and depression symptoms in the normal range, while 24.46% met the criteria for caseness (HADS score ≥ 11 on either subscale). This is slightly higher than the 12-month prevalence rate for all mental disorders in the general Australian population (20%; ABS, 2013b). A further 24.50% of the current sample had elevated anxiety and depression scores that fell in the range for suspicious cases (i.e., HADS score of 8 to 10 on either scale; Olssøn, Mykletun, & Dahl, 2005; Zigmond & Snaith, 1983), which indicates at least subclinical levels of anxiety and/or depressive symptoms are present. It is widely understood that subclinical symptoms reflect an increased risk of developing a disorder, however, relatively little is known about the characteristics, trajectories and prognosis of this cohort as they remain relatively under-studied.

**Measures**

The first aim of this exploratory study was to investigate what subgroups could be identified in a non-clinical sample if mental health was conceptualised using measures of positive mental health and mental ill health. The second aim was to examine the impact of these subgroups on traditional model testing procedures such as structural equation modelling. This was done using a simple mediation model, which posits that the satisfaction of basic psychological needs mediates the relationship between stress and mental health. Note that while the model may have some intrinsic interest of its own, its primary purpose in this study is to facilitate a comparison of results from different statistical techniques, so it is not elaborated on in enormous detail.
and tests of alternative models are not reported in this paper.

Table 8 summarises the constructs of interest in this study and the indicators used to operationalise them. Each of these is subsequently described. Psychometric properties for each of the self-report measures used are examined in the Results Chapter, so they are not reported here to avoid duplication.

**Contextual variables - Social determinants of health.**

*Socio-demographics.*

In order to statistically control for variations in mental health and wellbeing due to different life stages and socio-economic profiles, a section of the questionnaire collected socio-demographic information, including birth year, gender, marital status, household composition, education, occupation and income. The wording of these items was based on those used in the most recent National Mental Health and Wellbeing survey (ABS, 2008).

Table 8

*Key Constructs of Interest and Their Operationalisation*

<table>
<thead>
<tr>
<th>Social determinants of health (Covariates)</th>
<th>Life Stress</th>
<th>Cognitive Processing</th>
<th>Coping</th>
<th>Basic Psychological Needs</th>
<th>Mental Health &amp; Wellbeing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>Perceived stress</td>
<td>Optimism</td>
<td>Avoidant</td>
<td>Autonomy</td>
<td>Positive affect</td>
</tr>
<tr>
<td>Gender</td>
<td></td>
<td>Locus of control</td>
<td>- Disengage</td>
<td>Competence</td>
<td>Negative affect</td>
</tr>
<tr>
<td>Marital status</td>
<td></td>
<td></td>
<td>- Distraction</td>
<td>Relatedness</td>
<td>Anxiety</td>
</tr>
<tr>
<td>Living arrangements</td>
<td></td>
<td></td>
<td>- Denial</td>
<td>Depression</td>
<td>Quality of life</td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
<td>- Blame self</td>
<td>Satisfaction</td>
<td>&amp; functioning</td>
</tr>
<tr>
<td>Employment</td>
<td></td>
<td></td>
<td>- Substance use</td>
<td></td>
<td>Satisfaction</td>
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<tr>
<td>Income</td>
<td></td>
<td></td>
<td>- Approach</td>
<td>with life</td>
<td></td>
</tr>
<tr>
<td>Physical health</td>
<td></td>
<td></td>
<td>- Take action</td>
<td></td>
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<tr>
<td>Health-related behaviours</td>
<td></td>
<td></td>
<td>- Reframe</td>
<td></td>
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<tr>
<td>- Tobacco use</td>
<td></td>
<td></td>
<td>- Plan</td>
<td></td>
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<tr>
<td>- Alcohol use</td>
<td></td>
<td></td>
<td>- Accept</td>
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<tr>
<td>- Drug use</td>
<td></td>
<td></td>
<td>- Humour</td>
<td></td>
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<tr>
<td>Domestic violence</td>
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<td>Seek support</td>
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<tr>
<td>Prior mental illness</td>
<td></td>
<td></td>
<td>- Emotional</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Family history of mental illness</td>
<td></td>
<td></td>
<td>- Instrumental</td>
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<td>- Vent</td>
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</table>
**Physical health.**

*Health Outcomes Short Form* (SF-36; Ware & Sherbourne, 1992). The SF-36 is a 36-item self-report questionnaire that measures health-related quality of life and functioning. It differentiates between physical and mental components and yields eight subscale scores and two summary measures. The physical component summary (PCS) comprises four subscales: physical functioning, role-physical, bodily pain, and general health scales. Each subscale is an aggregate of between two and 10 items with differing response formats for different items. For example, a general health item is “*In general, would you say your health is...*”, which is rated on a five-point format ranging from 1 (*Excellent*) to 5 (*Poor*). To score this measure, raw subscale scores are first standardised and then transformed using specified algorithms and Australian population norms (ABS, 2008). Higher scores indicate better physical health and functioning. Convergent and divergent validity for this measure have been widely demonstrated using principal components analysis. Reliability of the PCS usually exceeds 0.90 (Butterworth & Crosier, 2004).

**Alcohol and drug use.**

A set of five items was used to briefly assess drug and alcohol use. These items, which were adapted from a large longitudinal Australian cohort study (the Australian Longitudinal Study of Women’s Health) included: one item about the frequency of tobacco use rated on a four-point format, ranging from *Not at all* to *Daily*; two items measuring alcohol consumption to reflect both frequency (rated on a seven-point scale ranging from *I never drink alcohol* to *Everyday*) and quantity of alcohol consumed in a single session (rated on a four-point scale ranging from *1 or 2 drinks* to *9 or more drinks*); and, two items about patterns of drug use for non-medicinal purposes - one item specifically about marijuana use, the other item was about other illicit drugs, which were both rated on a three-point scale (*Never*, *More than 6 months ago*, *Less than 6 months ago*). Higher scores represent more recent substance use.

**Domestic violence.**

History of intimate partner violence (IPV) was assessed by asking the participants if they had ever been in a violent relationship with a partner or spouse. Response options were *Yes* or *No* (Loxton, Schofield, Hussain, & Mishra, 2006).

**Family history of mental illness.**

Respondents were asked if they or anyone in their immediate family (mother, father, sibling) had had anxiety, depression, substance use or any other mental illness.
Data was then collapsed to create a series of dichotomous variables that were scored 0 for No history of mental illness and 1 for History of Mental Illness for personal history of mental illness (HxMI), maternal HxMI, paternal HxMI, and sibling HxMI.

**Life stress.**

*Perceived Stress Scale* (PSS; (S. Cohen, Kamarck, & Mermelstein, 1983). The PSS (revised by Cohen & Williamson, 1988) is a 10-item scale measuring the degree to which life situations are appraised as stressful (i.e., unpredictable, uncontrollable, and overloading). Respondents are asked to indicate how often they have felt or thought a certain way in the past four weeks on a five-point scale from 0 (*never*) to 4 (*very often*), for example, “*In the past four weeks, how often have you been upset because of something that happened unexpectedly?*” Cohen and colleagues established content validity of PSS scores as well as concurrent and predictive validity and its factorial (structural) validity has been well supported (E.-H. Lee, 2012). In a psychometric review of the PSS with two college samples Roberti, Harrington, and Storch (2006) reported a Cronbach alpha coefficient of 0.89.

**Behavioural variables.**

*Coping Orientation to Problems Experienced scale* (Brief-COPE; Carver, 1997). Dispositional coping was measured with the 28-item Brief-COPE, which measures 14 different coping strategies. Individual coping strategies measured include active coping, reframing, planning, acceptance, denial, substance use, use of emotional support, use of instrumental support, venting, self-distraction, humour, religion, and self-blame. Each strategy is assessed by two items, which are rated on a four-point scale ranging from 1 (*I haven’t been doing this at all*) to 4 (*I have been doing this a lot*). Subscale scores are calculated by summing responses to the two items and range from two to eight, with higher scores indicating more frequent use of that coping strategy. No overall score is produced on this scale. As each coping strategy is measured with only two items, alpha coefficients are not calculated for the subscales. In the current study, inter-item correlations within each subscale were all significant at the $p < .001$ level, ranging from .19 (Mental disengagement) to .82 (Substance use).

It is worth noting that Carver (1997) developed this questionnaire based on a community sample of 168 participants who had been affected by a hurricane. Acknowledging the limitations from a factor analysis with a small sample size, Carver (1997) reported the factor structure obtained from item-level analyses. Only four subscales formed distinct factors: substance use, turning to religion, humour, and
behavioural disengagement. Items from the remaining scales formed two larger factors and Carver (1997) concluded that the structure approximated that of the full-length COPE questionnaire (Carver, Scheier, & Weintraub, 1989). However, rather than prescribing a rigid structure of the coping strategies assessed by the Brief-COPE, he recommended that researchers use the Brief-COPE flexibly and creatively as suits, for example, only selecting a sub-set of the subscales (Carver, 2007). Researchers using the Brief-COPE “regularly refer to this recommendation to justify an exploratory analysis to determine empirically how the data from their sample is to be analysed” (Krägeloh, 2011, p.127). However as one might predict, this flexibility has resulted in a lack of agreement and consistency regarding the factor structure of the Brief-COPE. Some of the more common factors or dimensions found are outline in Table 9.

Table 9

<table>
<thead>
<tr>
<th>No. of dimensions</th>
<th>Dimensions</th>
<th>Example reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>Active Passive/avoidant</td>
<td>Eldred, 2011</td>
</tr>
<tr>
<td>2</td>
<td>Adaptive Maladaptive</td>
<td>McGee, Williams, Nada-Raja, &amp; Olsson, 2011 Mahmoud, 2011</td>
</tr>
<tr>
<td>3</td>
<td>Approach Avoidance Help-seeking</td>
<td>Ebert, Tucker, &amp; Roth, 2010 Snell, Siegert, Hay-Smith, &amp; Surgenor, 2011</td>
</tr>
<tr>
<td>3</td>
<td>Problem-focused Active-emotional Avoidant-emotional</td>
<td>Deatherage, Servaty-Seib, &amp; Aksoz, 2014</td>
</tr>
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</table>

Although the population of interest differed in each of the studies mentioned in Table 9, all of them used PCA with varimax rotation. In 2012, Eisenbarth employed a different technique, cluster analysis. Two clusters of coping strategies were found in a sample of college students. The first cluster represented individuals with high problem-focused coping, moderate support seeking, high emotion-focused coping, and low avoidance. The second cluster consisted of participants characterised by low problem-focused coping, moderate support seeking, low emotion-focused coping, and high
More recently, Nielsen and Knardahl (2014) undertook a more comprehensive examination of coping strategies and how they relate prospectively to psychological distress in employees. Comparing the results from a number of different analytic techniques (t-tests, standardised means differences, Two-step cluster analyses, repeated measures ANOVA, and multinomial regression), they argued that a three-cluster solution offered the most stable results in terms of coping styles. The three clusters comprised: engagement coping style (active coping, use of emotional and instrumental support, planning, positive reframing and acceptance; characteristic of 35.0% - 43.9% of the samples), disengagement coping style (self-blame and self-distraction; characteristic of 23.6% - 25.6% of the samples), and low coping style (denial, substance use, and behavioural disengagement; characteristic of 30.5% - 41.4% of the samples).

Given the extremely diverse results reported in the literature, the psychometric properties of the Brief-COPE need to be assessed to clarify the most appropriate ways to model coping for use in subsequent analyses. To do this, the current study employed two different approaches. First, a person-centred approach was used to see if particular patterns of coping exist within the data. This was done with latent class analyses, which will be discussed in more detail shortly. Then the traditional, variable-centred approach was taken with factor analysis to examine the factorial (structural) validity (see Appendix B).

Cognitive variables.

Optimism.

*Life Orientation Scale, Revised* (LOT-R; Sheier, Carver & Bridges, 1994). The LOT-R assesses individual differences in dispositional optimism versus pessimism. The six-item scale (with four filler items) includes three positively worded items (optimism) and three negatively worded items (pessimism) measured on a five-point scale ranging from 1 (*I agree a lot*) to 5 (*I disagree a lot*) to indicate the respondent’s level of agreement with the statement, for instance, “In uncertain times, I usually expect the best.” Sheier et al. (1994) recommended reverse scoring the negative worded items and then summing the six items to yield a total score. This yields a possible score range of 6 to 24, with higher scores indicating more optimism. The LOT-R has been found to have adequate internal consistency (Cronbach’s alpha = 0.78) and excellent convergent and discriminant validity (Sheier et al., 1994).
**Locus of Control.**

*Internality, Powerful Others, and Chance Locus of Control Scale* (IPC; Levenson, 1973, 1981). Also known as the Multi-dimensional Locus of Control Scale, the IPC is a 24-item scale comprising three subscales that measure perceptions about the extent to which oneself, powerful others and chance have control over life events. Each subscale comprises eight items that are measured on a seven-point Likert-type scale ranging from -3 (*strongly disagree*) to +3 (*strongly agree*). A sample of an internal control subscale item is “Whether or not I get to be a leader depends mostly on my ability.” To avoid negative values, 24 points are added to scores on each subscale. Total scores for each subscale range from 7 to 56, with higher scores indicating stronger perceptions of control.

Levenson (1974) reported acceptable Kuder-Richardson reliabilities of between .64 and .78 for the three independent factors, and test-retest correlations over a 7-week span ranged from .66 to .73. The IPC has been modelled in the literature as a hierarchical construct with either two factors (i.e., internal and external; e.g., Rossier, Dahourou, & McCrae, 2005) or three factors (e.g., Gianakos, 2002; Levenson, 1981). The appropriateness of each of these options was assessed in this study as part of the measurement model to ascertain the optimal manner of modelling the construct prior to using it in structural models.

**Mediating variable.**

*Basic Need Satisfaction in Life Scale* (BNLS; Gagné, 2003). The 21-item scale measures the satisfaction of three basic psychological needs. Participants indicate on a seven-point scale, from 1 (*not true at all*) to 7 (*definitely true*), the extent to which their need for autonomy (seven items), relatedness (six items), and competence (eight items) are generally satisfied in their lives. A sample item from the autonomy subscale is “I feel like I can decide for myself how to live my life.” Scores range from 7 to 49 (autonomy), from 6 to 42 (competence), from 8 to 56 (relatedness), and from 21 to 147 (total score). Nine of the 21 items are negatively worded and were reversed scored prior to analyses. Higher scores reflect greater satisfaction. Gagné (2003) reported coefficient alphas of .69, .71, and .86 for the autonomy, competence, and relatedness scores, respectively.

Notably, Gagné (2003) did not report checking the structure of the measure to ensure that each subscale was unidimensional. In a review of the psychometric properties of the scale, Johnston and Finney (2010) found a clear method factor and
proposed a modified scale with 3 items (autonomy), 6 items (competence) and 7 items (relatedness). Cronbach alpha coefficients for the revised scales ranged between .55 and .82 but the authors recommended that future studies examine the factor structure to ensure that each scale is unidimensional and reliable. Accordingly, psychometric analysis of the BNLS was conducted prior to using it in the main analyses (see Appendix B).

**Affect/emotionality.**

*Positive and Negative Affect Schedule (PANAS; D. Watson, Clark, & Tellegen, 1988).* The PANAS is a 20-item measure, comprising two mood scales, one assessing positive affect (PA) and the other assessing negative affect (NA). Items are rated on a five-point response scale ranging from 1 (very slightly or not at all) to 5 (extremely) to indicate the extent to which respondents have felt a particular emotion (e.g., “enthusiastic”, “afraid”) in the past four weeks. Scores range from 10 to 50 for each scale, with higher scores reflecting more frequent emotions in each category. PA and NA are construed as broad mood dimensions that are orthogonal (independent) to each other, with correlations between PA and NA typically ranging from -.12 to -.23 over different time periods (Watson et al., 1988). Both scales have demonstrated high internal consistency (.84 to .90) and adequate test-retest reliability (Watson et al., 1988).

**Mental health and wellbeing.**

As noted in previously, the World Health Organization’s constitution (1946, 2006) defines health as “a state of complete physical, mental and social wellbeing and not merely the absence of disease or infirmity.” In 2007, the WHO went on to define mental health as “a state of wellbeing in which the individual realises his or her own abilities, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to his or her community” (Fact sheet No. 220, p.1)

In addition to the absence of psychopathology (symptoms of a mental disorder), this definition highlights the idea of positive emotional wellbeing, including optimal functioning and quality of life. Accordingly, the current study operationalises mental health and wellbeing using widely used measures of anxiety and depression, health-related quality of life and a measure of general life satisfaction.

**Common mental health problems.**

*The Hospital Anxiety and Depression Scale (HADS; Zigmond & Snaith, 1983).* The HADS is a measure of anxiety and depression that is widely used in non-clinical,
community-based health research. It consists of 14 items, seven items for anxiety and seven items for depression. Respondents are asked to indicate on a scale of 0 to 3, whereby 3 indicates higher symptom frequency, the extent to which they have felt certain ways in the past week, for example, “I feel tense or wound up”. Items on the depression scale emphasise anhedonia (loss of pleasure), which is regarded as a positive feature (Crawford et al., 2009), given that the tripartite theory of anxiety and depression suggests that anhedonia is important in differentiating depression from anxiety (L. A. Clark & Watson, 1991).

The HADS has good reliability ranging from .63 to .93 for both scales (average of .83; Bjelland, Dahl, Haug, & Neckelmann, 2002; Crawford, Henry, Crombie, & Taylor, 2001; Zigmond & Snaith, 1983) and strong convergent validity with other measures of anxiety and depression (Crawford & Henry, 2003). The clinical cut-off point for the identification of suspicious cases is ≥ 8 and ≥ 11 for safe cases on both subscales (Zigmond and Snaith, 1983; Bjelland et al, 2002) with good sensitivity and specificity reported (i.e., average of .80; Bejelland et al., 2002).

Quality of life and functioning.

Short Form 36 (SF-36; Ware & Sherbourne, 1992). Along with four subscales of physical health mentioned earlier, the SF-36 comprises four mental health-related subscales that measure positive emotional wellbeing in terms of quality of life and functioning: vitality (VT), social functioning (SF), role limitations due to emotional problems (RE), and mental health (MH). Each subscale is an aggregate of between two and 10 items with differing response formats for different items. For example, an item from the MH subscale is “Within the last 7 days….Have you felt calm and peaceful” with responses rated on a six-point Likert-type scale that ranges from “All of the time” to “None of the time”. As with PCS score, raw scores from these subscales are first standardised and then transformed using a specified algorithm and Australian norms (Centre for Health Service Development, 2005).

This measure is widely used around the world with researchers employing the component summary score (MCS) in their analyses or modelling the subscales individually. Gandek, Sinclair, Kosinski, and Ware (2004) reported reliability coefficients of between .83 (MH) and .87 (VT) for the four subscales. Results from the Australian National Household Survey (HILDA; Butterworth & Crosier, 2004) indicated Cronbach alpha coefficients of 0.83 (VT, RE, SF) and 0.82 (MH). Before deciding whether to model the subscales as individual indicators of mental health and
wellbeing or to use the mental health component summary score (MCS), the psychometric properties of the subscales with the current sample were checked (see Appendix B).

**Life satisfaction.**

*Satisfaction with Life Scale* (SWLS; Diener, Emmons, Larsen, & Griffin, 1985). The SWLS is a five-item measure with a seven-point response format ranging from 1 (*strongly disagree*) to 7 (*strongly agree*), for example, “In most ways my life is close to my ideal.” Total scores range from 5-35, with higher scores reflecting greater satisfaction with life. Diener et al. (1985) reported a test-retest correlation coefficient of 0.82 and coefficient alpha of 0.87. Pavot, Diener, Colvin, and Sandvik (1991) also reported that the SWLS has good internal consistency, with a Cronbach alpha coefficient of .85.

**Procedure**

For the purposes of this exploratory research, a cross-sectional design was used with participants recruited from a non-clinical population using a non-probabilistic sampling technique (i.e., purposive sampling). Ethical approval for the research was obtained from Swinburne University Human Research Ethics Committee (see Appendix A) as part of a larger research project interested in the prevention of common mental health problems.

The main analyses for this study consist of two phases. Each phase uses a different approach to the same data. This is done intentionally to highlight how the same data can tell very different stories, depending on the theoretical and statistical approach used. The first phase focusses on the identification of latent classes, which are subgroups of individuals within a sample that have similar patterns of responding across a set of items. The second phase explores the impact of latent subgroups on model development and testing.

The second phase of the analyses comprises three parts, beginning with a traditional approach to testing theoretical models using structural equation modelling (SEM). In this part of the analyses, the mediation model discussed in Chapter 4 is tested with the full sample. Then, multigroup SEM is used to examine the validity of the SEM model across the subgroups identified in phase one with LVMM. The final set of analyses employ an advanced technique, structural equation mixture modelling (mixture SEM), which combines latent class analysis with SEM. The results from the three different types of analyses are then compared.
Statistical Methods and Issues

All statistical analyses were conducted using IBM SPSS Statistics 24 (IBM, 2016) and Mplus 7.11 (L. K. Muthén & Muthén, 1998-2012). Four main statistical techniques (i.e., principal components analysis, latent variable mixture analysis, structural equation modelling, and structural equation mixture modelling) were used to analyse the data collected in this project. This section discusses the procedures and potential issues associated with these techniques.

Power, sample size, and effect size.

The ability of statistical tests to correctly identify whether in fact there is a difference between groups is referred to as the power of the test. Testing multiple hypotheses in a single study can significantly affect the Type 1 error rate and has implications for power. Type 1 errors refer to rejecting the null hypothesis when it is actually true (i.e., differences between groups are found when they do not really exist). Conversely, Type 2 errors occur when the null hypothesis is not rejected when it is actually false (i.e., difference between groups are not found when, in fact, they do exist). These errors are important because they can lead to wrong conclusions. For instance, in latent variable mixture modelling samples that are too small often lead to the underestimation of latent classes (i.e., a model with too few classes to adequately describe the observed covariance between the items is erroneously chosen; Dziak, Lanza, & Tan, 2014), which can give a misleadingly simplistic picture of differences that actually exist in the population.

A number of factors influence power including (a) the type of statistical test, (b) sample size, (c) number of variables, (d) effect size (the strength of the group differences, loadings or parameter estimates), and (e) the alpha level adopted to determine significance (e.g., .05 or .01) (Tabachnick & Fidell, 2013). In order to minimise the possibility of Type 1 errors in this research, a number of strategies were utilised. First, SEM was employed where possible because, amongst other things, it facilitates the testing of multiple hypothesised pathways simultaneously and accounts for measurement error, which helps minimise the likelihood of Type 1 errors. Second, adequate sample sizes were planned to ensure power and accuracy in parameter estimation. Third, an appropriate alpha level was selected (e.g., .05 or .01) for each analysis, adjusted for multiplicity and non-normality as necessary (see below). These were supplemented with effect size measures and confidence intervals where appropriate, to help assess the precision and accuracy of the parameter estimates.
Effect size (or strength of association) refers to the portion of variance in the outcome variable that is attributable to levels of an independent variables (Tabachnick & Fidell, 2013). Cohen’s (1992) guidelines were adopted for small ($\eta^2 = .02; d = .20$), medium ($\eta^2 = .15; d = .50$), and large ($\eta^2 = .35; d = .80$) effect sizes in order to filter trivial results from those that have practical utility. The width of the confidence intervals accompanying those measures attest to their precision and accuracy, such that a narrow interval is equivalent to saying that the parameter is estimated precisely because the standard error of the parameter estimate is small (Maxwell et al., 2008).

According to Dziak and colleagues (2014), the following sample sizes are needed for a latent class analysis with six items to achieve power of .80: $n = 74$ for large effect sizes, $n = 206$ for moderate effect sizes, and $n = 1,850$ for small effect sizes. Although they recommend multiplying these estimates by 1.15 “to err on the side of caution” (p.457), they also acknowledge that these estimates do not account for continuous variables nor covariates in the model. However, they postulate that the addition of covariates improves power because the addition of covariates to latent variable models assists with the identification of the latent variables (S. Clark & Muthen, 2009).

According to Kline (2010), large samples are needed for SEM, especially for complex models that require many parameters to be estimated. Traditionally, there have been several rules of thumb to guide researchers, including: five to 10 observations per parameter (Bentler & CHOU, 1987; Bollen & Lennox, 1991), and a ratio of 10:1 participants to parameters estimated (Nunnally & Bernstein, 1994). Accordingly, a sample size greater than 500 would be needed in this project to test the proposed theoretical model of stress and mental health with SEM. However, Wolf and colleagues (2013) point out that the rules of thumb are not specific and do not take other factors into account such as the level of communality across the variables or the degree of factor determinacy. In addition, multiple simulation studies have shown that sample sizes of 100 can provide accurate parameter estimates (e.g., Lei & Lomax, 2005), especially when the variables are reliable, the effects are strong and the model is not overly complex (Iacobucci, 2010).

Nevertheless, considerable attention was paid to refining the measurement model in this research in order to reduce overall error, improve power, and lend more precision and confidence to the parametric estimation. As such, attempts were made to
increase the ratio of participants per estimated parameter in this research by reducing model complexity through the use of items parcels and single indicator latent variables.

Actual power attained based on the achieved sample size was checked with the National Statistical Service’s sample size calculator (available online at http://www.nss.gov.au/nss/home.nsf/pages/Sample+size+calculator). Based on an estimated population size of 1.3 million (Australian university students), a prevalence rate of .67 for subthreshold anxiety and depression (Stallman, 2010) and a 95% confidence interval, the current sample of 375 provides adequate power with a standard error of .02.

Data preparation and screening.

Prior to analyses, data were screened for possible response sets, out-of-range values, missing values, and univariate and multivariate outliers (Tabachnick & Fidell, 2013). Possible response sets were determined by examining questionnaires and, in the case of online surveys, visual inspection of the raw data file for any patterns of responses (e.g., sequential, diagonal or vertical line patterns) that would indicate that the questions were not given due consideration. Frequency analyses were conducted for each variable to identify out-of-range and missing values.

Missing data.

Most statistical methods assume the absence of missing data and are only able to include observations that are complete. Although missing data is a pervasive issue in health and social science data, it is a particularly important issue because it has the potential to bias results and undermine the validity of research results.

The impact of missing data depends upon why it is missing, the patterns of missing data, and how much of it is missing (Schafer & Graham, 2002). Reasons for missing data are generally classified as: missing completely at random, missing at random, and missing not at random (MNAR; Sterne et al., 2009). Missing completely at random (MCAR) implies no systematic difference between the missing values and the observed values, and often occurs as a result of equipment malfunction (e.g., repeated measures may be missing due to computer failure or an extended interruption to internet service). Missing at random (MAR) denotes any systematic difference between missing values and the observed values that can be explained by differences in observed data (e.g., in the current study participants who live with their parents are less likely than others to report their household income because they indicate they don’t know it). Missing not at random (MNAR) refers to the presence of systematic
differences between missing and observed values due to unobserved data (e.g., participants with a history of domestic violence may be more likely to miss survey items relating to that topic because of strong feelings of shame, fear or embarrassment).

Biases associated with data that is either MCAR or MAR are considered to be less problematic and can be readily overcome using a variety of statistical methods (see Schafer & Graham, 2002, for an overview of the various techniques). In contrast, MNAR is a serious problem because the pattern of missing data is related to the dependent variables. That is, certain cases are not available for analysis and therefore any analyses based only on the complete cases may not generalise to the whole population. Hence, associated results and interpretations may be biased (Graham, 2012; Kline, 2010).

Given the potential issues associated with the presence of missing data, a four-step approach was taken to address missing data in this research. First, any cases with more than 25% of data missing were removed from analysis. This is in accordance with findings from simulation studies that have demonstrated that up to 25% of data can be missing without unduly biasing parameter estimates when missing values are replaced with maximum likelihood or multiple imputation methods (Byrne, 2001; Newman, 2003).

Second, the patterns of missing data for each variable with more than 5% of data missing were examined using SPSS Missing Values Analysis (MVA). MVA conducts a series of diagnostic tests to examine the data for indications of systematic data loss. In particular, these analyses generate Little’s MCAR $\chi^2$ statistic, which indicates whether the missing data are missing completely at random. If the result is not significant ($p > .05$), then MCAR can be assumed. If the result is significant ($p < .05$) then this assumption cannot be made (Little & Rubin, 2002). Instead, attention turns to the separate variance t-tests and patterns of missing values table to determine whether the difference is likely to be MAR or MNAR. MAR may be assumed if the missing data can be predicted from observed variables (other than the dependent variable). Conversely, if missingness (i.e., whether the data is missing or not) is related to the dependent variable, then MNAR is inferred.

Third, full information maximum likelihood (FIML) estimation methods were employed to deal with missing values throughout the analyses (Arbuckle, 1996). FIML approaches do not impute missing values; rather they use data from cases where the information is available to generate a full information matrix and then that is used in
analyses (Cunningham, 2010). The strength of FIML methods lies in their ability to deal with the missing data, and estimate parameters and standard errors simultaneously (Graham, 2012). The particular FIML methods utilised in this research include robust maximum likelihood (MLR) for continuous data and weighted least squares estimation (SWLS) for categorical data, which are discussed in more detail below (see SEM: Methods of Estimation). It is important to note that FIML methods assume missing values are missing at random (i.e., MCAR or MAR), such that cases with missing data follow the same multivariate distribution as complete cases. However in reality, this assumption may not be always accurate.

**Outliers.**

Potential univariate outliers were identified among continuous variables using standardised z-scores greater than 3.29 ($p < 0.001$, two-tailed test), box plots and normal probability plots. Univariate outliers represent extreme values on a variable that are disconnected from the rest of the cases. On the plots, they are visible as cases that lie a considerable distance from the others. In large samples, a few extreme scores (i.e., standardised scores greater than 3.29) are to be expected but they can lead to Type I and Type II errors by having a greater impact on regression coefficients than any of the other observations or cases (Tabachnick & Fidell, 2013). In order to reduce that level of impact, identified outliers were deleted and treated as missing values.

Multivariate outliers were assessed using the chi-square ($\chi^2$) distribution and Mahalanobis distance ($p < 0.001$), which is the distance of a particular case to the centroid of remaining cases (Tabachnick & Fidell, 2013). However, Mahalanobis distance is sensitive to failures of normality, which is a common feature of mental health variables. Therefore, when multivariate outliers were identified, analyses were conducted with and without the outliers to determine whether they had a substantial effect on the results. If a substantial effect was found, the outliers were deleted. If not, the outliers were retained.

**Assumption testing.**

The multivariate techniques employed in this research share a number of assumptions regarding: independence of observation, collinearity, homogeneity of variance, normality, linearity, and homoscedasticity. Violations of these assumptions can lead to biased results and can cause estimated covariance matrices that are not positive definite. Non-positive definite matrices cannot be used for most multivariate analyses.
Kline (2010) notes that positive definite matrices are characterised by four properties: (a) The matrix is invertible, or non-singular, so that the inverse of the data matrix can be derived as part of the linear algebra operations that comprise most multivariate analyses; (b) All eigenvalues of the matrix are positive; (c) The determinant of the matrix (i.e., the sum of the eigenvalues) is greater than zero; and (d) None of the correlations or covariances are out of bounds (i.e., the maximum value for the covariance between any two variables is less than or equal to the square root of the product of their variances). These four properties are particularly salient in SEM, which requires a positive definite matrix to run.

The following section discusses the methods used for testing these multivariate assumptions and details the steps taken to address any violations.

**Independence of observations.**

Most hypothesis tests, including the techniques employed in this research, require independent observations. That means that each observation or measurement is not influenced by any other observation or measurement (Gravetter & Wallnau, 2013). The critical concern is that there is no predictable, consistent relationship between the two observations that might be explained, for example, by belonging to the same group. Failure to consider the variability in scores explained by non-independence can lead to biased parameter estimates and standard errors (McDonald, 2014).

**Normality.**

Most multivariate techniques assume that data comes from one or more normally distributed populations. Violations of this assumption are particularly problematic for SEM when ML estimation is used because it can bias Pearson correlations (by up to +.14; Bishara & Hittner, 2015) and it impacts the $\chi^2$ statistic and standard errors. In the field of mental health, skewed distributions are common, especially with clinical measures of symptoms and dysfunction. Hence several steps were taken in this study to address assumptions of multivariate normality.

First, data were screened for univariate normality. Univariate normality refers to the distribution of scores on a single variable, whereas multivariate normality refers to the distribution of all combinations of variables. Screening univariate normality was done using histograms and normal probability plots, which were respectively checked for symmetry and whether cases lined up along the diagonal.

Second, statistics for skewness (i.e., the symmetry of the distribution) and kurtosis (i.e., the peakiness of the distribution) for individual variables were examined.
Values on both statistics are around zero for a normal distribution. However, in line with Chou & Bentler’s (1995) recommendations, values of skewness within the range of -2 to +2 were assumed to be normally distributed, whereas values greater than 3 were considered to be severely skewed (West, Finch, & Curran, 1995). If any observed variables deviate substantially from univariate normality, then the multivariate distribution will not be normal.

There are statistical tests to detect variations from multivariate normality (e.g., Mardia’s coefficient and Cox-Small test), however, Kline (2010) pointed out that all such tests are limited because slight departures from normality can be statistically significant in a large sample. He asserts that most instances of multivariate normality can be detected through inspection of univariate distributions. Hence, this was undertaken as part of the preliminary analysis.

Transformations (e.g., logarithmic, Box-Cox, rankit) are commonly recommended to remedy non-normality before analysing data with a normal theory method, such as ML. Transformations apply a mathematical transformation to compress one part of the distribution more than another to change its shape (Kline, 2010). However, the decision was made not to transform variables in this research for several reasons: (a) the scale of the original variables is lost when scores are transformed; and, (b) the results of analyses of transformed scores do not directly apply to the original scores, which makes interpretation of the results difficult and also limits one’s ability to compare results to other studies using the same variable. Instead of transforming skewed variables, the decision was made to use SEM estimation methods and fit statistics that are robust to violations of the normality assumption (see Model Estimation and Model Evaluation sections below).

Linearity, homoscedasticity and homogeneity of variance.

Linearity and homoscedasticity among residuals are features of multivariate normality (Kline, 2010). Linearity refers to the assumption that there is a constant, straight-line relationship between the analysed variables. This assumption is important because regression-based methods, including SEM which is employed in this study, only capture the linear relationships among variables; potential non-linear relationships are ignored and therefore missed. Homoscedasticity refers to the assumption that the variability in scores for continuous variables is the same at all values of other continuous variables (i.e., uniform distribution) in ungrouped data. Both linearity and homoscedasticity were examined using normal probability plots for the standardised
residuals and bivariate scatterplots of the standardised residuals and predicted scores. In grouped data, homoscedasticity is referred to as homogeneity of variance and was tested for using Levene’s test of homogeneity of variance.

As mentioned earlier, the decision was made not to transform scores to enhance linearity, homoscedasticity or homogeneity of variance because of the concern that transformation changes the nature of the relationship being measures (i.e., resulting correlation is monotonic rather than linear; (Bishara & Hittner, 2015), which makes it harder to interpret results and compare them to other studies. Instead, a more stringent alpha (α) level was applied for moderate violation (.025) and for severe violations (.01), which is in accordance with recommendations by Tabachnick and Fidell (2013).

**Collinearity.**

Collinearity occurs when separate variables actually measure the same thing (Kline, 2010). This leads to problems with the correlation matrix due to variables being very highly correlated (e.g., >.90). This can occur as a result of either bivariate or multivariate correlations, which is known as multicollinearity. This can occur at either the observed indicator or the latent variable level. According to Bagozzi (2010), variables that are multicollinear contain redundant information and are not all required in the same analysis. Essentially, one of the variables can be written as an exact linear combination of other variables. This has implications for the correlation matrix as it makes it rank deficient (i.e., there are more defined columns than there are variables), which leads to unstable matrix inversion. If multicollinear variables are included in the same analysis, they also inflate the size of error terms, making the parameter estimates more uncertain (Tabachnick & Fidell, 2013).

Multicollinearity can be screened using tolerance statistics, which indicates the proportion of total standardised variance that is unique (i.e., not explained by all the other variables). Kline (2010) suggests that tolerance values <.10 may indicate extreme multivariate collinearity. To overcome collinearity, redundant variables can be dropped from the analysis or combined to form an index. In this study, redundant variables were dropped from the analysis rather than combined to ensure ease of interpretation and to facilitate straight forward comparison of the results with those from other studies using the same measures.

**Latent variable mixture modelling.**

Latent variable mixture modelling (LVMM), or finite mixture modelling as it is known in the statistics literature (McLachlan & Peel, 2000), is a group of analyses that
are interested in the similarities and differences among people in a population. As discussed in Chapter 5, identifying and understanding these similarities and differences can provide a more accurate and nuanced view of the population and in turn potentially provides answers to questions such as who to target with intervention efforts and why some people respond differently to intervention efforts (Nylund-Gibson & Hart, 2014).

LVMM is often referred to as a person-centred analytic approach because it is primarily interested in uncovering subgroups of people with similar profiles but who differ from other subgroups in important qualitative or quantitative ways (Nylund-Gibson & Hart, 2014; Wang & Wang, 2012). It does this by looking at patterns in the data formed by particular combinations of responses to observed measures of interest.

These patterns are not always readily apparent to researchers and clinicians because they are based on people’s responses to multiple measured items, not just a single item. Hence, class membership is latent (unobserved) and is a function of the set of observed variables (indicators) specified. Class membership is conceptualised as a categorical latent variable, which is assumed to account for the association between the observed items (B. Muthén, 2001).

Rather than assuming that data comes from a single homogenous population and that everyone in a population can be described by a single probability distribution (as traditional SEM does), LVMM describes the population using a mixture of distributions, which correspond to each of the latent subgroups (McCrea, 2013). The joint distribution is a mixture (i.e., weighted sum) of the component distributions (G. Lubke, 2012) and each class has its own mean and parameters (see Figure 8 earlier in this chapter).

As part of LVMM, the probabilities of belonging to each of the latent classes is calculated for each person in the data set (when summed they equal one). Each person is allowed fractional membership in all classes to reflect the varying degrees of uncertainty and measurement error (Muthén, 2001). The latent classes are based on these probabilities and each individual can be assigned to the class they most likely belong to using posterior probabilities.

LVMM assumes local independence (Muthén, 2001). That is, the correlations or covariances between items among individuals in the same latent class are assumed to be zero (i.e., independent) once the individual’s class membership is taken into account (Vermunt & Magidson, 2004). Note that this assumption does not imply that the observed variables are independent in the full sample because the full data set is a
mixture of several latent classes (Collins & Lanza, 2010). However in mental health research, it does mean that underlying differences in severity between individuals should be accounted for by the extraction of additional latent classes (McCrea, 2013).

LVMM is flexible in terms of the type of data that can be analysed and the names of LVMM analyses vary according to the type of data used (i.e., cross-sectional or longitudinal), the scale of the observed and latent variables (i.e., continuous, categorical, or hybrid), and whether variability is allowed within the subgroups. Typically, latent class analysis (LCA) is used to describe LVMM based on cross-sectional categorical data and may include binary, nominal or ordinal observed variables for the class indicators. When the indicators are continuous, historically it has been referred to as latent profile analysis (LPA, Lazarsfeld & Henry, 1968). Latent transitional analysis and latent class growth analysis extend these techniques for longitudinal data and model the change in people’s scores over time (Muthén, 2001).

For the purposes of this research, LPA is used, with continuous observed indicators and a categorical latent class variable.

The procedure for LPA used in this research is described next, along with relevant points and issues that merit consideration.

**Stage 1: Model specification.**

Key questions to be addressed by these analyses are: (1) Are there distinct latent classes in the sample population that substantively differ in terms of their mental health and wellbeing? (2) If so, how many are there? (3) Does membership across these groups differ with respect to other variables, such as covariates? (4) Can those covariates predict what class an individual is likely to belong to?

**Selecting the indicators.**

As mentioned earlier, the subgroups that emerge in LPA are a function of the set of items in the analysis. This means that the latent class variable is defined by the variation and heterogeneity in the selected items (Nyland-Gibson & Hart, 2014). Changing even one item by adding, removing or substituting a measure can change the latent class variable, so thoughtful and careful selection of items is required.

As detailed in the measurement section above, the current study operationalises mental health and wellbeing using well known measures of anxiety and depression (HADS), health-related quality of life (SF-36 MCS) and life satisfaction (SWLS). These variables were used as latent class indicators along with positive and negative affect in LPA for the purpose of identifying subgroups within the sample population that differ in
terms of risk for common mental health problems. The affect variables were added because they represent basic units of analysis with well-established links to morbidity. Most notably, negative affect is implicated in the development and presentation of most psychiatric diagnoses. It is anticipated that this set of indicator variables will capture the characteristics that are important and relevant to common mental health problems while being able to distinguish among the resulting classes.

*Determine how many classes to be investigated.*

After selecting the measured items to be used in LPA, the next step is to determine the number of classes to be investigated. Some authors (e.g., Berlin, Williams, & Parra, 2014; Ram & Grimm, 2009) recommend estimating one more class than is expected and comparing the fit statistics. However, in practice, an exploratory approach is usually taken with a series of models run starting with one class and then increasing the number of classes until non-meaningful solutions are achieved or the model does not converge (Nyland-Gibson & Hart, 2104). In this study, three classes (equivalent to non-clinical, subclinical, and clinical) were expected, so the series of models to be run started with two classes and increased until non-meaningful solutions were achieved or the model did not converge.

*Stage 2: Model estimation.*

Once the LPA model has been specified and the analysis is run, Mplus searches for the maximum likelihood (ML) estimates via the Expectation-Maximization (EM) algorithm. The EM algorithm assumes that the data is composed of multiple multivariate normal distributions and it works to find the optimal distribution for the data when some of the variables in the model are unobserved (i.e., when there are latent variables, Muthén, 2001). In LPA, the latent class variable ($c$) is seen as missing data. The EM algorithm attempts to estimate these values using an iterative two-step process that includes an expectation (E) step and a maximization (M) step. The E step involves estimating the missing values as a function of the observed variables using regression. The M step updates the covariance matrix based on the data from the E step. That covariance matrix is then used in the next E step to estimate the missing values and the two-step process continues until there is minimal difference between the covariance matrices (Baraldi & Enders, 2010).

The goal of ML estimation is to identify the set of parameter values associated with the greatest likelihood of yielding the observed data. This is known as the global maximum likelihood solution. However, the estimation algorithm can get stuck on
inferior solutions, known as local maxima (McCrea, 2015). This can often be overcome by repeating the estimation using a wide range of different starting values. In Mplus, this is done by specifying the number of sets of ‘random starts’ to be used. (e.g., increasing STARTS = 20 4 to 600 120, whereby 20 and 600 different random starting values respectively are used in the first stage; Asparouhov & Muthén, 2014). Although there is no guarantee that the best solution is not just a local maxima, there is increased confidence that it is the global maximum if the same log-likelihood is obtained from several different sets of starting values (G. Lubke, 2012). If the log-likelihood is not replicated in at least two final-stage solutions, it may be a sign of a local solution and/or problems with the model (Berlin et al., 2013). If the model is unidentified, it means that a unique ML solution does not exist (Collins & Lanza, 2010). The model results are presented from the solution with the highest model log-likelihood.

**Model evaluation and model selection.**

Once the series of unconditional models has been estimated, evaluating the fit of the models and choosing among the different class models becomes the primary task. This task, which essentially involves making a decision about how many classes best reflect the phenomenon under study is informed by tests of model fit and how readily the model can be interpreted.

Ram and Grimm (2009) provide a useful flowchart to guide decisions about model selection, which applies nicely to other types of LVMM including LPA, even though it was initially developed in their work on growth curve mixture modelling. The first step is to check the model output for potential problems, such as error messages and warnings generated by the software regarding local maxima, negative variances, correlations greater than one, or estimation problems.

The second step is to compare models with different numbers of classes using information criteria (IC)-based statistics, including Bayesian Information Criteria (BIC; Schwartz, 1978), Akaike Information Criteria (AIC; Akaike, 1987), and Sample-size Adjusted BIC (aBIC; Selove, 1987). The AIC is a measure of the goodness of fit that considers the number of model parameters whereas the BIC is a measure of the goodness of fit that considers the number of model parameters and the number of observations. Better model fit is indicated by lower values on these fit statistics.

The BIC is often the preferred IC, since Lubke and Neale (2008) identified it as the best performing measure for identifying the ‘true’ model out of all the measures they tested in a simulation study. A difference of 10 or more is said to be strong evidence
that the model with the lower BIC is the more appropriate model. Like the BIC, the aBIC applies a penalty for adding parameters to the model, but not as high as the BIC (Kenny, Kaniskan, & McCoach, 2015).

Although these information criteria (IC) are based on sound statistical theory, none of them indicate whether the specified model is a close fit to the data. They are relative, in so much as they simply compare two models, which may or may not be two (equally) poor models. Therefore, other measures are needed.

In the past, the chi-square test ($\chi^2$) was used as a measure of absolute fit to assess how consistently the model reproduces the data (i.e., the variance-covariance matrix). However, chi square is sensitive to sample size and the size of the correlations in the model, such that it is almost always significant with large samples (e.g., >200) and the larger the correlations in the model, the poorer the fit (Kenny et al., 2015). Hence, its utility is very restricted and it is not appropriate for the current study, given the sample size ($n = 375$) and variables that are moderately to highly correlated.

The third step that Ram and Grimm (2009) suggest in the model evaluation process is to examine the entropy value. Entropy assesses the accuracy with which models classify individuals into their most likely class. Although it is not an indicator of model quality, it can assist with choosing between models with different classes, especially when the classification of individuals in the sample to their most likely class will be used in subsequent analyses (as is the case in this research). The entropy value provided in Mplus is the relative entropy, which is a rescaled value so that it has a range from zero to one. Higher scores (greater than .80) reflect greater classification accuracy and adequate separation between classes (B. O. Muthén, 2008).

In the fourth step, comparisons between two models are made with likelihood ratio tests and bootstrapping procedures, such as the Lo-Mendell-Rubin adjusted likelihood ratio test (LMR; Lo, Mendell, & Rubin, 2001) and the bootstrap likelihood ratio test (BLRT; McLachlan & Peel, 2000). These tests compare the $k$ class model (e.g., 4-class model) and the $k - 1$ class model (e.g., 3-class model) to determine whether there is a statistically significant improvement in fit with the inclusion of one more class. For both tests, $p$-values less than .05 indicate the $k$ class model is a better fit to the data.

Nylund and colleagues (2007) point out that the usual likelihood ratio chi-square test (i.e., 2 times the log-likelihood difference) should not be used to test a $k - 1$ versus $k$ class model because two times the log-likelihood difference is not chi-square
distributed. However, the LMR test corrects the distribution for the two times log-likelihood difference by doing a $k - 1$ class analysis with the $k$ class analysis and using the derivatives from both models to compute the $p$-value. The BLRT is obtained by bootstrapping (i.e., repeating) that same procedure to give the true (bootstrap) distribution of two times the log-likelihood difference. The $p$-value is estimated by comparing that to the non-bootstrapped two times the log-likelihood difference (Asparouhov & Muthén, 2016), with a low $p$-value leading to the rejection of the $k - 1$ model as usual.

In addition to the above four-step approach recommended by Ram and Grimm (2009), bivariate goodness of fit statistics and residuals can provide useful information on how well the model is able to replicate the relationships between pairs of variables that are seen in the data and which pairs of variables are causing problems if the overall model fit is poor. Standardised residuals greater than three can be considered to be large (Agresti, 2010) and indicate that the model does not capture that bivariate relationship very well. In a well-fitting model, there would be very few, if any, residuals that large.

The preferred model needs to fit the data well but it is also important to avoid adopting a model with too many classes, which overfits the data and models random noise (McCrea, 2015). Overfitting the data leads to a model that is a function of the specific sample rather than the population it represents. Consideration also needs to be given to the size of the smallest class: for instance, a four-class model may provide the best fit to the data but if the additional class is relatively small (e.g., < 1% of the entire sample and/or numerically $n < 25$; Berlin et al., 2013), then one needs to be able to defend the benefit of this additional class given the possibility of low power and precision relative to the other larger classes (Lubke & Neale, 2006).

At this point of the process, the primary decision to make is which model or models are best suited for the objectives of the analyses. Above all, the classes need to be substantively meaningful. In LPA, each class is interpreted and labelled based on the class means for the continuous indicator variables (Muthén & Muthén, 2012). Ram and Grimm (2009) describe it as “an art – informed by theory, past findings, past experience, and a variety of statistical fit indices” (p.571). Collin and Lanza (2010) point out that none of the model fit tests are perfect so, essentially, it comes down to a judgement call.

*Extending the model with covariates.*

Once the preferred number of classes has been decided, covariates are added to
that model to explore the characteristics of the people in each class (Nyland-Gibson & Hart, 2014) and to predict class membership (Muthén & Muthén, 2012). This is called the conditional LPA model. The covariates (e.g., socio-demographic variables) can be on any scale (e.g., binary, ordinal, continuous). Traditionally, multinomial logistic regression of the latent class variable onto the covariates is used and the classification and prediction of class membership are performed simultaneously. This yields odds ratios like normal logistic regression. However, the inclusion of covariates into a LPA often changes class classification and causes problems in model estimations. As mentioned earlier, the formation of latent classes is based upon the observed items specified in the model. If one changes the items, the latent classes can change. If one of the covariates has a direct effect on the original indicator variables, then its inclusion in the model can change the intended meaning of the latent classes. If some covariates do not vary across latent classes, then some regression coefficients in the multinomial logit mode will be undefined (Muthén & Muthén, 2012).

Due to these issues, it is common practice to estimate class membership with the unconditional model, save the data and merge it with the original data set for further regression analysis (Muthén & Muthén, 2012). However, in a simulation study, Bolck, Croon, and Hagenaars (2004) found that this technique underestimates the associations between the covariates and class membership because the uncertainty related to class membership is not taken into account (Di Mari, Oberski, & Vermunt, 2016). To correct for the uncertainty, Vermunt (2010) built on earlier work by Bolck and colleagues (2004) and proposed a three-step ML-based correction method. First, the unconditional latent class model is estimated. Then in the second step, the most likely class variable is created using the latent class posterior distribution obtained from step one and the classification uncertainty is computed. This accounts for the measurement error in the latent classes. In the third step, the most likely class variable is entered into the LPA as a latent class indicator variable with uncertainty rates prefixed at the probabilities from step two. At this point, the covariates are entered into the model as auxiliary variables. This method, which is now automated in Mplus with the specification of (R3STEP) in the auxiliary function, has performed well in simulation studies (Asparouhov & Muthén, 2014, 2016) and has been shown to produce trustworthy parameter estimates, mean squared error and confidence interval coverage, superior to other methods of correction for latent class models with continuous indicators (Bakk, Tekle, & Vermunt, 2013; Gudicha & Vermunt, 2013).
**Structural equation modelling.**

Unlike LVMM that focus on the similarities and differences between people, structural equation modelling (SEM) is a more traditional analytic tool in as much as it focuses on relations among the variables (Little & Rubin, 2002). More specifically, SEM is a family of related statistical techniques that allow the relations among multiple independent variables and multiple dependent variables to be estimated and tested simultaneously (Wang & Wang, 2012). SEM comprises two parts: a measurement model, which describes the relationships between a construct and its indicators (observable measures); and, a structural model, which specifies relationships between different theoretical constructs (i.e., latent variables; Kline, 2010). The two combine to form a full structural equation model that specifies both a theory and its measurement.

SEM has several advantages over alternative techniques such as multiple regression and analysis of variance. These include the ability to: (a) estimate and model measurement error in observed variables, which improves the accuracy of parameter estimation; (b) estimate complex multi-level pathways amongst multiple independent, dependent, mediating and/or moderating variables simultaneously, which vastly improves statistical power; and (c) provide test statistics and indices of model fit that allow hypothesised models to be systematically evaluated and compared.

Ullman (2006) presented a general procedure for conducting SEM involving four steps: model specification, model estimation, model evaluation, and model modification. Each of these stages will be considered in turn, as applied in this research.

**Stage 1: Model Specification.**

Specification of the measurement and structural model is perhaps the most important step in SEM (Kline, 2010) as the results from later steps assume that the model is basically correct. Kline (2010) recommends addressing each of these components sequentially so that issues concerning the measurement model are resolved before the structural relationships are examined.

Costner (1969, cited in Roberts & Thatcher, 2009) noted that the nature and direction of relationships between construct and indicators are important because they constitute a secondary theory that bridges the gap between abstract theoretical constructs and measurable empirical phenomena (i.e., how constructs are operationalised). Errors in the measurement model or even mere variations in what indicators are employed in different studies undoubtedly contribute to variations across studies and may contribute to some of the seemingly contradictory findings in the
mental health literature.

As discussed in Chapter 4, a particularly pervasive issue in model specification relates to the nature of constructs and whether items are correctly modelled as formative or reflective indicators (Bollen & Bauldry, 2011; Franke et al., 2008; Lee & Cadogan, 2013). However, given that the primary purpose of this study is to explore and illustrate the impact of latent subgroups in model testing, rather than model development per se, the decision was made to model formative latent variables as reflective measurement models for this study.

*Measurement invariance.*

Another statistical issue of concern to this research is measurement invariance, also known as equivalence. Measurement invariance pertains to whether scores on a construct have the same meaning under different conditions (Millsap, 2012). The different conditions might involve consistency of measurement over populations (e.g., males and females), latent classes, methods of test administration (e.g., pencil and paper format versus electronic administration), or time of measurement.

In a comprehensive review of the invariance literature, Vandenberg and Lance (2000) recommended a specific hierarchical sequencing of invariance tests in which moving on to the next test depends on the outcome of the previous test. To begin with, an omnibus test of each latent variable and its indicators is undertaken, which evaluates whether it can be assumed that the sample variance/covariance matrices come from the same population. This is done by setting the variances and covariances to equality across groups and using a chi-square test. If the chi-square test statistic is not significant, it can be assumed that the sample variances and covariances came from the same population and are invariant. Conversely, if the chi-square test statistic is significant, it cannot be assumed that the constructs mean the same thing to across groups and further invariance testing is needed.

In the current study, the focus of invariance testing was on establishing metric and scalar invariance as a precondition for further analyses. These tests involve demonstrating that the corresponding factor coefficients and intercepts are equivalent across the groups (Cunningham, 2010). If there was no evidence of variation across groups or different assessment times, then measurement is considered to be invariant. If significant differences are found, separate analyses need to be run for each group.

*Structural model.*

In contrast to the measurement model, which focusses on the relationships
between indicators and their latent constructs, the structural model focuses on relationships between the constructs. Essentially, the structural model implies that the covariance matrix of the indicators has a specific structure (Kline, 2010). Once the model parameters have been estimated, SEM compares the resulting covariance matrix to a covariance matrix that is purely data-driven (Franke et al., 2008). If the two matrices are consistent with each other, then the structural model is considered to be a plausible explanation of the relations between the measures.

In this project, the proposed model of mental health and wellbeing was specified and included direct effects and indirect (mediating) effects. A direct effect describes the direct relationship between two variables (i.e., path coefficient). Indirect effects refer to relationships between two variables through one or more intervening (or mediator) variables. The mediator variables are presumed to transmit some of the causal effects of antecedent variables onto subsequent variables (Kline, 2010). For example, using the model depicted in Figure 9, stress (exogenous variable) is hypothesised to have some of its effect on mental health (endogenous variables) through its influence on the satisfaction of basic psychological needs (mediator variable).

![Figure 9](image_url)

*Figure 9. A simple cross-sectional mediator model: a’ represents the strength of the relation between stress and satisfaction of basic psychological needs; b’ represents the strength of the relation between basic psychological needs and mental health, c’ represents the direct effect between stress and mental health; ε₁ represents the unexplained part of basic psychological needs; and ζ₃ represents the disturbance term (unexplained part) of mental health.*

In the past, the predominant methods of establishing mediation have been based on Baron and Kenny’s (1986) causal steps approach. Applied to the current example, the first step would be to demonstrate a significant relationship between stress and
mental health ($c'$). The second step would be to establish that there is a significant relationship between stress and satisfaction of basic psychological needs ($a'$). The third step would be to show that satisfaction of basic psychological needs is significantly related to mental health and wellbeing. The final step would be to show that the strength of the relationship between stress and mental health reduces or is no longer significant when satisfaction of basic psychological needs is added to the model.

Despite its widespread use, this approach has been criticized by many statisticians due to the technical criteria and potential implications of the final step (D. P. MacKinnon, 2008; Shrout & Bolger, 2002; Zhao, Lynch, & Chen, 2010). The most notable objection relates to its potential to significantly stifle and impair theory building because it ignores potential suppressor effects. Suppressor effects occur when a predictor variable actually has zero (or close to zero) correlation with the dependent variable while paradoxically still contributing to the predictive validity of the other measures (Horst, 1941, cited in Ludlow & Klein, 2014). In essence, these variables suppress irrelevant variance in the other predictor variable(s) thereby indirectly allowing for a more concise estimate of the predictor-criterion relationship (Ludlow & Klein, 2014). The problem with suppressor effects is that the variables behave in unexpected, indirect ways, which are inconsistent with and not identifiable through bivariate correlations (for a concise summary, see Zhao et al., 2010).

Instead, current recommendations for mediation analysis simply require one step: a significant indirect effect $a' \times b'$ to be demonstrated with either a Sobel test or bootstrap test (e.g., Zhao et al., 2010; Iacobucci, 2008; Preacher & Hayes, 2004, 2008). Bootstrapping is the more powerful of the two options. It involves a re-sampling method that generates an empirical sampling distribution of $a' \times b'$. It takes cases from the observed data that are randomly selected to generate new data sets, which allow $a'$, $b'$, and $a' \times b'$ to be estimated. This process is repeated numerous times (e.g., 5000) to simulate drawing samples from the population (Kline, 2010). After $a' \times b'$ is estimated for each data set, the associated confidence intervals are used to estimate the indirect effects, based on the mean of those estimates (Zhao et al., 2010).

Note that significant indirect effects imply the presence of mediating variables, however, they do not imply causality if only cross-sectional data is used. When measures are collected concurrently, patterns in the data are correlational and the temporal sequence of the variables cannot be established. Maxwell and Cole (2007) contend that “mediation consists of causal processes that unfold over time” (p.23) and
thus require longitudinal designs to provide a more rigorous test of mediation by controlling for prior levels of the dependent variable. However, longitudinal modelling is beyond the scope of this project which primarily focuses on the identification of latent classes and their likely implications for model testing. The design of this study will be discussed further shortly.

Stage 2: Model estimation.

Estimation methods.

Once data-related issues are resolved and the structural model is specified, the parameters (structural pathways) in the model can be estimated. Estimation involves the use of numerical algorithms to reconstruct a set of parameter estimates that are as close as possible to the covariances in the observed data but still adhere to restrictions implied by the specified model (Tomarken & Waller, 2003). In an iterative process, starting values are estimated for specified parameters in an attempt to reproduce the sample covariance matrix. These reproduced covariances are then compared to the observed covariances to evaluate how well the estimates account for the observed data (Tomarken & Waller, 2005). After a series of iterations, and when the parameter estimates cannot be improved, the estimation is said to have ‘converged’ (Ullman, 2006). Then the overall fit of the model to the data can be evaluated.

There are numerous estimators (i.e., algorithms) available in SEM that differ according to the specific weight matrix used when calculating parameter estimates (Weston & Gore, 2006). Each has particular strengths and weaknesses that make it appropriate under different conditions. For example, Asymptotic Distribution Free (ADF) is suited to non-normal data, but only when samples are very large (N > 500; Hu, Bentler & Kano, 1992). Maximum likelihood (ML) is the most frequently used technique, however, it assumes that measured variables are continuous and multivariate normal (Tabachnick & Fidell, 2013). Violations of these assumptions can lead to biased estimates. In this research, the key dependent variables, anxiety and depression, are not expected to be normally distributed in the population (i.e., most people in the community are mentally healthy). Therefore, the decision was made to use Robust Maximum Likelihood (MLR), which uses maximum likelihood parameter estimates with standard errors and a chi-square test statistic that are robust to non-normality and non-independence. Within MLR, Quasi-Newton algorithms are used to calculate parameter estimates that maximise the likelihood that data are drawn from the population, taking into account missing values (Kline, 2010; L.K. Muthén, 2008).
**Stage 3: Model evaluation.**

**Assessment of model fit.**

After models are specified and estimated, they are evaluated for adequate fit to the data. Model fit can be examined in terms of the significance and strength of parameter estimates, the proportion of variance explained in the dependent variables and the values of test statistics and fit indices (Wang & Wang, 2012). The test statistics and fit indices assess whether the relationships specified in the proposed model adequately reflect the variances and covariances observed within the data (Weston & Gore, 2006). If the degree of discrepancy between the specified model and the observed data is less than that expected by chance, there is initial support for the proposed model (Kline, 2010).

At present, the generally recognised and recommended fit indices are the chi-square ($\chi^2$) test, the Comparative Fit Index (CFI), and the Standardised Root Mean Square Residual (SRMR) (Bentler, 2007, 2010; Iacobucci, 2010). Although some authors also report the Tucker-Lewis Index (TLI) and the Root Mean Square Error of Approximation (RMSEA), both of these indices penalise for model complexity and, thus, may be discounted in cases where complex models are specified a priori (Bagozzi, 2010). In addition, the RMSEA is unreliable with small degrees of freedom and/or small sample size (Kenny et al., 2015). Each of these tests of model fit will be considered in turn.

The $\chi^2$ statistic is the principal index of exact fit and a non-significant $\chi^2$ value ($p > .05$) indicates excellent fit to the data. However, $\chi^2$ (based on maximum likelihood) becomes overestimated as non-normality increases or when models are misspecified (Curran, West, & Finch, 1996). The Satorra-Bentler (SB) rescaled $\chi^2$ statistic corrects for this (Satorra & Bentler, 1988). The SB scaling method adjusts the $\chi^2$ statistic, standard errors, and fit indices for the amount of multivariate kurtosis in the data and the degrees of freedom, thus yielding less biased estimates of model fit and more accurate standard errors of the estimated parameters (Finney & DiStefano, 2006). Note that just like normal theory $\chi^2$, SB $\chi^2$ is proportional to sample size, which means that when sample sizes are large, there is inflated risk of rejecting a valid model. One suggestion to overcome this problem is to adjust the statistic by its degrees of freedom (i.e., $\chi^2/df$). If the outcome does not exceed 3.0, then the model is considered to demonstrate reasonable fit (Kline, 2010; Iacobucci, 2010). Alternatively, Bagozzi (2010; Bagozzi & Yi, 2012) recommends relying on indices of approximate model fit.
Indices of approximate model fit can be categorised into two broad categories: incremental fit indices and residual-based fit indices. Both the CFI and TFI belong to the category of incremental fit indices, which assess the fit of the specified model to a null model. Scores range from 0 to 1, with values closer to 1 indicative of better fit. In contrast, the RMSEA and the SRMR are residual-based fit indices, which measure the difference between the sample covariance matrix and the covariance matrix implied by the specified model. Lower values (i.e., closer to 0) for these indices indicate better fit.

Hu and Bentler (1998; 1999) recommended that good model fit is indicated by a non-significant $\chi^2$ with $p \geq .05$, CFI and TLI $\geq .95$, RMSEA $\leq .06$, and SRMR $\leq .08$. Others have suggested that these cut-off criteria are too conservative in some situations and, for example, CFI and TLI $\geq .90$ may be meaningful (Marsh, Hau, & Wen, 2004; Perry, Nicholls, Clough, & Crust, 2015). Conversely, Bagozzi (2010) has suggested a more stringent criterion of SRMR $\leq .07$ be used to ensure that residuals that are unacceptably high are not overlooked when averaged with all the others.

In addition to reporting the SB $\chi^2$, CFI and SRMR for each model in this research, standardised residuals are also examined when evaluating model fit. Standardised residuals can be interpreted as the residual correlation not explained by the model. In particular, the average standardised variance residual and the average standardised residual covariance residuals are of interest because, when squared, they represent the percentage of variance not explained by the model (Iacobucci, 2010). Although guidelines have not been established regarding the acceptable size of residuals, Ullman (2006) notes that “clearly smaller is better” (p.45).

**Stage 4: Model modification.**

When specified models do not fit the data well, or if there is conflicting evidence about model fit, the final stage of SEM involves post hoc modifications (re-specification). The goal of modification is to find the model with a properly specified covariance structure that fits the data and is theoretically justified (Kline, 2010). This involves adjusting the estimated model by freeing or setting parameters that may be the source of misfit to the data (Weston & Gore, 2006). In this research, sources of misfit to the data were identified using two statistics: standardised residuals and modification indices. Standardised residuals represent the difference between predicted and observed covariance. Large standardised residuals (greater than 2) indicate that the model does not explain the observed covariance between a pair of variables very well (Byrne, 2001). In contrast, modification indices indicate the expected decreases in $\chi^2$ relative to
the loss of one degree of freedom associated with allowing a particular parameter to be freely estimated. For large models, a change in $\chi^2$ value greater than 10 for one degree of freedom indicates a significant improvement in model fit and takes Type I error into consideration. Poor model fit can also be due to sample specific variations (e.g., correlated error terms that reflect minor secondary factors) or incorrectly specified models, consequently modifications made in this study were only made if theoretically meaningful.

**Multigroup structural equation modelling.**

To examine how well the full sample model fit the mental health subgroups, multigroup SEM was initially employed. Multigroup SEM is a widely-used technique that extends the SEM procedure described above by testing the measurement and structural models with different groups that exist within the sample. Yuan and Chan (2016) recently described it as a fundamental technique for testing measurement invariance and group comparisons.

Using the most likely class membership classifications from the LPA five-class model, subgroup membership data was saved and merged with the main data file. To ensure adequate power for the multigroup analysis, only the two largest subgroups were used: Thriving (Low risk; $n = 133$) and Getting By (Marginal risk; $n = 119$) subgroups. The subgroups were specified in the SEM syntax using the Grouping and UseObservations functions in Mplus. Class-specific syntax was also added to the syntax for the Thriving subgroup, to control for differences in subgroup size, factor means, and parameter estimates. Once specified and run, model fit for each group was evaluated using the same method as described above, namely SB $\chi^2$, CFI and SRMR fit statistics, normalised residuals, and $R^2$ statistics to determine how much variance is explained by the model for each group.

It is worth noting that usually the groups used in multigroup SEM are based on established, well-known variables such as gender (male vs. female), geographical location (clinic X vs. clinic Y), or type of intervention received (psychotropic medication vs. CBT vs. active control). In this study, the mental health subgroups were formed through latent classes and, as such, are not widely-used, well-established categories. As a result, the choice to use multigroup SEM in this study was somewhat unorthodox. Given that the purpose of this analysis was to check the validity of the full sample model across subgroups present in the sample, the use of multigroup SEM seems reasonable. After all, it provides an indication of how well the model might fit.
specific groups of people within the sample. However, if the focus of the study was on model development or matching models and interventions to people, then multigroup SEM would not be appropriate. This is because one of the limitations of multigroup SEM is that it does not account for the uncertainty around subgroup (latent class) membership. Class membership is based on posterior probabilities, which means that there is chance that individuals will be incorrectly assigned to one class, when they truly belong in another. Ideally this uncertainty and risk of misclassification should be accounted for in the SEM analyses. This would require the use of much more advanced statistical techniques, such as structural equation mixture modelling.

**Structural equation mixture models.**

Structural equation mixture models or mixture SEM (Jedidi, Jagpal, & DeSarbo, 1997) seeks to combine the best of person-centred and variable-centred analyses into a single analytic technique. Essentially, mixture SEM builds on finite factor mixture models (Asparouhov & Muthén, 2016; S. L. Clark et al., 2013; K.-H. Yuan & Bentler, 2010), which focus on how observed variables (e.g., items on a scale) relate to latent variables (e.g., the construct being measured by a scale) and how these relationships might differ across unobserved groups (i.e., measurement invariance). With mixture SEM, the focus is on how latent variables relate to each other and how these relationships might differ across unobserved groups (i.e., structural invariance). The basic tenet of mixture SEM is that it might be overly simplistic to assume a homogenous population when investigating relationships between variables, as they may differ across unobserved groups (i.e., latent classes). In this study, the aim of the mixture SEM analysis is to explore the number of latent classes required to adequately explain differences in structural relationships among stress, basic psychological need satisfaction, and mental health across classes.

**Preliminary steps and considerations.**

The general procedure for conducting mixture SEM involves a series of steps similar to SEM including the specification and estimation of models, model evaluation and comparisons, and model selection. However, the model specification and estimation step is a lot more involved than regular SEM. Mixture SEM is built in various steps; it involves testing different model variations with an increasing number of latent classes (S. L. Clark et al., 2013).

As with LVMM, a basic assumption of mixture SEM is that the distribution of observed data is a mixture distribution, which is “a weighted sum of two or more
component distributions and the weights correspond directly to the relative size of a component” (Tueller & Lubke, 2010, p.167). Each component distribution reflects a latent class. In mixture SEM, it is assumed that the component distributions are multivariate normal, and a structural equation model is imposed on the within-class mean vector and covariance matrix. Note that it is generally unrealistic to assume a priori that the variances of the factors are invariant across classes (Tueller & Lubke, 2010), therefore, models are specified with class-specific factor variances. Mixture SEM takes all available information (variables and pathways) into consideration when forming classes, so one would anticipate that the preferred number of classes in mixture SEM may differ from those identified in LVMM, which does not include any regression pathways.

As with LVMM, local maxima can be an issue in mixture SEM. To avoid mistakenly accepting local maxima, multiple sets of random starting values need to be used when fitting mixture models (Tueller & Lubke, 2010). The goal is to replicate the best log-likelihood value across multiple starting values because it suggests that the results obtained have occurred more often than expected by chance. Even though this enhances confidence in the results, the replication of the best log-likelihood value is not necessary or sufficient to guarantee that the global maximum has been found (S. Clark et al., 2013).

**Model specification.**

For the purposes of this study, three variations of the mixture SEM were tested; each one reflecting a different hypothesis about how mental health is related to perceived stress and basic psychological need satisfaction. The three variations differ in terms of how much measurement and structural invariance is present. This has important implications for how the mixture model is interpreted, especially whether or not the same constructs are being measured in each latent class (see Clark et al., 2013, for a more comprehensive discussion). The first model variation (MM1) is a measurement invariant model in which factor loadings, parameter estimates (slopes), variances and residual variances are specified to be equal across classes. This is referred to as the constrained model and is the default in Mplus. If this model holds, then classes can be directly compared. In the second model variation (MM2), the means, intercepts and slopes are free to vary across classes. If this model holds, the class differences are likely to be due to other factors and have to be interpreted accordingly. The third model variation (MM3) is the least restrictive model; it allows all of the parameters to freely
vary across classes. Support of this model indicates that the constructs in the model may not be measured the same way across classes and the measures tap into different constructs for each class. This occurs when subgroups of individuals interpret questions differently or have a different understanding of the construct being measured.

Each of the three variations were tested in turn with an increasing number of classes, up to five classes. (This was the optimal number of classes found in the LVMM analyses.)

**Model comparison and selection.**

The number of latent classes in mixture SEM can be examined using the BIC (Schwartz, 1978), AIC (Akaike, 1987), and aBIC (Sclove, 1987) as with LVMM. However, based on extensive simulation studies, Asparouhov and Muthén, (2015), Clark and colleagues (2013), Nyland and colleagues (2007), and Yuan and Bentler (2010) recommend the BIC and aBIC for comparing mixture models because they are the most likely to lead to acceptance of the true model solution. Lower values on these statistics indicate better model fit.

Generally, models with different structural relations between latent variables are not nested (Tueller and Lubke, 2010) so the LMR and BLRT can be examined as well. Significant p-values (i.e., $p < .05$) for these tests indicate that $k$-1 class is a statistically better fit to the data. According to simulation studies by Tuller and Lubke (2010), the BLRT is the most reliable test of model fit but due consideration also needs to be given to the form of the structural model(s) to ensure that they make sense and are meaningful, given the number of classes.

Once the preferred model and the optimal number of classes have been selected, the next step is to examine the latent classes identified in that solution. Similarities and differences across the latent classes can be readily compared using the latent variable multinomial logistic regressions that form part of the mixture SEM output generated by Mplus. Muthén (2000) suggests that the next step in the model development process would be to identify and refine each of the measurement models before further examining the regression relationships between the latent variables within each latent class. Modifications indices can be requested in Mplus to assist with this process. However, this step goes beyond the scope of the current study, which has sought to look at mental health and related data using a person-centred approach to data, rather than the traditional variable-centred approach and to gauge the extent to which unobserved heterogeneity could be affecting mental health research and limiting our ability to
screen for mental health problems, target interventions, and improve effectiveness in mental health.

**Data Analysis Plan and Hypotheses**

The research plan adopted for this project is summarised in Table 10.

<table>
<thead>
<tr>
<th>Research Task</th>
<th>Purpose</th>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Confirm psychometric properties of the measures</td>
<td>To ensure the measures are valid and reliable for use with the current population</td>
<td>CFA analyses of participants’ responses prior to conducting reliability analyses</td>
</tr>
<tr>
<td>Latent variable mixture models</td>
<td>To investigate what latent subgroups exist within the data To identify risk subgroups To develop risk profiles of participants in these subgroups</td>
<td>LPA with affect, anxiety, depression, quality of life and life satisfaction variables</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LPA controlling for covariates, including social determinants of health, LOT-R, IPC, BNLS, and dispositional coping responses</td>
</tr>
<tr>
<td>Measurement and structural models</td>
<td>To test the proposed mediational model with the full sample</td>
<td>SEM mediational analyses of hypothesised pathways between stress and mental health and wellbeing</td>
</tr>
<tr>
<td>Subgroup analyses</td>
<td>To test the validity of the mediational model across the latent subgroups</td>
<td>Multigroup SEM with subgroups of n &gt; 100</td>
</tr>
<tr>
<td>Mixture structural equation modelling</td>
<td>To simultaneously test the mediational model and account for heterogeneity</td>
<td>Mixture SEM controlling for covariates</td>
</tr>
</tbody>
</table>

*Note. CFA = Confirmatory factor analysis; LPA = Latent Profile Analysis; LOT-R = Life Orientation Scale, Revised; IPC = Internality, Powerful Others, and Chance Locus of Control Scale; BNLS = Basic Need Satisfaction in Life Scale; SEM = Structural equation modelling.*

This data analysis plan was designed to investigate the following areas and research questions, which have emerged from the early chapters:

1. Measurement integrity
   a. Are the measures used in this study psychometrically sound?
   b. What is the best way to model dispositional coping for this non-clinical sample?
c. Does the structure of the Basic Need Satisfaction in Life Scale that was previously established in the literature replicate to an independent sample?

2. Identifying unobserved heterogeneity in the sample
   a. What mental health-based latent classes exist within the data?
   b. What are the characteristics of each class or subgroup?
   c. How are the subgroups similar and how do they differ from each other?
   d. To what extent do the subgroup profiles reflect risk of common mental health problems?
   e. What are the best predictors of risk subgroup?
   f. How do these subgroups compare to current methods used to identify mental health risk and subthreshold individuals?

3. Illustrating the typical model development process
   a. Does the satisfaction of basic psychological needs mediate the relationship between stress, coping, and mental health and wellbeing outcomes?

4. Exploring the (unseen) impact of unobserved heterogeneity in model development
   a. Are the measurement and mediational models previously established with the full sample equally valid across the latent mental health subgroups?
   b. If not, why doesn’t the model fit each subgroup?
   c. What might that mean for prevention and treatment research and interventions?

Chapter Summary

This chapter has described the methods employed for the current study. The cross-sectional design of the project was outlined and details of the participants from various psychological constructs were described and statistical issues and methods of analyses were discussed. Finally, the data analysis plan and specific questions that the study addresses were described. These questions form the focus of the remainder of the thesis. The results of the analyses are reported in the next chapter and provide preliminary evidence that meaningful groups of at-risk adults can be identified in non-clinical populations and that mechanisms underlying mental health and wellbeing are not the same for all individuals, rather they differ for individuals in different subgroups.
Chapter 6  Results

This chapter reports the results of the empirical study, which explores how mental health data can be conceptualised, operationalised and analysed in a way that improves our ability to screen for mental health problems and target interventions. Two potential options include: (a) broadening the way mental health is operationalised to include the positive dimension of mental health and wellbeing, in line with the WHO’s (2004, 2014) definition of mental health; and (b) using person-centred approaches to analyse data rather than just the variable-centred, regression-based approaches typically used for model testing and intervention. Consistent with the Data Analysis Plan in Chapter 5, the analyses have been divided into four parts. The first section reports the preliminary analyses undertaken to ensure that the measures could be confidently used in subsequent analyses. The second section reports the results of latent profile analysis (LPA), which was used to assess whether latent classes (subgroups) could be identified based on people’s scores on a set of variables designed to assess both the positive and negative dimensions of mental health. These include emotionality (positive and negative affect), anxiety, depression, mental health-related quality of life and functioning, and satisfaction with life. The LPA model is then extended to investigate whether these classes could be identified according to their profile on a range of demographic, lifestyle, cognitive and coping-related measures.

The focus of the study then turns towards examining the role that subgroups can play in testing psychological models of mental health and wellbeing. The examination begins with traditional, regression-based SEM. Using the full sample, the relationships between stress, basic psychological need satisfaction (BPNS) and mental health are examined. It is hypothesised that BPNS mediates the relationship between stress and mental health, such that the more satisfied one’s needs are for autonomy, competence and relatedness, the more it buffers the effect of stress on mental health and wellbeing. The SEM results for the full sample \( (n = 375) \) indicated that BPNS partially mediates the relationship between stress and mental health. The model explains a substantial portion of the variance (individual differences) in mental health and wellbeing within the community, which is potentially very encouraging.

However, in light of the subgroups identified via LPA, one may wonder whether the model applies equally across all subgroups or whether it differs across the groups in important ways. This is investigated in two ways. First, some simple subgroup analyses are conducted using the grouping function in SEM. To ensure sufficient power only the...
two largest mental health subgroups are used. Those subgroups include participants with low to marginal risk of mental health problems \((n = 269)\). The model is tested with each subgroup separately and compared to the results of SEM with the full sample. This yields some curious findings.

However, multigroup SEM is typically based on well-established, observed groups (e.g., based on gender, socio-economic status, geographical area) but in this case, the mental health subgroups used are latent. As latent subgroups are formed based on posterior probabilities (i.e., the probability of being assigned to a class after all background information and the observed data have been taken into account; P. Lee, 2012), there is a chance that some participants get misclassified and are incorrectly assigned to one subgroup when they should be in another. To overcome this issue, the final set of analyses for this study employ an advanced hybrid technique that tests structural equation models and forms latent classes at the same time, namely mixture SEM. The chapter concludes with some summary comments that preface the final chapter.

**Part One  Preliminary Analyses**

As described in Chapter 5, all models were estimated using Mplus version 7.4 (Muthén & Muthén, 1998–2016) with all available data and robust (Full Information) maximum likelihood estimation used to handle missing data (Graham, 2012).

**Data screening and assumption testing.**

Prior to analysis, data were screened for missing values and possible response sets (Tabachnick & Fidell, 2013). No evidence was found when responses were screened for patterns and/or endorsement of the same category for whole scales. Patterns of missing data were examined through the Missing Values Analysis in IBM SPSS Statistics 23. The results from a series of Little’s MCAR \(\chi^2\) tests were not significant for all measures except Income. Essentially, participants who declined to indicate their personal income range \((n = 30)\) also declined to indicate their household income range. All other missing values were treated as missing at random (Kline, 2010). Using the criterion of no more than 25% missing values on any survey (Byrne, 2001; Newman, 2003), the responses from one participant were omitted. The final cross-sectional sample size was 375, which provided adequate power to examine subclinical symptoms within an Australian university population (proportion = .675; Stallman, 2010) with an estimated standard error of .02, \(p = .048\).

Visual inspection of normality plots and histograms revealed relatively normal
distributions for Perceived Stress, Optimism, Anxiety, Life Satisfaction, and Positive Affect. Depression scores were mildly skewed (as expected) but not sufficient to merit transformation. More detailed psychometric analyses were conducted on the remaining measures prior to assumption testing, as evidenced in the Appendix B.

**Modelling dimensions of mental health and wellbeing.**

Prior to specifying the full measurement model, the best way to model mental health and wellbeing needed to be clarified. As discussed in earlier chapters, theoretical definitions of these concepts overlap considerably; the operationalisation of these concepts varies even more widely across studies; and the ensuing results have yielded a questionable distinction between these concepts. Hence, before examining the relationships between mental health, mental ill-health and life satisfaction, the validity of the measurement model for anxiety, depression, mental health-related quality of life, and life satisfaction was examined through a second order confirmatory factor analyses (CFA).

Means, standard deviations and bivariate correlations between the observed affect, mental health and wellbeing variables are presented in Table 11. Overall, the mental health variables appear to be moderately correlated. A four-factor CFA of mental health and wellbeing demonstrated good discriminant validity, with items loading on their respective construct as expected and simple structure. Model fit statistics indicated that it was a reasonable fit to the data (Satorra-Bentler \( \chi^2 \) (224) = 492.45, \( p < .001 \), CFI = .93, RMSEA = .06 [90% CI: 0.5, 0.6], SRMR = .05). All normalized residuals were below 2.35.
Table 11

*Inter-Correlations between Affect, Mental Health and Wellbeing Observed Variables*

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Affect</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Positive Affect</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(.92)</td>
</tr>
<tr>
<td>2. Negative Affect</td>
<td></td>
<td></td>
<td>-.39</td>
<td></td>
<td>(.89)</td>
<td></td>
</tr>
<tr>
<td><strong>Mental health problems</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Anxiety</td>
<td>-.49</td>
<td></td>
<td></td>
<td></td>
<td>(.85)</td>
<td></td>
</tr>
<tr>
<td>4. Depression</td>
<td>-.58</td>
<td>.58</td>
<td>.62</td>
<td></td>
<td>(.82)</td>
<td></td>
</tr>
<tr>
<td><strong>Quality of Life &amp; Functioning</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. SF-36 MCS</td>
<td>.62</td>
<td>-.65</td>
<td>-.66</td>
<td>-.66</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Subjective wellbeing</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Life Satisfaction</td>
<td>.52</td>
<td>-.43</td>
<td>-.46</td>
<td>-.55</td>
<td>.54</td>
<td>(.85)</td>
</tr>
</tbody>
</table>

Mean                      | 32.94 | 22.05 | 7.92 | 4.56 | 41.53 | 22.69 |
Standard deviation         | 8.34  | 8.10  | 4.20 | 3.65 | 12.17 | 6.77  |
Possible score range       | 10 - 50 | 10 - 50 | 0 - 21 | 0 - 21 | 0 - 100 | 5 - 35 |

*Note.* All correlations were significant at the .01 level. MCS = Mental Health Component Summary. *N* = 375.
Part Two  Person-Centred Analyses

Latent profile analysis.

In contrast to traditional regression analysis and model testing, which focuses on explaining variance within and across variables, the main goal of LVMM is to identify patterns of responses across variables. It seeks to uncover subgroups of people who have similar profiles but who might differ from other subgroups in important qualitative or quantitative ways (Nyland-Gibson & Hart, 2014; Wang & Wang, 2012). This is done based on each individuals’ scores on the variables of interest (Berlin et al., 2014). As mentioned in Chapter 5, the variables can be continuous, ordinal and/or categorical, and can be related (or unrelated) to one another. When the variables are continuous, the analyses are traditionally referred to as latent profile analysis (LPA).

In this study, the mental health and wellbeing variables were all continuous, whilst the demographic variables were a mix of categorical (e.g., gender, history of mental illness) and continuous (e.g., age, health) variables. Both types of variables were integrated into the analyses with Asparouhov and Muthén’s (2014a; 2014b) approach to LPA with the R3STEP auxiliary command, which enables the number of latent profiles present in the sample to be identified while controlling for differences in demographic, background, and behavioural characteristics.

Identifying latent profiles and drawing their general portrait.

An exploratory approach was taken to find groupings of individuals who share similar data patterns in order to determine the extent to which these patterns may relate to anxiety and depression. The affect, mental health and wellbeing variables were specified as latent class indicators in the model, as shown in Figure 10. Positive affect and negative affect were modelled as composite indices (rather than individual indicators) to ensure parsimony and to facilitate comparisons with other studies.
Figure 10. A graphical representation of the latent class model. QOL = quality of life.

Table 12

Descriptive Statistics for the Six Indicators in the Latent Profile Analysis

<table>
<thead>
<tr>
<th>Variable</th>
<th>M</th>
<th>SD</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Range</th>
<th>Cronbach’s α</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive affect</td>
<td>32.94</td>
<td>8.33</td>
<td>-0.33</td>
<td>-0.33</td>
<td>10 - 50</td>
<td>-</td>
</tr>
<tr>
<td>Negative affect</td>
<td>22.05</td>
<td>8.09</td>
<td>0.68</td>
<td>-0.25</td>
<td>10 - 47</td>
<td>-</td>
</tr>
<tr>
<td>Anxiety</td>
<td>7.92</td>
<td>4.19</td>
<td>0.51</td>
<td>-0.04</td>
<td>0 - 20</td>
<td>.85</td>
</tr>
<tr>
<td>Depression</td>
<td>4.56</td>
<td>3.64</td>
<td>1.03</td>
<td>0.60</td>
<td>0 - 17</td>
<td>.82</td>
</tr>
<tr>
<td>Mental Health QOL</td>
<td>41.53</td>
<td>12.15</td>
<td>-0.55</td>
<td>-0.46</td>
<td>6 - 65</td>
<td>-</td>
</tr>
<tr>
<td>Life satisfaction</td>
<td>22.69</td>
<td>6.76</td>
<td>-0.28</td>
<td>-0.70</td>
<td>5 - 35</td>
<td>.85</td>
</tr>
</tbody>
</table>

Note. Cronbach’s alpha coefficient provided for unidimensional scales only, as it is not a valid indicator of reliability for multi-dimensional scales (Cronbach & Shavelson, 2004). N = 375.

Model estimation.

Models were examined with one to seven latent classes. As detailed in the Data Analysis Plan, replication of the best log-likelihood was verified to avoid local maxima for each model. Models with at least two classes were checked to ensure that the null model (H₀) log-likelihood for the BLRT was equal to the best log-likelihood value of the model with one less class (k-1).
The number of classes was examined using the Bayesian Information Criteria (BIC), Akaike Information Criteria (AIC), and Sample-size Adjusted BIC (aBIC). Better model fit is indicated by lower values on these fit statistics. The Lo-Mendell-Rubin adjusted LRT test (LMR) and bootstrapped likelihood ratio test (BLRT) were examined as well with significant p-values (i.e., \( p < .05 \)) for these tests indicating that \( k-1 \) class is a statistically better fit to the data. In selecting the final model, due consideration was also given to parsimony and whether the latent profiles made sense clinically.

Table 13 shows the information criteria (IC), entropy, and likelihood ratio tests for models with one to five latent profiles. The \( p \)-value of the BLRT test suggested that adding profiles beyond five was necessary but when models with six or more classes were specified, the log-likelihood could not be estimated, which indicates poor fit. Entropy scores were acceptable across all identified models, which indicate good (crisp) class membership classification. All of the fit indices suggest that a five-class solution is the best fit with the data. The average probabilities for most likely class membership are shown in Table 14 for the five-class solution.

<table>
<thead>
<tr>
<th>No. of profiles ((k))</th>
<th>Log-likelihood</th>
<th>AIC</th>
<th>BIC</th>
<th>aBIC</th>
<th>Entropy</th>
<th>LMR test</th>
<th>LMR ( p )-value</th>
<th>BLRT</th>
<th>BLRT ( p )-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-7216.05</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>-6786.83</td>
<td>13611.66</td>
<td>13686.27</td>
<td>13625.99</td>
<td>.89</td>
<td>838.24</td>
<td>.000</td>
<td>858.45</td>
<td>.000</td>
</tr>
<tr>
<td>3</td>
<td>-6694.69</td>
<td>13441.38</td>
<td>13543.48</td>
<td>13460.98</td>
<td>.84</td>
<td>179.95</td>
<td>.142</td>
<td>184.28</td>
<td>.000</td>
</tr>
<tr>
<td>4</td>
<td>-6648.09</td>
<td>13362.19</td>
<td>13491.78</td>
<td>13387.08</td>
<td>.82</td>
<td>91.00</td>
<td>.003</td>
<td>93.19</td>
<td>.000</td>
</tr>
<tr>
<td>5</td>
<td>-6621.75</td>
<td>13323.50</td>
<td>13480.58</td>
<td>13353.67</td>
<td>.82</td>
<td>51.44</td>
<td>.508</td>
<td>52.68</td>
<td>.000</td>
</tr>
</tbody>
</table>

Note. The log-likelihood could not be estimated for models with six or more classes, indicating poor fit. AIC=Akaike Information Criterion; BIC=Bayesian Information Criterion; aBIC=Sample-Size-Adjusted BIC; LMR=Lo–Mendell–Rubin Adjusted LRT test; BLRT=Bootstrap Likelihood Ratio Test. \( N = 375 \).
Table 14

*Average Class Probabilities for Most Likely Class Membership by Latent Profile*

<table>
<thead>
<tr>
<th>No. of profiles (k)</th>
<th>n</th>
<th>% of sample</th>
<th>1 Class</th>
<th>2 Class</th>
<th>3 Class</th>
<th>4 Class</th>
<th>5 Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>16</td>
<td>4.27%</td>
<td>0.965</td>
<td>0.035</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>2</td>
<td>74</td>
<td>19.73%</td>
<td>0.008</td>
<td>0.915</td>
<td>0.049</td>
<td>0.028</td>
<td>0.000</td>
</tr>
<tr>
<td>3</td>
<td>33</td>
<td>8.80%</td>
<td>0.000</td>
<td>0.064</td>
<td>0.811</td>
<td>0.124</td>
<td>0.001</td>
</tr>
<tr>
<td>4</td>
<td>119</td>
<td>31.73%</td>
<td>0.000</td>
<td>0.017</td>
<td>0.042</td>
<td>0.831</td>
<td>0.110</td>
</tr>
<tr>
<td>5</td>
<td>133</td>
<td>35.47%</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.086</td>
<td>0.914</td>
</tr>
</tbody>
</table>

*Note. N = 375.*

Figures 11 to 14 display the *profile plots* for each of the LPA models. A profile plot is essentially a line graph that illustrates the patterns across variables found, based on the number of classes specified. Each line represents a different class and the values plotted are the mean scores for the class on each of the measures. Together, this information helps create a profile for each class – what variables individuals within a class are typically high or low on, and how that compares to individuals in other classes or subgroups. Hence, the profile plots can also help with decisions around whether all the classes are needed (because they are substantively meaningful and differ from the other classes) or not, and whether the latent classes correspond to subgroups that are already known about (such as those based purely on symptom severity). Once the number of classes is chosen, labelling the classes/profiles is considered.
Figure 11. Two-class model of mental health subgroups. $N = 375$.

Figure 12. Three-class model of mental health subgroups. $N = 375$. 
Figure 13. Four-class model of mental health subgroups. $N = 375$. 
Figure 14. Five-class model of mental health subgroups. *N* = 375.
Visual inspection of the profile plots reveals that the two- to four-class models are readily interpretable and correspond fairly closely with known subgroups based on risk for mental ill-health (e.g., 2-classes: low v. high risk; 3-classes: low, moderate and high risk). The size of the subgroups (% of total sample) in these solutions is also in line with expectations (based on previous research with non-clinical populations and university students; e.g., Haller, Cramer, Lauche, Gass & Dobos, 2014; Stallman, 2010).

However, careful inspection of the five-class model led to its selection because it provides a more nuanced view of mental health with distinct patterns of affect, mental health and wellbeing. It was also statistically superior to the other models. Based on the pattern of results for the five-class model (see Figure 14), each class was assigned a summary label, inspired by Keyes and Lopez (2002; Keyes & Lopez, 2002) US-based research on mental health. Keyes and Lopez (2002) accurately point out, the labels cannot fully convey all the mental health dynamics underlying each profile but, nevertheless, they serve a useful purpose and are recognisable by positive psychology academics and practitioners.

The first and largest latent class was characterised by strong mental health including high positive affect, normal levels of anxiety and depressive symptoms (i.e., HADS scores < 8.0) and high quality of life and life satisfaction. Individuals with this level of emotional wellbeing (i.e., happy and satisfied) and negligible or no symptoms of anxiety and depression, are likely to have a low risk of developing a mental illness. Previous research in positive psychology has found that individuals exhibiting these characteristics are typically flourishing (Keyes, 2005b, 2007; Keyes et al., 2010), so this subgroup was labelled Thriving.

The second latent class comprised individuals who reported elevated symptoms of anxiety. Although the average anxiety score for this subgroup sat right on the clinical cut-off point for the HADS (i.e., score ≥8), individuals in this subgroup reported fairly low negative affect and few symptoms of depression. They also reported reasonably high levels of positive affect, life satisfaction, quality of life and functioning, so the subgroup was labelled Getting By and was classified as marginal risk.

Individuals in the third subgroup reported similar levels of affect and anxiety to the Getting By group but they reported more depressive symptoms and somewhat lower quality of life and life satisfaction. Mean anxiety and depression scores for this group hovered around the clinical cut-off line (i.e., HADS score ≥8) indicating an elevated or
moderate risk of mental health problems. Consequently, this subgroup was labelled Struggling.

Whilst individuals in the fourth subgroup reported similar levels of positive affect and depressive symptoms to the previous group, they reported significantly more negative affect and lower life satisfaction, quality of life and functioning. Anxiety scores for individuals in this group were generally in clinical range, indicating that they would probably meet the criteria for an anxiety disorder. Therefore, it was classified as high risk and was labelled Floundering.

The final latent class was labelled Languishing and was classified as very high risk due to very poor mental health and significantly impaired quality of life and functioning. Individuals in this group reported low positive affect, high negative affect, and marked anxiety and depressive symptoms, which were well above the clinical cut-off line indicating that they are highly likely to meet the criteria for anxiety and/or depressive disorders.

In Table 15, the colour coding highlights similarities and differences between the five latent profiles.

<table>
<thead>
<tr>
<th>Profile</th>
<th>Label</th>
<th>Portion n, %</th>
<th>Positive Affect</th>
<th>Negative Affect</th>
<th>Anxiety</th>
<th>Depression</th>
<th>Quality of life &amp; Functioning</th>
<th>Satisfaction with life</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Thriving</td>
<td>133, 35.47%</td>
<td>High</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td>2</td>
<td>Getting by</td>
<td>119, 31.73%</td>
<td>High average</td>
<td>Low average</td>
<td>Borderline</td>
<td>Low</td>
<td>High average</td>
<td>High average</td>
</tr>
<tr>
<td>3</td>
<td>Struggling</td>
<td>33, 8.80%</td>
<td>Low average</td>
<td>Low average</td>
<td>Borderline</td>
<td>Borderline</td>
<td>Low average</td>
<td>Low average</td>
</tr>
<tr>
<td>4</td>
<td>Floundering</td>
<td>74, 19.73%</td>
<td>Low average</td>
<td>High</td>
<td>Clinical</td>
<td>Borderline</td>
<td>Low average</td>
<td>Low average</td>
</tr>
<tr>
<td>5</td>
<td>Languishing</td>
<td>16, 4.27%</td>
<td>Low</td>
<td>High</td>
<td>Clinical</td>
<td>Clinical</td>
<td>Low</td>
<td>Low</td>
</tr>
</tbody>
</table>

Note. Rating system adapted from Dowdy et al. (2015). SD = standard deviation. Low: $z < -1SD$; Low average: $-1 \leq z < 0SD$; High average: $0 \leq z \leq 1SD$; High: $z > 1SD$.

Borderline = subgroup mean is within one point of clinical cut-off score on the HADS. 

$N = 375$. 
Characterising the participants within each latent profile.

Tables 16 and 17 present the sociodemographic, behavioural and clinical characteristics of the five mental health latent profiles.

Table 16

<table>
<thead>
<tr>
<th>Mental Health Latent Profiles - Sociodemographic and Background Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Characteristic</td>
</tr>
<tr>
<td>Gender; female, ( n , (%) )</td>
</tr>
<tr>
<td>Age; years, ( M , (SD) )</td>
</tr>
<tr>
<td>Marital status</td>
</tr>
<tr>
<td>Never married, ( n , (%) )</td>
</tr>
<tr>
<td>Married/De facto, ( n , (%) )</td>
</tr>
<tr>
<td>Has child(ren), ( n , (%) )</td>
</tr>
<tr>
<td>Living arrangements</td>
</tr>
<tr>
<td>Living alone, ( n , (%) )</td>
</tr>
<tr>
<td>Lives with children, ( n , (%) )</td>
</tr>
<tr>
<td>Lives with parents, ( n , (%) )</td>
</tr>
<tr>
<td>Education</td>
</tr>
<tr>
<td>Less than 12 years of education, ( n , (%) )</td>
</tr>
<tr>
<td>Tertiary educated, ( n , (%) )</td>
</tr>
<tr>
<td>Paid or self-employed, ( n , (%) )</td>
</tr>
</tbody>
</table>

*Note.* \% = Portion of subgroup.
Table 17

*Mental Health Latent Profiles - Clinical Characteristics*

<table>
<thead>
<tr>
<th></th>
<th>Thriving (n = 133)</th>
<th>Getting by (n = 119)</th>
<th>Struggling (n = 33)</th>
<th>Floundering (n = 74)</th>
<th>Languishing (n = 16)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mental health history</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Personal history of mental illness, n (%)</td>
<td>32 (24.1%)</td>
<td>47 (39.5%)</td>
<td>15 (45.5%)</td>
<td>46 (62.2%)</td>
<td>13 (81.3%)</td>
</tr>
<tr>
<td>Family history of mental illness</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maternal mental illness, n (%)</td>
<td>32 (24.1%)</td>
<td>39 (32.8%)</td>
<td>6 (18.20%)</td>
<td>32 (43.2%)</td>
<td>7 (43.8%)</td>
</tr>
<tr>
<td>Paternal mental illness, n (%)</td>
<td>17 (12.8%)</td>
<td>21 (17.6%)</td>
<td>6 (18.2%)</td>
<td>24 (32.4%)</td>
<td>3 (18.8%)</td>
</tr>
<tr>
<td>Sibling mental illness, n (%)</td>
<td>53 (39.8%)</td>
<td>36 (30.3%)</td>
<td>12 (36.4%)</td>
<td>31 (41.9%)</td>
<td>6 (37.5%)</td>
</tr>
<tr>
<td>Intimate partner violence, n (%)*</td>
<td>28 (25.0%)</td>
<td>28 (29.8%)</td>
<td>4 (16.0%)</td>
<td>17 (27.4%)</td>
<td>6 (60.0%)</td>
</tr>
<tr>
<td><strong>Health behaviours</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-smoker, n (%)</td>
<td>94 (70.7%)</td>
<td>70 (58.8%)</td>
<td>24 (72.7%)</td>
<td>55 (74.3%)</td>
<td>8 (50.0%)</td>
</tr>
<tr>
<td>Alcohol and drug use</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drinks alcohol at least weekly, n (%)</td>
<td>47 (35.5%)</td>
<td>43 (36.1%)</td>
<td>4 (21.2%)</td>
<td>24 (32.4%)</td>
<td>7 (43.8%)</td>
</tr>
<tr>
<td>&gt; 5 alcoholic drinks per session, n (%)</td>
<td>32 (27.8%)</td>
<td>28 (26.9%)</td>
<td>6 (30.0%)</td>
<td>13 (21.0%)</td>
<td>2 (15.4%)</td>
</tr>
<tr>
<td>Marijuana use &gt; 6 months ago, n (%)</td>
<td>59 (44.4%)</td>
<td>56 (47.1%)</td>
<td>13 (39.4%)</td>
<td>29 (39.2%)</td>
<td>3 (18.8%)</td>
</tr>
<tr>
<td>Marijuana use ≤ 6 months, n (%)</td>
<td>19 (14.3%)</td>
<td>16 (13.4%)</td>
<td>6 (18.2%)</td>
<td>6 (8.1%)</td>
<td>5 (31.3%)</td>
</tr>
<tr>
<td>Other illicit drug &gt; 6 months ago, n (%)</td>
<td>36 (27.1%)</td>
<td>28 (23.5%)</td>
<td>11 (33.3%)</td>
<td>8 (10.8%)</td>
<td>2 (12.5%)</td>
</tr>
<tr>
<td>Other illicit drug ≤ last 6 months n (%)</td>
<td>13 (9.8%)</td>
<td>13 (10.9%)</td>
<td>4 (12.1%)</td>
<td>0 (0.0%)</td>
<td>3 (18.8%)</td>
</tr>
<tr>
<td>Health service usage in last 12 months</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Seen GP for MH, n (%)</td>
<td>30 (22.7%)</td>
<td>40 (34.2%)</td>
<td>14 (43.8%)</td>
<td>43 (58.9%)</td>
<td>8 (50.0%)</td>
</tr>
<tr>
<td>Seen psychologist or psychiatrist, n (%)</td>
<td>10 (7.6%)</td>
<td>16 (13.4%)</td>
<td>6 (18.2%)</td>
<td>25 (33.81%)</td>
<td>6 (37.5%)</td>
</tr>
<tr>
<td>Seen other MH professional, n (%)</td>
<td>12 (9.2%)</td>
<td>6 (5.1%)</td>
<td>3 (9.7%)</td>
<td>16 (22.2%)</td>
<td>5 (31.3%)</td>
</tr>
<tr>
<td><strong>Clinical characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SF-36</td>
<td>51.10 (7.78)</td>
<td>51.19 (8.48)</td>
<td>53.66 (9.62)</td>
<td>52.45 (9.08)</td>
<td>51.74 (9.57)</td>
</tr>
<tr>
<td>Physical Component Summary, M (SD)</td>
<td>52.06 (5.60)</td>
<td>43.17 (6.84)</td>
<td>33.55 (8.06)</td>
<td>28.66 (7.74)</td>
<td>18.00 (7.40)</td>
</tr>
<tr>
<td>Mental Component Summary, M (SD)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HADS</td>
<td>4.22 (2.22)</td>
<td>8.21 (2.34)</td>
<td>7.88 (2.61)</td>
<td>12.01 (2.76)</td>
<td>17.13 (1.96)</td>
</tr>
<tr>
<td>Anxiety, M (SD)</td>
<td>1.85 (1.52)</td>
<td>3.50 (1.86)</td>
<td>7.48 (2.9)</td>
<td>7.77 (2.55)</td>
<td>13.69 (2.12)</td>
</tr>
<tr>
<td>Depression, M (SD)</td>
<td>27.67 (4.83)</td>
<td>23.12 (5.04)</td>
<td>15.19 (4.88)</td>
<td>18.14(5.15)</td>
<td>13.53 (4.94)</td>
</tr>
</tbody>
</table>

*Note. % = Percentage of subgroup. *% of participants who have had a partner. N = 375.*
Mental health latent profiles and symptom severity

As previously discussed, subgroups in mental health research and practice are frequently formed on the basis of symptom severity. When the HADS is used for this purpose, individuals are assigned to one of four categories, based on their subscale scores: normal (0 – 7), mild (8-10), moderate (11-14), and severe (15-21) (Whelan-Goodinson, Ponsford, & Schönberger, 2009). The clinical cut-off score for each subscale is ≥8, which indicates probable anxiety or depression. These scores help inform treatment planning (e.g., scores greater than 15 on either scale may flag the need to consider psychotropic medication as an initial and/or adjunct treatment option) and repeated administrations of the measure can help track change over time. How do the current mental health latent profiles compare to the subgroups based on symptom severity?

To investigate the range of scores on the HADS and what portion of individuals had scores above the clinical cut-off point within each latent profile, a cross-tabulation and a subgroup comparison of the HADS scores were performed in SPSS. Table 18 presents the results of the cross-tabulation. To better understand the spread of scores within each latent profile, Figure 15 displays the distribution of HADS scores for each of the latent profiles compared to the overall sample.

Table 18

<table>
<thead>
<tr>
<th>Cross-Tabulation of Anxiety and Depression Scores by Latent Profile</th>
</tr>
</thead>
<tbody>
<tr>
<td>HADS Anxiety</td>
</tr>
<tr>
<td>M</td>
</tr>
<tr>
<td>-----</td>
</tr>
<tr>
<td>Profile 1: Thriving</td>
</tr>
<tr>
<td>Profile 2: Getting by</td>
</tr>
<tr>
<td>Profile 3: Struggling</td>
</tr>
<tr>
<td>Profile 4: Floundering</td>
</tr>
<tr>
<td>Profile 5: Languishing</td>
</tr>
</tbody>
</table>

*Note. Clinical range indicated by a HADS score ≥8. N = 375.*
Figure 15. Subgroup comparison of anxiety and depression scores. Solid colour = distribution of scores in the subgroup. Whitesmoke = distribution of scores across the full sample. $N = 375$. 
This figure shows the overlap of HADS scores across the subgroups. The distribution of scores in the Thriving (Low risk) and Languishing (Very high risk) subgroups are as expected, clustering at low and high end of the scale respectively. However, the three middle subgroups show considerable overlap and spread of scores. Whilst the HADS scores in the Floundering (High risk) subgroup tend towards the higher end of the scale, as one would expect, the distribution of scores for the Getting By and Struggling subgroups both cluster towards the middle and overlap and spread. With mean anxiety scores for both groups close to the clinical cut-off score for the HADS (i.e., ≥8, which indicates probable anxiety or depression), the range and distribution of anxiety scores for these subgroups indicate that significant variation exists in terms of the number and type of anxiety symptoms experienced by individuals within the groups: some individuals experience just a few symptoms while other individuals experience clinically significant levels of anxiety. A similar pattern exists with depression scores in the Struggling subgroup, where over 45% of the individuals report depressive symptoms in the clinical range. This is pertinent because if just the HADS was used to screen for mental health problems in practice, then half of the Struggling group would be flagged as potentially needing treatment for depression (and anxiety), while the other half does not.

Considerable overlap in the range and distributions of anxiety and depressive scores across the subgroups poignantly highlights that the latent classes were not formed purely on the basis of symptomatology. Instead the latent classes reflect common patterns of responding across all of the mental health and wellbeing variables included in the LPA and, consequently, reflect categories of emotional wellbeing and “complete” mental health (Keyes, 2007).

**Latent variable mixture model.**

To determine the extent to which demographic, cognitive and behavioural variables predict mental health profile membership, a latent variable mixture model was run, as described in the Method Chapter (see section: Extending the model with covariates). Vermunt’s (2010) three-step ML approach was employed, which involves specifying the covariates as auxiliary variables, and adding the (BCH) command for continuous variables and another similar command for categorical variables, named DCAT (Asparouhov & Muthén, 2014). Whilst the BCH command tests the equality of means across profiles, the DCAT command provides a between-profile comparison of the estimated probability of each characteristic. Table 19 presents the results from the
equality of means and chi-square tests comparing the profiles to one another on the
demographic, background, cognitive and behavioural variables.

Results from the equality of means (chi-square) tests in Table 20 indicate that
significant differences exist between latent classes on the basis of: marital status, living
situation, paid employment, personal and parental history of mental illness, smoking
status, recent illicit drug use, and nearly all cognitive and behavioural (coping) variables
measured. Odd ratios and confidence intervals for these factors are provided in Table 21
and 22. Note the exaggerated odds ratio effect evident for history of mental health and
perceived stress. This exaggeration occurs when the incidence in the outcome is higher
than 10% (Zhang & Yu, 1998). Hence, risk ratios were calculated for these variables to
provide a more accurate indication of relative risk.

The results indicate that when the other variables are held constant, a history of
mental illness increases the risk of being in the Getting By (marginal risk) latent
subgroup by 55%, the Struggling (moderate risk) group by 105%, the Floundering
subgroup by 139%, and the Languishing (very high risk) subgroup by 232% compared
to the Thriving (low risk) latent profile. In practical terms, this means that an individual
who has had a mental disorder in the past is two to 13 times more likely to be in an
elevated risk group than someone who has not experienced a mental illness.

Similarly, if the other variables are held constant, a one standard deviation
increase in perceived stress increases the risk of being in the Getting By subgroup with
marginal risk by 129%, the Struggling group with moderate risk by 143%, the
Floundering group with high risk by 174%, and the Languishing group with very high
risk by 179% compared to the Thriving (low risk) group.

These results are consistent with previous research and clinical experience to the
extent that both previous mental illness and high levels of stress are well-known risk
factors for mental illness. Notably, gender, maternal mental illness, and intimate partner
violence (IPV) did not differ significantly across the mental health subgroups even
though they are well known social determinants of mental health too.

Results highlight that the use of substances to cope with stress more than
doubles the odds of being in the higher risk mental health subgroups. Distracting or
blaming oneself for problems significantly increases the odds also. In contrast,
optimism acts as a protective factor such that a one point increase in optimism reduces
the odds of being in the marginal risk group by 57%, 75% for the moderate risk group,
56% for the high-risk group, and 81% for the very high risk group. Similar reductions in
odds (and risk) were associated with higher BPNS-Autonomy (e.g., 66% reduction in the odds of being in the high-risk group) and BPNS-Competence (e.g., 80% reduction in the odds of being in the very high risk group), when all other variables are held constant.
Table 19

Comparison of Latent Profiles on Age, Physical Health, Cognitive and Behavioural Variables

<table>
<thead>
<tr>
<th>Continuous variables</th>
<th>$\chi^2$</th>
<th>Thriving</th>
<th>Getting by</th>
<th>Struggling</th>
<th>Floundering</th>
<th>Languishing</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$M$ (S.E.)</td>
<td>$M$ (S.E.)</td>
<td>$M$ (S.E.)</td>
<td>$M$ (S.E.)</td>
<td>$M$ (S.E.)</td>
</tr>
<tr>
<td>Socio-demographic</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
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<tr>
<td>Perceived stress</td>
<td>442.14***</td>
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<td>18.24</td>
<td>.38</td>
<td>19.41</td>
</tr>
<tr>
<td>Optimism</td>
<td>184.36***</td>
<td>23.72</td>
<td>.34</td>
<td>20.22</td>
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<tr>
<td>BPNS - Autonomy</td>
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<td>BPNS - Competence</td>
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<tr>
<td>BPNS - Relatedness</td>
<td>94.91***</td>
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<td>.07</td>
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<tr>
<td>Behavioural (coping)</td>
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</tr>
<tr>
<td>Mental distraction</td>
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<td>.13</td>
<td>5.38</td>
<td>.15</td>
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</tr>
<tr>
<td>Denial</td>
<td>71.32***</td>
<td>2.24</td>
<td>.07</td>
<td>2.73</td>
<td>.12</td>
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</tr>
<tr>
<td>Behavioural disengagement</td>
<td>143.75***</td>
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<td>.08</td>
<td>3.05</td>
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</tr>
<tr>
<td>Use Substances</td>
<td>59.78***</td>
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<td>.07</td>
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<td>.16</td>
<td>3.54</td>
</tr>
<tr>
<td>Blame self</td>
<td>139.93***</td>
<td>3.58</td>
<td>.13</td>
<td>4.62</td>
<td>.15</td>
<td>4.69</td>
</tr>
<tr>
<td>Vent</td>
<td>6.09 n.s.</td>
<td>4.42</td>
<td>.14</td>
<td>4.48</td>
<td>.15</td>
<td>4.32</td>
</tr>
<tr>
<td>Take Action</td>
<td>68.57***</td>
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<tr>
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<td>5.71</td>
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<td>4.70</td>
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<tr>
<td>Positive reframe</td>
<td>99.64***</td>
<td>6.13</td>
<td>.14</td>
<td>5.38</td>
<td>.15</td>
<td>4.20</td>
</tr>
<tr>
<td>Acceptance</td>
<td>19.85**</td>
<td>5.91</td>
<td>.13</td>
<td>5.72</td>
<td>.14</td>
<td>5.34</td>
</tr>
<tr>
<td>Use humour</td>
<td>14.38**</td>
<td>5.15</td>
<td>.17</td>
<td>4.71</td>
<td>.19</td>
<td>3.93</td>
</tr>
<tr>
<td>Seek emotional support</td>
<td>29.83***</td>
<td>5.40</td>
<td>.16</td>
<td>5.22</td>
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<td>4.26</td>
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<tr>
<td>Seek instrumental support</td>
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<td>.15</td>
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<tr>
<td>Turn to religion</td>
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<td>3.28</td>
<td>.20</td>
<td>2.63</td>
</tr>
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</table>

Note. n.s.: not significant, * $p \leq .05$, ** $p \leq .01$, *** $p \leq .001$. BPNS = Basic psychological need satisfaction. LOC = Locus of control.

Reference group = Thriving (Low risk). Overall chi-square statistics calculated with 4 degrees of freedom. Bold values are statistically significant at $p \leq .05$. 
Table 20

*Estimated Probabilities of Background Characteristics within Each Profile*

<table>
<thead>
<tr>
<th>Categorical variables</th>
<th>$\chi^2$</th>
<th>Thriving</th>
<th>Getting by</th>
<th>Struggling</th>
<th>Floundering</th>
<th>Languishing</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Socio-demographic</strong></td>
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<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Marital status</td>
<td>54.75***</td>
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<td></td>
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<td></td>
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<td>Never married</td>
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<td>.51</td>
<td>.44</td>
<td>.52</td>
<td>.57</td>
<td></td>
</tr>
<tr>
<td>Married/defacto</td>
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<td>.31</td>
<td>.56</td>
<td>.38</td>
<td>.36</td>
<td></td>
</tr>
<tr>
<td>Has child(ren)</td>
<td>3.79 n.s.</td>
<td>.56</td>
<td>.39</td>
<td>.40</td>
<td>.38</td>
<td>.43</td>
</tr>
<tr>
<td>Living situation</td>
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<td></td>
</tr>
<tr>
<td>Lives with children</td>
<td>.75</td>
<td>.66</td>
<td>.49</td>
<td>.70</td>
<td>.48</td>
<td></td>
</tr>
<tr>
<td>Lives with parents</td>
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<td>.28</td>
<td>.51</td>
<td>.24</td>
<td>.52</td>
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<tr>
<td>Education</td>
<td>13.89 n.s.</td>
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<tr>
<td>Less than 12 years</td>
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<td>.12</td>
<td>.06</td>
<td>.07</td>
<td>.06</td>
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<tr>
<td>Year 12 or equivalent</td>
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<td>.43</td>
<td>.43</td>
<td>.32</td>
<td>.53</td>
<td></td>
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<tr>
<td>Tertiary</td>
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<td>.46</td>
<td>.45</td>
<td>.58</td>
<td>.40</td>
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<tr>
<td>Employment</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No paid employment</td>
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<td>.30</td>
<td>.56</td>
<td>.30</td>
<td>.56</td>
<td></td>
</tr>
<tr>
<td>Has paid employment</td>
<td>.76</td>
<td>.70</td>
<td>.45</td>
<td>.70</td>
<td>.44</td>
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<tr>
<td><strong>Background</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Previous mental illness</td>
<td>53.31***</td>
<td>.23</td>
<td>.39</td>
<td>.48</td>
<td>.65</td>
<td>.82</td>
</tr>
<tr>
<td>Maternal mental illness</td>
<td>14.09**</td>
<td>.77</td>
<td>.66</td>
<td>.94</td>
<td>.52</td>
<td>.57</td>
</tr>
<tr>
<td>Paternal mental illness</td>
<td>10.58*</td>
<td>.87</td>
<td>.84</td>
<td>.80</td>
<td>.65</td>
<td>.82</td>
</tr>
<tr>
<td>Intimate partner violence</td>
<td>4.28 n.s.</td>
<td>.31</td>
<td>.23</td>
<td>.27</td>
<td>.25</td>
<td>.61</td>
</tr>
<tr>
<td><strong>Health behaviours</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-smoker</td>
<td>61.42***</td>
<td>.72</td>
<td>.57</td>
<td>.79</td>
<td>.74</td>
<td>.48</td>
</tr>
<tr>
<td>Drinks alcohol &gt; weekly</td>
<td>3.50 n.s.</td>
<td>.37</td>
<td>.35</td>
<td>.20</td>
<td>.33</td>
<td>.46</td>
</tr>
<tr>
<td>&gt;5 alcoholic drinks per single session</td>
<td>3.51 n.s.</td>
<td>.31</td>
<td>.22</td>
<td>.37</td>
<td>.20</td>
<td>.16</td>
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<tr>
<td>Recent drug use – Cannabis</td>
<td>11.53 n.s.</td>
<td>.14</td>
<td>.14</td>
<td>.17</td>
<td>.08</td>
<td>.32</td>
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<tr>
<td>Recent drug use – Other illicit</td>
<td>59.44***</td>
<td>.09</td>
<td>.13</td>
<td>.11</td>
<td>0</td>
<td>.20</td>
</tr>
</tbody>
</table>

*Note.* In the case of significant chi-square, bold values indicate the profile with the highest probability. *n.s.: not significant, * $p \leq .05$, ** $p \leq .01$, *** $p \leq .001$. $N = 375$. 
Table 21

Odds Ratios for Significant Covariates

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Getting by</th>
<th>Struggling</th>
<th>Floundering</th>
<th>Languishing</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OR 95% CI</td>
<td>OR 95% CI</td>
<td>OR 95% CI</td>
<td>OR 95% CI</td>
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<tr>
<td>Socio-demographic</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Married/De facto</td>
<td>.56 .32</td>
<td>1.00</td>
<td>.43 2.89</td>
<td>.72 .37</td>
</tr>
<tr>
<td>Lives with children</td>
<td>.92 .49</td>
<td>1.00</td>
<td>.38 .14</td>
<td>.99 .83</td>
</tr>
<tr>
<td>Has paid employment</td>
<td>.86 .48</td>
<td>1.52</td>
<td>.40 .17</td>
<td>.92 .88</td>
</tr>
<tr>
<td>Background</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>History of mental illness</td>
<td>1.88 1.07</td>
<td>3.32 1.85</td>
<td>3.06 1.33</td>
<td>7.04 4.28</td>
</tr>
<tr>
<td>Maternal mental illness</td>
<td>1.29 .72</td>
<td>2.32 1.72</td>
<td>.47 .17</td>
<td>1.30 1.65</td>
</tr>
<tr>
<td>Paternal mental illness</td>
<td>1.31 .65</td>
<td>2.65</td>
<td>1.31 .46</td>
<td>3.73 2.72</td>
</tr>
<tr>
<td>Illicit Drug use, &gt;6 months ago</td>
<td>.79 .44</td>
<td>1.41</td>
<td>1.44 .62</td>
<td>3.34 .27</td>
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<tr>
<td>Cognitive</td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>Perceived stress</td>
<td>7.88 4.24</td>
<td>14.65 5.71</td>
<td>16.14 6.72</td>
<td>38.72 65.73</td>
</tr>
<tr>
<td>Optimism</td>
<td>.53 .33</td>
<td>.84 1.78</td>
<td>.25 .12</td>
<td>.49 .44</td>
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<tr>
<td>BPNS - Autonomy</td>
<td>.62 .37</td>
<td>1.04</td>
<td>.29 .14</td>
<td>.60 .34</td>
</tr>
<tr>
<td>BPNS - Competence</td>
<td>.58 .36</td>
<td>.95 1.98</td>
<td>.62 .30</td>
<td>1.26 .32</td>
</tr>
<tr>
<td>BPNS - Relatedness</td>
<td>.87 .55</td>
<td>1.38</td>
<td>.73 .39</td>
<td>1.38 .62</td>
</tr>
<tr>
<td>Behavioural (coping)</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Mental distraction</td>
<td>1.70 1.29</td>
<td>2.25 1.89</td>
<td>1.68 1.12</td>
<td>2.52 1.97</td>
</tr>
<tr>
<td>Denial</td>
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<td>1.83 1.10</td>
<td>3.04 1.93</td>
</tr>
<tr>
<td>Behavioural disengagement</td>
<td>1.24 .89</td>
<td>1.75</td>
<td>1.48 .94</td>
<td>2.34 1.57</td>
</tr>
<tr>
<td>Use substances</td>
<td>2.11 1.45</td>
<td>3.08 2.15</td>
<td>2.61 1.69</td>
<td>4.04 2.37</td>
</tr>
<tr>
<td>Blame self</td>
<td>1.44 1.13</td>
<td>1.85</td>
<td>1.43 1.00</td>
<td>2.04 2.15</td>
</tr>
<tr>
<td>Take Action</td>
<td>1.04 0.75</td>
<td>1.45</td>
<td>0.80 0.48</td>
<td>1.33 0.62</td>
</tr>
<tr>
<td>Plan</td>
<td>1.31 0.91</td>
<td>1.88</td>
<td>1.26 0.77</td>
<td>2.07 1.74</td>
</tr>
<tr>
<td>Positive reframe</td>
<td>0.65 0.47</td>
<td>0.88</td>
<td>0.47 0.30</td>
<td>0.74 0.47</td>
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<tr>
<td>Acceptance</td>
<td>0.90 0.68</td>
<td>1.21</td>
<td>1.01 0.66</td>
<td>1.56 0.71</td>
</tr>
<tr>
<td>Use humour</td>
<td>0.82 0.67</td>
<td>1.00</td>
<td>0.75 0.55</td>
<td>1.02 0.72</td>
</tr>
<tr>
<td>Seek emotional support</td>
<td>0.80 0.58</td>
<td>1.10</td>
<td>0.59 0.37</td>
<td>0.96 0.75</td>
</tr>
<tr>
<td>Seek instrumental support</td>
<td>1.06 0.78</td>
<td>1.45</td>
<td>1.17 0.73</td>
<td>1.88 1.41</td>
</tr>
</tbody>
</table>
Table 22

*Risk Ratios for the Most Significant Predictors of Mental Health Latent Profile*

<table>
<thead>
<tr>
<th></th>
<th>Getting by</th>
<th>Struggling</th>
<th>Floundering</th>
<th>Languishing</th>
</tr>
</thead>
<tbody>
<tr>
<td>OR</td>
<td>RR</td>
<td>OR</td>
<td>RR</td>
<td>OR</td>
</tr>
<tr>
<td><strong>Background</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>History of mental illness</td>
<td>1.88</td>
<td>1.55</td>
<td>3.06</td>
<td>2.05</td>
</tr>
<tr>
<td><strong>Cognitive</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Perceived stress</td>
<td>7.79</td>
<td>4.82</td>
<td>16.14</td>
<td>6.79</td>
</tr>
<tr>
<td><strong>Behavioural (coping)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Use substances</td>
<td>2.11</td>
<td>2.05</td>
<td>2.61</td>
<td>2.52</td>
</tr>
</tbody>
</table>

*Note.* Reference group = Thriving (Low risk). RR = Risk ratio. Baseline prevalence rates for Perceived stress and Use substance were 9.1% and 2.3% respectively, which were calculated as z-scores > 0 in the reference group. *N* = 375.

**Predicting mental health latent profile.**

Figures 16 and 17 present a profile plot of the subgroups, based upon their estimated (standardised) means across the full range of psychological variables measured (based on z-scores and raw scores respectively). Five clear patterns in the emotional, behavioural and cognitive variables are evident that map to the latent classes.

*Figure 16. Latent probability (profile) plot with z-scores. BPN = Basic psychological need satisfaction. MCS = Mental health component summary.*
Figure 17. Latent probability (profile) plot with raw scores. BPN = Basic psychological need satisfaction. MCS = Mental health component summary.

Inspection of Figure 16 reveals that the strongest predictors of mental health subgroup in this study are perceived stress and the SF-36 MCS. The capacity for the Perceived Stress Scale to differentiate between the latent classes is illustrated in the error plot in Figure 18. The overlap of the stems for the Languishing and Floundering subgroups indicates that the measure may not accurately distinguish individuals that achieve a certain score (i.e., 23 on the revised 6-item scale). However, this is unlikely to be of practical significance given that both the Floundering and Languishing subgroups are at high risk of mental illness and upon identification would (ideally) be referred for further assessment and treatment. In light of this, perceived stress appears to be an adequate indicator of mental health subgroup in this study.

The other measure that appears to differentiate between the subgroups is the SF-36 MCS. It yields the largest gap between subgroups (see Figures 16 and 17) and acceptable error plot based on the normed scores (see Method chapter for details on how these were calculated). However, a box plot reveals significant overlap of scores, especially within the Struggling and Floundering subgroups (see Figure 20). In practice this would mean that individuals scoring between 35 and 38 on the MCS may be
incorrectly assigned to one of the groups (e.g., Floundering) instead of the other (e.g., Struggling). Although this suggests that the SF-36 may not be an ideal screening tool or predictor of mental health class membership, further investigation is probably merited before ruling it out entirely.

Figure 18. Error plot for perceived stress scores.
Figure 19. Error plot for SF-36 mental health component summary (MCS) scores.

Figure 20. Box plot for SF-36 mental health component score.

To gain a clearer understanding of the behavioural profiles of the mental health
subgroups, Figure 21 plots the sample means of all 14 coping strategies and Table 23 reports the odds ratios. As one would expect, Thriving is characterised by very low use of avoidant coping strategies and very high use of productive coping strategies, including positively reframing, taking action, using humour and support seeking. Getting By demonstrates a similar pattern of coping but with slightly less productive coping and slightly more avoidance.

In contrast, the Languishing profile is characterised by high use of avoidant and unproductive strategies, such as self-blame, disengaging, and denial, and low use of more productive coping strategies such as positively reframing, making a plan, taking action, and seeking support from others. This coping pattern is consistent with previous research into stress and psychopathology, and fits with clinical experience and observation of increasingly dysfunctional coping patterns in clients as symptom severity increases.
### Table 23

**Odds Ratios with the Wald Test of Significance for Individual Coping Responses**

<table>
<thead>
<tr>
<th>Coping strategy</th>
<th>Getting by</th>
<th></th>
<th></th>
<th>Struggling</th>
<th></th>
<th></th>
<th>Languishing</th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>OR</td>
<td>95% CI</td>
<td>OR</td>
<td>95% CI</td>
<td>OR</td>
<td>95% CI</td>
<td>OR</td>
<td>95% CI</td>
</tr>
<tr>
<td>Mental distraction</td>
<td>1.74</td>
<td>1.30</td>
<td>2.32</td>
<td>1.58</td>
<td>1.04</td>
<td>2.39</td>
<td>2.00</td>
<td>1.38</td>
</tr>
<tr>
<td>Denial</td>
<td>1.37</td>
<td>.92</td>
<td>2.05</td>
<td>1.94</td>
<td>1.14</td>
<td>3.28</td>
<td>1.89</td>
<td>1.19</td>
</tr>
<tr>
<td>Blame self</td>
<td>1.47</td>
<td>1.13</td>
<td>1.90</td>
<td>1.46</td>
<td>1.01</td>
<td>2.12</td>
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<td>1.55</td>
</tr>
<tr>
<td>Behavioural disengagement</td>
<td>1.23</td>
<td>.87</td>
<td>1.75</td>
<td>1.45</td>
<td>.90</td>
<td>2.32</td>
<td>1.53</td>
<td>1.01</td>
</tr>
<tr>
<td>Use Substances</td>
<td>2.12</td>
<td>1.44</td>
<td>3.14</td>
<td>2.72</td>
<td>1.74</td>
<td>4.26</td>
<td>2.34</td>
<td>1.52</td>
</tr>
<tr>
<td>Take Action</td>
<td>1.05</td>
<td>.75</td>
<td>1.46</td>
<td>.82</td>
<td>.48</td>
<td>1.37</td>
<td>.64</td>
<td>.41</td>
</tr>
<tr>
<td>Plan</td>
<td>1.30</td>
<td>.89</td>
<td>1.89</td>
<td>1.31</td>
<td>.78</td>
<td>2.21</td>
<td>1.64</td>
<td>1.02</td>
</tr>
<tr>
<td>Positive reframe</td>
<td>.64</td>
<td>.46</td>
<td>0.89</td>
<td>.47</td>
<td>.29</td>
<td>.76</td>
<td>.47</td>
<td>.31</td>
</tr>
<tr>
<td>Acceptance</td>
<td>.92</td>
<td>.68</td>
<td>1.24</td>
<td>1.01</td>
<td>.63</td>
<td>1.60</td>
<td>.75</td>
<td>.50</td>
</tr>
<tr>
<td>Use humour</td>
<td>.83</td>
<td>.67</td>
<td>1.02</td>
<td>.72</td>
<td>.52</td>
<td>1.01</td>
<td>.74</td>
<td>.56</td>
</tr>
<tr>
<td>Seek emotional support</td>
<td>.78</td>
<td>.56</td>
<td>1.08</td>
<td>.56</td>
<td>.34</td>
<td>.93</td>
<td>.74</td>
<td>.56</td>
</tr>
<tr>
<td>Seek instrumental support</td>
<td>1.08</td>
<td>.79</td>
<td>1.48</td>
<td>1.25</td>
<td>.77</td>
<td>2.04</td>
<td>1.40</td>
<td>.92</td>
</tr>
<tr>
<td>Vent</td>
<td>1.05</td>
<td>.81</td>
<td>1.37</td>
<td>1.12</td>
<td>.75</td>
<td>1.66</td>
<td>1.13</td>
<td>.80</td>
</tr>
<tr>
<td>Turn to religion</td>
<td>.95</td>
<td>.80</td>
<td>1.13</td>
<td>.75</td>
<td>.53</td>
<td>1.06</td>
<td>.98</td>
<td>.76</td>
</tr>
</tbody>
</table>

*Note.* Reference group = Low risk (Non-clinical). OR = Odds ratio. CI = Confidence intervals. BPNS = Basic psychological need satisfaction. Odds ratios significant at $\leq 0.05$ are in boldface. $N = 375$. 
Figure 21. Behavioural (coping) profiles for the mental health subgroups. N = 375.

The plot illustrates that individuals in the Struggling and Languishing subgroups are far less likely to seek support from other people than the other three subgroups. The tendency to disengage and socially withdraw is common in depression, so this pattern fits with expectations too. Although curiously, it appears that the Floundering subgroup experience similar levels of depression to the Struggling subgroup but they are much more likely to seek social support.

The only strategy that appears to clearly distinguish between the five latent profiles is behavioural disengagement. The lack of variation between the subgroups on the other coping strategies means that they are not able to differentially predict subgroup membership within the five-class model. Also, the cross-over lines in the plot highlight that differences between latent subgroups are not uniform across variables. This has implications for latent variable analyses. It flags that the intercepts differ across subgroups (i.e., measurement invariance) and it suggests that coping variables may not be related to each other in the same way across all of the subgroups (i.e., structural invariance).

Interim Summary

This phase of analyses aimed to identify latent subgroups that exist within the
normal population and develop profiles for them. The results highlighted patterns in emotional, behavioural and cognitive variables that clearly distinguish between five subgroups (see Table 15). These patterns are ordinarily hidden in research and regression-based analyses, which often compare subgroups just based on symptom severity or those high versus low on a specific factor.

Overall, the most significant predictors of risk group were a history of mental illness and high levels of perceived stress. Other important predictors included optimism, satisfaction of basic psychological needs, seeking emotional support, and avoidant coping strategies such as distracting and blaming oneself, disengaging, and using substances to cope. Frequent use of positive reframing and active problem solving also significantly decreased the likelihood of being in the high-risk subgroups compared to the low risk (Thriving) group.

Results from the latent variable multinomial logistic regressions revealed optimism and greater satisfaction of basic psychological needs for autonomy and relatedness increased the probability of being in the non-clinical subgroup. Conversely, frequent use of avoidant coping strategies and low satisfaction of basic psychological needs greatly increased the probability of being in the higher-risk subgroups.

Although these results are preliminary and further replication is needed, the results have some clear implications for model development and intervention/program evaluation. First, results from the LPA have shown that there are five distinct subgroups of people present within the sample who have markedly different characteristics and behavioural profiles. Analysing them as a single sample prohibits the identification of important differences between subgroups that may exist in the variables and processes that underpin mental health and psychopathology (e.g., coping variables may not be related to each other in the same way across all of the subgroups). Second, differences in means and standard errors across the subgroups indicate that the intercepts for variables in SEM vary across subgroups and therefore need to be specified accordingly (i.e., measurement invariance). Failure to do this potentially increases the chances of poor model fit and, in turn, the rejection of potentially useful theoretical models.

If accurate models are rejected, then important opportunities for identifying and developing targeted interventions are likely to be missed. Failure to identify these differences may well be contributing to the limited effectiveness seen in mental health practice today.

Equally, if theoretical models are accepted because they fit the data for full
sample, and intervention programs are developed on the basis of these, potentially important differences between the subgroups will be inevitably missed. These differences could be the key to designing more effective interventions.

Therefore, the following sections explore the extent to which latent subgroups potentially impact model testing results. To begin with, a novel model of stress, basic psychological needs, and mental health is tested using SEM with the full sample. The model is then tested using multigroup SEM to examine whether the model is accurate and equally valid across the latent subgroups just identified.

As mentioned earlier, this two-step process is important here because it clearly illustrates the importance of subgroups in model development and testing procedures. However, from a purely statistical standpoint, it is not strictly appropriate because multigroup analyses are usually based on well-known and established variables. Therefore, the final set of analyses employ a more advanced statistical technique that tests the model and forms the latent classes at the same time.

As the latent classes are formed on the basis of what variables are included in the model, it is expected that the number of latent classes identified in the final analysis, using mixture SEM, will differ from those just found in LPA (which only used the affect and mental health measures). Bear in mind that these analyses are exploratory, designed to ascertain the extent to which latent subgroups potentially impact model testing results, and illustrate how effectiveness in mental health practice may be compromised and limited by some of the basic assumptions and common practices in mental health research and evaluation.

Part Three     Traditional Structural Equation Modelling

In contrast to LPA, which focuses on the similarities and differences between people by identifying response patterns across variables, traditional SEM focuses on the relationships among multiple observed and latent variables. The purpose of SEM is often to discover if the hypothesised relationships among the variables are a good fit to the data. This is done by estimating the proportion of variance in the dependent (outcome) variables that is attributable to variation in the independent (predictor) variables and to estimate the relative contribution of the independent variables to the shared variance in the dependent variables (Grissom & Kim, 2012). When the fit is good, it provides support for the theorised connections among the variables. The significance of those relationships is often indicated by the amount of shared variance explained in the outcome variables (i.e., $R^2$; Fairchild, Mackinnon, Taborga, & Taylor,
2009).

**SEM with the full sample.**

This illustration starts with the mediational model posited in Chapter 4. It is hypothesised that one of the key mechanisms through which stress and cognitive processes affect mental health is through their impact on people’s basic psychological needs. Table 24 shows the inter-correlation matrix, together with means, standard deviations, and reliability coefficients for each of the observed variables used to examine the relationships between stress, basic psychological needs, and mental health and wellbeing.

Note that positive and negative affect are not included in these SEM models, unlike the previous LPA models. This is because affect (especially negative affect) routinely correlates very, very highly with psychological distress and mental illness, which violates the assumption of conditional independence and often leads to issues with linear dependency.

Table 24

*Overall Correlations, Means, Standard Deviations and Alpha Coefficients for Observed Variables*

<table>
<thead>
<tr>
<th>Measure</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Perceived stress (6 items)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. BPNS - Autonomy</td>
<td>-.41</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. BPNS - Competence</td>
<td>-.48</td>
<td>.59</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. BPNS - Relatedness</td>
<td>-.28</td>
<td>.60</td>
<td>.48</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Anxiety</td>
<td>.67</td>
<td>-.47</td>
<td>-.55</td>
<td>-.39</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Depression</td>
<td>.56</td>
<td>-.57</td>
<td>-.53</td>
<td>-.50</td>
<td>.63</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. SF-36 MCS</td>
<td>-.70</td>
<td>.51</td>
<td>.54</td>
<td>.36</td>
<td>-.66</td>
<td>-.66</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8. Life Satisfaction</td>
<td>-.48</td>
<td>.54</td>
<td>.50</td>
<td>.48</td>
<td>-.46</td>
<td>-.55</td>
<td>.55</td>
<td></td>
</tr>
</tbody>
</table>

| M                             | 17.61| 5.12 | 4.96 | 5.55 | 7.92 | 4.56 | 51.92| 22.69|
| SD                            | 7.02 | 1.17 | 1.19 | 1.01 | 4.20 | 3.65 | 19.72| 6.77 |

*Note.* All correlations significant at the .001 level (two-tailed). Cronbach’s alpha reliability coefficients for each of the (sub)scales are displayed in parentheses on the horizontal. *N* = 375.

Inspection of the correlation matrix reveals a strong correlation between Perceived Stress and the SF-36 MCS (.70). According to Tabachnick & Fidell (2013),
correlations greater than .70 included within the same analysis can lead to issues of multicollinearity. Recommended options for dealing with multicollinearity include omitting one of the variables or forming a composite variable from the scores of the two highly correlated variables. However, prior to taking such action, collinearity diagnostics were re-run in SPSS to verify whether this was the problem. The tolerance values (i.e., the proportion of variance in the outcome variable that cannot be accounted for by the other predictors) was greater than .20 and the variance inflation factor (VIF; i.e., 1/tolerance) was less than 10.00, which are the general rules of thumb used to indicate potentially problematic variables (Kleinbaum, Kupper, Muller, & Nizam, 2007). Consequently, both variables were retained for the analyses.

**Measurement model.**

The measurement model is portrayed in Figure 22.

![Figure 22](image)

*Figure 22.* Visual diagram of the measurement model. Only the significant pathways are displayed for visual clarity. BPNS = Satisfaction of basic psychological needs. MCS = SF-36 Mental health component summary (quality of life). LifeSat = Satisfaction with Life. $N = 375$. 
For the initial measurement model, the mental health variables were specified as indicators of a higher-order latent variable. Note that the correlations between the latent variables are all moderate to high, which is to be expected with this mix of psychological variables. Model fit statistics for the measurement model indicated a close fit to the data ($\chi^2(17) = 68.89, p < .001$, CFI = .96, RMSEA = .09 [90% CI: .06, .113], SRMR = .04). Although the standardised residuals indicated that the model did not adequately explain the relationship between life satisfaction and BPN – Relatedness, there were no feasible improvements to the measurement model that made sense, based on the modification indices.

**Structural model.**

The mediation model was specified with age and history of mental health included as independent variables in the model to control for their well-known influence on stress and mental health. Model fit statistics indicated that the structural model was a good fit to the data ($\chi^2(27) = 97.82, p < .001$, CFI = .95, RMSEA = .08 [90% CI: 0.07, 0.10], SRMR = .04). The standardised parameter estimates are presented in Figure 23.

As expected, the standardised parameter estimates indicate that previous mental illness significantly predicts current mental health ($B = .13, p < .001$) and stress ($B = .36, p < .001$). Age directly influences stress ($B = -.21, p = .001$) but not mental health ($B = -.01, p = .649$). Parameter estimates between the three latent variables are all moderately strong and significant, ranging from .47 to -.61, and indicate that BPN partially mediates the relationship between stress and mental health. In practical terms, this means that as stress increases, satisfaction of basic needs reduce, and mental health deteriorates. With indirect effects of .34, $p < .001$, relative to total effects of .81, $p < .001$, the indirect effect size of stress on mental health via basic psychological needs is moderately large (41.98%; Fairchild, et al., 2009).

According to the $R^2$ statistics, this model explains 94% of the variance in mental health, which is surprisingly high. This implies that most of the variance in mental health is explained by the variables in this model. If this is correct, then perceived stress and satisfaction of basic psychological needs are critical factors that underpin mental health and wellbeing in the community.
Based on these findings, one could conclude that basic psychological need satisfaction is a significant (albeit partial) mediator in the relationship between stress and mental health and, therefore, a worthy target for intervention. The findings also suggest that improvements in mental health are highly likely to result from reductions in perceived stress and increased satisfaction of one’s basic psychological needs for competence, autonomy, and relatedness. Therefore, any intervention that significantly reduces perceived stress and increases satisfaction of basic psychological needs is likely to improve mental health outcomes for people.

Although further research would be needed to confirm the model, if supported, one could argue that perceived stress and basic psychological need satisfaction represents key transtheoretical factors, which could be actively assessed and targeted in prevention and treatment interventions to improve mental health outcomes. They are transtheoretical to the extent that interventions from any theoretical (and disciplinary) persuasion potentially tap into these variables. For instance, psychotropic medication, physical activity, mindfulness and/or problem solving with a counsellor can help people reduce their stress levels directly and the human interaction that takes place within those interventions can help meet one’s need for relatedness also. Practitioners promoting and
supporting individuals’ choices increase one’s sense of autonomy, and psychoeducation and skills training can help one feel more competent. Hence interventions from any persuasion could potentially help improve mental health outcomes and in these ways, the model illustrates how mental health outcomes can be significantly improved.

Extrapolating further, one might argue that the transtheoretical model also sheds light on why controlled conditions in randomised controlled trials demonstrate improvement in mental health, albeit not usually to the same extent as the intervention arm of the trial. Within the controlled condition, if participants’ basic psychological needs are supported and enhanced (e.g., through choice, information received, rapport with researchers or other participants in the study) and stress is reduced (which can occur naturally in a process known as regression towards the mean or when a crisis is averted), then improvements in mental health could be expected.

Based on the strength of the current results, one might expect that the perceived stress - basic psychological need satisfaction – mental health relationship would apply to pretty much everyone in the sample and, potentially, the wider community. However, as noted in the early chapters, models usually fit some people and not others, which may be one reason why biopsychosocial interventions help some people but not others. Therefore, before getting carried away any further with conclusions and potential implications of the current model, the next section examines how well the model fits the subgroups identified in part two.

**Part Four  Subgroup Analyses**

**SEM with subgroups.**

To better understand the extent to which subgroups in mental health can affect the testing of theoretical models, this section tests whether the mediation model identified in the previous section applies equally across the latent profiles identified in Part 2. Particular attention is given to the Thriving (low risk) and Getting By (marginal risk) latent profiles for two reasons: first, they were the largest subgroups, which helps ensure that the following analyses have adequate power; and, second, subclinical populations are often understudied, even though they offer the greatest potential for effective and efficient prevention and early intervention, and therefore merit closer examination. In the current study, this is represented by the Getting By subgroup.

As an initial step, the mediation model was run with each of the Thriving and Getting By subgroups separately. On both occasions, the model failed to converge due to problems with the mental health latent variable. This flagged non-invariance issues.
Although before undertaking invariance testing across the subgroups, the model was re-run with the mental health outcome variables re-specified as lower-order single indicator latent variables. The adjusted model was a good fit to the data for the full sample (Satorra-Bentler $\chi^2(16) = 37.36, p = .002$, CFI = .99, RMSEA = .06 [90% CI: 0.04, 0.09], SRMR = .03). The pathways from perceived stress and basic psychological needs, and the four mental health variables were all significant (see Figure 24), with the model explaining between 54% and 76% of the variables in the outcome variables. This served as a baseline for future comparisons.

Next the grouping option in Mplus was employed. The single indicator latent variables were respecified for each subgroup to take into account: (a) classification error associated with the assignment of participants to a latent class based on their posterior class membership probabilities, and (b) the differences in variance and sample size between subgroups (Asparouhov & Muthén, 2014; Vermunt, 2010). Table 25 shows the alpha reliability coefficients and corrected standard errors for the overall sample and subgroups, which were used to specify the single indicator latent variables in the model. The standardised scores for this were taken from the SEM analyses in Part 3.

Table 25

<table>
<thead>
<tr>
<th>Latent variable</th>
<th>Full sample (N = 375)</th>
<th>Thriving (low risk) (n = 133)</th>
<th>Getting By (marginal risk) (n = 119)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\alpha$</td>
<td>$SE$</td>
<td>$\alpha$</td>
</tr>
<tr>
<td>Perceived stress</td>
<td>.87</td>
<td>.13</td>
<td>.88</td>
</tr>
<tr>
<td>Anxiety</td>
<td>.85</td>
<td>.15</td>
<td>.86</td>
</tr>
<tr>
<td>Depression</td>
<td>.82</td>
<td>.18</td>
<td>.82</td>
</tr>
<tr>
<td>SF-36 MCS</td>
<td>.70</td>
<td>.17</td>
<td>.79</td>
</tr>
<tr>
<td>Satisfaction with life</td>
<td>.89</td>
<td>.11</td>
<td>.90</td>
</tr>
</tbody>
</table>

Note. $SE = Standard error. MCS = Mental component summary score.

The lower-order model was then run for the Thriving and Getting By subgroups separately. Model fit statistics indicated that it was a very good fit to the data for the Thriving subgroup (Satorra-Bentler $\chi^2(16) = 15.27, p = .505$, CFI = 1.00, RMSEA = .00 [90% CI: 0.00, 0.07], SRMR = .04) but a poor fit for the Getting By (marginal risk) subgroup (Satorra-Bentler $\chi^2(16) = 34.74, p = .004$, CFI = .84, RMSEA = .10 [90% CI: 0.05, 0.14], SRMR = .07). Not surprisingly, when the subgroups were examined
together (using the grouping function in Mplus), the baseline statistics indicated a poor fit to the data (Satorra-Bentler $\chi^2(34) = 72.34, p < .001$, CFI = .89, RMSEA = .09 [90% CI: 0.06, 0.12], SRMR = .06). The chi-square contributions from each group were: Thriving (low risk) = 22.79, and Getting By (marginal risk) = 49.54. Figure 25 and 26 presents the standardised pathway coefficients for each subgroup compared to the full sample.

*Figure* 24. Structural model with the standardised parameter estimates for the full sample. Only the significant pathways are displayed for visual clarity. Hx MH = History of mental illness. BPNS = Satisfaction of basic psychological needs (A = Autonomy; C = Competence; R = Relatedness). MCS = SF-36 Mental health component summary (quality of life). LifeSat = Satisfaction with life. $N = 375$
Figure 25. Structural model with the standardised parameter estimates for the Thriving subgroup (n = 133).
Figure 26. Structural model with the standardised parameter estimates for the Getting By subgroup (n = 133). *Note*. The BPNS-R standard error (.20) was not significant. Only significant pathways are displayed for clarity.
Figure 27. Structural model with the standardised parameter estimates for the combined Thriving and Getting By subgroups (n = 252). Only the significant pathways are displayed for visual clarity. Hx MH = History of mental illness. MCS = SF-36 Mental health component summary (quality of life). BPNS = Satisfaction of basic psychological needs (A = Autonomy; C = Competence; R = Relatedness). SWL = Satisfaction with Life.

Inspection of the standardised pathway coefficients for the subgroups revealed some significant differences from the patterns and figures obtained for the full sample (Figure 27). For instance, the relationship between stress and basic psychological need satisfaction was strong for the full sample (B = .56) but was not significant for either subgroup when analysed separately. Basic psychological need satisfaction was a significant predictor of depression in the Thriving subgroup but not in the Getting By group and it was not significantly related to anxiety or quality of life for either group.

The proportion of variance explained also differs quite markedly across the two subgroups compared to the overall sample also (see Table 26). The fairly low $R^2$ figures for the mental health outcome variables in the Getting By (marginal risk) group
indicates that the model is not a good representation of the mechanisms that underpin mental health and wellbeing for them. This is further born out in the summary of indirect effects of stress on the mental health variables in Table 27.

Table 26

Comparison of Variance Explained for the Latent Variables by Subgroup

<table>
<thead>
<tr>
<th>Latent variable</th>
<th>Full sample N = 375</th>
<th>Thriving (low risk) n = 133</th>
<th>Getting By (marginal risk) n = 119</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( R^2 ) ( p )</td>
<td>( R^2 ) ( p )</td>
<td>( R^2 ) ( p )</td>
</tr>
<tr>
<td>Basic Psychological Needs</td>
<td>.32 &lt;.001</td>
<td>.15 .328</td>
<td>.17 .580</td>
</tr>
<tr>
<td>Anxiety</td>
<td>.71 &lt;.001</td>
<td>.29 .001</td>
<td>.18 .051</td>
</tr>
<tr>
<td>Depression</td>
<td>.69 &lt;.001</td>
<td>.29 .030</td>
<td>.16 .094</td>
</tr>
<tr>
<td>Mental health-related quality of life</td>
<td>.77 &lt;.001</td>
<td>.19 .025</td>
<td>.24 .003</td>
</tr>
<tr>
<td>Satisfaction with life</td>
<td>.55 &lt;.001</td>
<td>.27 .001</td>
<td>.10 .283</td>
</tr>
</tbody>
</table>

Table 27

Comparison of Indirect Effects of Stress on Mental Health via Basic Psychological Needs by Subgroup

<table>
<thead>
<tr>
<th>Latent variable</th>
<th>Full sample N = 375</th>
<th>Thriving (low risk) n = 133</th>
<th>Getting By (marginal risk) n = 119</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \text{Estimate} ) ( p )</td>
<td>( \text{Estimate} ) ( p )</td>
<td>( \text{Estimate} ) ( p )</td>
</tr>
<tr>
<td>Anxiety</td>
<td>.18 &lt;.001</td>
<td>.02 .581</td>
<td>-.02 .378</td>
</tr>
<tr>
<td>Depression</td>
<td>.33 &lt;.001</td>
<td>.12 .029</td>
<td>-.04 .251</td>
</tr>
<tr>
<td>Mental health-related quality of life</td>
<td>-.19 &lt;.001</td>
<td>-.05 .168</td>
<td>-.03 .256</td>
</tr>
<tr>
<td>Satisfaction with life</td>
<td>-.36 &lt;.001</td>
<td>-.17 .006</td>
<td>-.05 .111</td>
</tr>
</tbody>
</table>

These results indicate that basic psychological needs play a small and insignificant role in the relationship between stress and mental health for people who have reasonable to strong mental health. This finding sits in stark contrast to the conclusions one may have made based on the overall sample results, that is, that basic psychological need satisfaction plays a significant role mediating in the relationship between stress and mental health, and that along with perceived stress, basic psychological need satisfaction potentially represents a key mechanism underpinning mental health and wellbeing in the community.

That said, inspection of the standardised pathway coefficients for the subgroups did reveal three pathways that were consistently significant across the subgroups,
although the strength of the parameter estimates varied somewhat. These included the relationships between (a) stress and anxiety, (b) stress and quality of life, and (c) basic psychological needs and life satisfaction. These findings are consistent with the wider literature (e.g., Kulmala et al., 2013; Wiegner, Hange, Björkelund, & Ahlborg, 2015) and indicate that some pathways and mechanisms may be more universal than others.

To identify the source of difference between the two groups, further invariance testing was undertaken. To begin with, metric invariance was tested in which the chi-square from an unrestricted model (i.e., with all parameters allowed to be unequal across groups) was compared to the chi-square from a model with only the factor loading constrained to equal across groups. No intercepts were estimated in these models and the means were set to zero, which was required for the model to be identified. The unrestricted model (with all parameters freely estimated in the two groups) fit the data well (CFI = .96, RMSEA = .07 [90% CI: 0.02, 0.11], SRMR = .04) and the overall chi-square was significant, $\chi^2(20) = 32.60, p = .037$. The metric invariance model with factor loadings constrained to equal across groups was a significantly poorer fit, $\chi^2(20) = 32.60, p = .037$, $\Delta \chi^2(14) = 39.74, p < .001$, indicating non-invariant factor loading(s). Examination of the unstandardised parameter estimates revealed that the HADS depression scale was non-invariant across groups. Comparing the chi-square from a model with specific factor loadings were unconstrained to the metric invariance model, revealed partial metric invariance (Byrne, Shavelson, & Muthén, 1989). That means that some of the difference between individuals arises from differences in the way they respond to the depression scale rather than differences on the latent variable. In this case, individuals in the Thriving subgroup report nil or minimal symptoms of depression, which leads to little variance within that class. Conversely, individuals in the Getting By subgroup report quite a range of depressive symptoms leading to a wide range of scores and large variance within that class. Consequently, caution is needed when comparing these subgroups (Vermunt & Magidson, 2004) as the correct regression relationships between the latent variables across and within the classes remain unclear.

To find the correct regression relationships between latent variables across and within classes, more advanced statistical techniques are needed, such as structural equation mixture modelling (Tueller & Lubke, 2010; Jedidi, et al., 1997) and Bayesian finite mixture models (K.-H. Yuan & Bentler, 2010). The next section of this chapter considers how the problems with latent variable models can be overcome within a
single analysis by employing mixture SEM.

**Structural Equation Mixture Modelling.**

Similar to multigroup SEM analyses, mixture SEM assesses the fit of a specified model across subgroups. However, in mixture SEM, group membership is not observed or determined a priori. Instead the subgroups (latent classes) are determined as part of the analyses, taking into account various forms of unobserved heterogeneity. For example, there may be differences in how variables relate with each other for different subgroups (i.e., structural differences) or the meaning of different constructs for different people (i.e., measurement invariance; Vermunt, Tran, & Magidson, 2008) (i.e., measurement invariance; Vermunt & Magidson, 2014).

As noted in the Method chapter, mixture SEM analyses involve fitting a series of models with differing constraints on the model, with an increasing number of classes. The first model variation to be tested, MM1, is a measurement invariant model in which factor loadings, parameter estimates (slopes), variances and residual variances are specified to be equal across classes. If this constrained model holds, then classes can be directly compared. In the second model variation (MM2), means, intercepts and slopes are free to vary across classes. If this model holds, the class differences can be due to other factors and have to be interpreted accordingly. The third model variation (MM3) is the least restrictive model as it allows all of the parameters to freely vary across classes. Support of this model indicates that the constructs in the model may not be measured the same way across classes; in other words, the measures tap into different constructs within each class. This is relevant when subgroups of individuals have different interpretations of the construct.

Models were fitted with an increasing number of classes and the fit of the different models was compared. As with LPA, the number of latent classes in mixture SEM was examined using the BIC, AIC, and aBIC. Lower values on these statistics indicate better model fit. The LMR and BLRT were examined as well, with significant $p$-values (i.e., $p < .05$) for these tests indicating that $k$-1 class is a statistically better fit to the data. Due consideration was also given to the form of the SEM model given the number of classes.
Table 28

Fit of the Mixture SEM Models with Higher-order Mental Health Latent Variable

<table>
<thead>
<tr>
<th>Model Description</th>
<th>k</th>
<th>Log-likelihood</th>
<th>AIC</th>
<th>BIC</th>
<th>aBIC</th>
<th>Entropy</th>
<th>LMR test</th>
<th>LMR p-value</th>
<th>BLRT</th>
<th>BLRT p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constrained model (Mplus default – invariant)</td>
<td>1</td>
<td>-2911.33</td>
<td>5860.38</td>
<td>5966.40</td>
<td>5880.74</td>
<td>.60</td>
<td>15.42</td>
<td>.033</td>
<td>16.29</td>
<td>.000</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>-2903.19</td>
<td>5856.23</td>
<td>5973.04</td>
<td>5877.86</td>
<td>.70</td>
<td>10.55</td>
<td>.623</td>
<td>11.14</td>
<td>.013</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>-2897.62</td>
<td>5853.61</td>
<td>5983.20</td>
<td>5878.50</td>
<td>.72</td>
<td>7.22</td>
<td>.533</td>
<td>7.63</td>
<td>.217</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>-2893.80</td>
<td>5852.87</td>
<td>5994.02</td>
<td>5880.02</td>
<td>.76</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>n.a.</td>
<td>5852.87</td>
<td>5994.02</td>
<td>5880.02</td>
<td>.76</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Means, intercepts and slopes free to vary (partially invariant)</td>
<td>1</td>
<td>-2911.33</td>
<td>5851.24</td>
<td>5969.05</td>
<td>5873.87</td>
<td>.30</td>
<td>30.56</td>
<td>.060</td>
<td>31.42</td>
<td>.000</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>-2895.62</td>
<td>5831.08</td>
<td>5972.45</td>
<td>5858.23</td>
<td>.58</td>
<td>28.91</td>
<td>.329</td>
<td>48.07</td>
<td>.000</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>-2789.54</td>
<td>5829.67</td>
<td>5994.60</td>
<td>5861.34</td>
<td>.55</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>n.a.</td>
<td>5829.67</td>
<td>5994.60</td>
<td>5861.34</td>
<td>.55</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>n.a.</td>
<td>5829.67</td>
<td>5994.60</td>
<td>5861.34</td>
<td>.55</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Measurement parameters free to vary (non-invariant)</td>
<td>1</td>
<td>-2911.33</td>
<td>5773.58</td>
<td>5907.10</td>
<td>5799.22</td>
<td>.62</td>
<td>114.67</td>
<td>.240</td>
<td>117.09</td>
<td>.000</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>-2852.79</td>
<td>5747.40</td>
<td>5912.33</td>
<td>5779.08</td>
<td>.60</td>
<td>41.31</td>
<td>.572</td>
<td>42.18</td>
<td>n.a.</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>-2831.70</td>
<td>5721.81</td>
<td>5918.15</td>
<td>5759.52</td>
<td>.57</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>n.a.</td>
<td>5721.81</td>
<td>5918.15</td>
<td>5759.52</td>
<td>.57</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>n.a.</td>
<td>5721.81</td>
<td>5918.15</td>
<td>5759.52</td>
<td>.57</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. n.a. = log-likelihood for H_0 was not calculated as solution did not converge (despite Miterations being increased, as suggested). N = 375.

Table 28 shows the information criteria (IC), entropy, and likelihood ratio tests for the models. The p-value of the BLRT tests suggested that adding profiles beyond four was necessary but when models with five or more classes were specified, error messages arose indicating that the best log-likelihood was not replicated and, in the six-class model, the latent variable covariance matrix was not positive definite. Further inspection revealed that there were less than five participants in two of the classes, suggesting that the model was trying to extract too many classes (Miettunen, Nordström, Kaakinen, & Ahmed, 2016).

The BIC results suggest that the two-class measurement constrained model was the best fit. Inspection of the technical output indicated a measurement problem in one class due to a correlation greater or equal to one between the two latent variables, mental health and basic psychological need satisfaction (r = 1.026). Although a correlation greater than one is feasible in some situations (i.e., a one unit change on one factor leads to a change in the other factor that is greater than one), more often than not
it indicates measurement issues such as a linear dependency and lack of discriminant validity between the observed measures. As the problem relates to the higher-order variable, the decision was made to re-run the mixture SEM models with the mental health indicators as lower order variables (akin to Figure 24).

Results for the re-specified mixture SEM are presented in Table 29. The AIC and BLRT suggest that a seven-class model merits testing, however when it was attempted, the first-order derivative product matrix was non-positive definite. Further inspection revealed that two of the seven classes contained less than five individuals, so the parameter estimates could not be reliably estimated.
Table 29

*Fit of the Re-Specified Mixture Structural Equation Models with Lower-order Mental Health Outcome Variables*

<table>
<thead>
<tr>
<th>Model</th>
<th>Log-likelihood</th>
<th>AIC</th>
<th>BIC</th>
<th>aBIC</th>
<th>Entropy</th>
<th>LMR test</th>
<th>LMR p-value</th>
<th>LRT</th>
<th>BLRT p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single class</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MM1</td>
<td>-2883.80</td>
<td>5831.59</td>
<td>5957.25</td>
<td>5855.73</td>
<td>n.a.</td>
<td>n.a.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Two classes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MM1</td>
<td>-2861.68</td>
<td>5799.37</td>
<td>5948.59</td>
<td>5828.03</td>
<td>.83</td>
<td>43.02</td>
<td>.044</td>
<td>44.22</td>
<td>.000</td>
</tr>
<tr>
<td>MM2</td>
<td>-2838.97</td>
<td>5771.94</td>
<td>5956.51</td>
<td>5807.39</td>
<td>.47</td>
<td>88.65</td>
<td>.012</td>
<td>89.65</td>
<td>.000</td>
</tr>
<tr>
<td>Three classes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MM1</td>
<td>-2841.05</td>
<td>5770.09</td>
<td>5942.87</td>
<td>5803.27</td>
<td>.76</td>
<td>40.15</td>
<td>.274</td>
<td>41.28</td>
<td>.000</td>
</tr>
<tr>
<td>MM2</td>
<td>-2813.41</td>
<td>5734.81</td>
<td>5946.86</td>
<td>5775.54</td>
<td>.67</td>
<td>58.53</td>
<td>.429</td>
<td>59.43</td>
<td>.000</td>
</tr>
<tr>
<td>MM3</td>
<td>-2806.66</td>
<td>5731.31</td>
<td>5909.66</td>
<td>5751.02</td>
<td>.66</td>
<td>57.52</td>
<td>.016</td>
<td>58.73</td>
<td>.020</td>
</tr>
<tr>
<td>Four classes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MM1</td>
<td>-2828.81</td>
<td>5757.95</td>
<td>5953.96</td>
<td>5795.32</td>
<td>.77</td>
<td>23.81</td>
<td>.290</td>
<td>24.48</td>
<td>.000</td>
</tr>
<tr>
<td>MM2</td>
<td>-2775.21</td>
<td>5704.43</td>
<td>6006.80</td>
<td>5762.50</td>
<td>.74</td>
<td>53.32</td>
<td>.746</td>
<td>53.92</td>
<td>.000</td>
</tr>
<tr>
<td>Five classes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MM1</td>
<td>-2819.44</td>
<td>5750.88</td>
<td>5970.79</td>
<td>5793.12</td>
<td>.81</td>
<td>18.22</td>
<td>.343</td>
<td>18.73</td>
<td>.429</td>
</tr>
<tr>
<td>MM2</td>
<td>-2753.27</td>
<td>5690.53</td>
<td>6051.81</td>
<td>5759.92</td>
<td>.70</td>
<td>42.67</td>
<td>.219</td>
<td>43.17</td>
<td>.020</td>
</tr>
<tr>
<td>Six classes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MM1</td>
<td>-2810.15</td>
<td>5744.31</td>
<td>5987.78</td>
<td>5791.07</td>
<td>.78</td>
<td>22.17</td>
<td>.099</td>
<td>22.80</td>
<td>.000</td>
</tr>
<tr>
<td>MM2</td>
<td>-2739.33</td>
<td>5692.66</td>
<td>6112.84</td>
<td>5773.36</td>
<td>.71</td>
<td>24.28</td>
<td>.838</td>
<td>24.55</td>
<td>.667</td>
</tr>
</tbody>
</table>

*Note. N = 375.*

Inspection of the remaining fit statistics reveals that there is no clear cut, single best solution. The *p* values of the adjusted log-likelihood tests of both two-class models confirm that two classes provide a better fit than the single-class model. Among the two-class models, the aBIC, AIC and log-likelihood indicate that the partial invariant model (MM2) fits best, while the BIC favours the non-invariant model, MM1. This mixed pattern of support continued when extra classes were added to the model. Within the three-class model, the indices indicate that the partial invariant model provides the best fit. The results of the four-, five- and six-classes models are consistent with respect to the best fitting model, which is again the partial invariant model. For the partially invariant model, the indices are also in agreement with respect to the need for a fourth and fifth class. The BLRT (perhaps the most reliable test of model fit, according to
simulation studies by Tuller and Lubke (2010) indicates that six classes are needed for the constrained model but five classes suffice for the partial invariant model. For the five-class model, the aBIC, AIC and log-likelihood favour the partial invariant model. Based on these results, the five-class partial invariant model would be the preferred model. However, inspection of the parameter reveals some anomalies, including standardised parameter estimates and indirect effects close to one. Such figures generally flag measurement issues or result from model misspecification. Similar anomalies were found in the four- and six-class partial invariant models. Although the constrained three-class model (which had the lowest BIC value) seemed to avoid these issues, the modification indices flagged similar issues, namely basic psychological need satisfaction covaries with life satisfaction for some people (i.e., Class 1) and depression for others (i.e., Class 3). This suggests that there are important differences across the groups in the way the constructs are measured (i.e., no configural invariance) and/or manifest (i.e., no weak invariance). A non-invariant covariance matrix means that factor scores and parameter estimates cannot be sensibly compared across classes.

With this in mind, a final model variation was tested (MM3) in which basic psychological need satisfaction was freed to covary with life satisfaction (in Class 2) and depression (in Class 3). The resulting BIC, aBIC and adjusted log-likelihood tests favoured the three-class non-invariant model and indicated that it was a superior fit to the data and its substantive interpretation made the most sense as well. The fit statistics are displayed in Table 29.

Table 30 provides a comparison of the variance explained for each of the classes compared to the variance explained by the model when tested with the full sample. None of the class specific models explain as much variance in mental health as the full sample SEM, except for the Class 1 model, which explains 76% of the variance in depression within that class. It is worth noting that only Class 1 retained the same mediation model that was tested with the full sample and that class represented just 39.47% of the overall sample.

Post hoc analyses show that individuals in Class 1 tend to have the highest levels of stress, anxiety and depression and lowest mental health-related quality of life and functioning compared to the other two classes (see Table 31). In contrast, individuals in Class 3 tend to have lower symptoms of stress, anxiety and depression and better mental health. Results of the latent variable multinomial logistic regressions that form part of the mixture SEM output also indicate that individuals in Class 1 and 2 are much more
likely to employ avoidant coping strategies than individuals in Class 3. Conversely, individuals in Class 2 are much more likely to be female and report significantly less positive affect than individuals in Class 3. However, the range of scores for each of these factors varies markedly within each class, which reinforces the point that these classes were not formed purely on the basis of mental health scores but rather individuals were clustered on the basis of how the variables relate to each other.

Table 30

Comparison of Variance Explained by the Three-class Partial Invariant Mixture Model (MM3) and the Full-sample SEM Model

<table>
<thead>
<tr>
<th>Latent variable</th>
<th>Full sample</th>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$R^2$</td>
<td>$p$</td>
<td>$R^2$</td>
<td>$p$</td>
</tr>
<tr>
<td>Basic Psychological Needs</td>
<td>.32</td>
<td>&lt;.001</td>
<td>.25</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Anxiety</td>
<td>.71</td>
<td>&lt;.001</td>
<td>.60</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Depression</td>
<td>.69</td>
<td>&lt;.001</td>
<td>.76</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Mental health-related quality of life</td>
<td>.77</td>
<td>&lt;.001</td>
<td>.58</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Satisfaction with life</td>
<td>.55</td>
<td>&lt;.001</td>
<td>.48</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

Note. n.a. = Values undefined because the variables were free to covary with the Basic Psychological Need Satisfaction latent variable.

Table 31

Characteristics of the Three-Class Partially Invariant Model (MM3)

<table>
<thead>
<tr>
<th>Class</th>
<th>Class proportion</th>
<th>Age</th>
<th>History of mental illness</th>
<th>Stress</th>
<th>Anxiety</th>
<th>Depression</th>
<th>MCS</th>
<th>Life satisfaction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>M (SD)</td>
<td></td>
<td>M (SD)</td>
<td>M (SD)</td>
<td>M (SD)</td>
<td>M (SD)</td>
<td>M (SD)</td>
</tr>
<tr>
<td>1</td>
<td>148, 39.47%</td>
<td>31.04</td>
<td>56.76%</td>
<td>19.30</td>
<td>9.76</td>
<td>5.99</td>
<td>36.19</td>
<td>20.41</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(12.38)</td>
<td></td>
<td>(4.86)</td>
<td>(4.44)</td>
<td>(4.09)</td>
<td>(1.71)</td>
<td>(6.63)</td>
</tr>
<tr>
<td>2</td>
<td>49, 13.07%</td>
<td>27.20</td>
<td>32.65%</td>
<td>18.29</td>
<td>8.64</td>
<td>5.35</td>
<td>38.50</td>
<td>19.85</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(10.19)</td>
<td></td>
<td>(4.76)</td>
<td>(4.02)</td>
<td>(3.60)</td>
<td>(11.87)</td>
<td>(5.68)</td>
</tr>
<tr>
<td>3</td>
<td>178, 47.47%</td>
<td>31.11</td>
<td>29.78%</td>
<td>16.03</td>
<td>6.22</td>
<td>3.13</td>
<td>47.08</td>
<td>25.34</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(11.04)</td>
<td></td>
<td>(4.08)</td>
<td>(3.26)</td>
<td>(2.59)</td>
<td>(9.04)</td>
<td>(6.16)</td>
</tr>
</tbody>
</table>

Note. $N = 375$.

The next step in the model development process would be to identify and refine each of the measurement models before further examining the relationships between the latent variables within each group. However, this is a topic for further research. The
primary objective of this study has been to explore the extent to which the mediation model supported in Part 3 actually applies to individuals within the sample. According to the mixture SEM results just reported, the mediation model is valid for just 40% of the sample (i.e., MM3 Class 1 = 39.47%). The other 60% of the sample comprises two latent classes (subgroup) for whom basic psychological need satisfaction either means something slightly different or it is related to depression and/or life satisfaction in a way that is not well represented by the hypothesised mediation model.

**Chapter Summary**

Effective and efficient prevention and treatment first requires accurate and timely recognition of individuals at-risk along with an accurate understanding of what factors to target for who, when, and how. To-date it has been common practice to screen people based on symptoms of psychological distress or psychopathology. However, this paper has argued that such an approach misses the positive elements of mental health and the protective factors that potentially help mitigate risk and so it doesn’t necessarily provide an accurate guide to risk status. Therefore, the first aim of this study was to determine if meaningful groups of at-risk adults could be identified and differentiated between based on a combination of self-reported measures that capture both positive aspects mental health and wellbeing and symptoms of common mental health problems (i.e., anxiety and depression).

Using latent profile analysis, five latent classes were readily identified and easily interpreted: Thriving (low risk), Getting By (minimal risk) and Struggling (moderate risk), Floundering (high risk) and Languishing (very high risk). Although the latter two classes comprised individuals at high risk of an anxiety disorder and at very high risk for comorbid anxiety and depression respectively, profile analysis demonstrated that the latent classes were not formed purely on the basis of pathological symptoms but they captured particular response patterns across affect, quality of life and wellbeing measures also. These results are consistent with the idea that some factors play a protective role and potentially counterbalance an individual’s risk factors. The risk status assigned to each class reflects that balance.

The latent classes closely resemble Keyes’ (2002, 2005, 2007) model of complete mental health, which was originally based on a national sample in the United States. This suggests that the model may apply to Australian samples too. However, the current study did not find evidence for Keyes’ lowest prevalent subgroup (i.e., < 1%) who were identified as having a mental illness and yet were flourishing at the same
The analysis was then extended to include a range of covariates to determine if they could predict class membership. Age, gender, socioeconomic status, physical health, domestic violence and health behaviours have been previously identified as key social determinants of mental health, so these were added into the analyses as covariates. Only perceived stress levels and a history of mental illness significantly predicted class membership in this study and increased risk.

The second aim of this empirical study was to investigate how important it is to consider subgroups in model testing. The traditional top-down approach to testing models and mechanisms was employed initially, using a common regression-based analysis (i.e., SEM) with the full sample. Results indicated that basic psychological need satisfaction (partially) mediates the relationship between stress and mental health such that an increased sense of competence, autonomy and relatedness potentially mitigates some of the effects of stress and is associated with more adaptive coping responses and better mental health and wellbeing. Conversely, lower satisfaction of these needs is associated with poorer mental health and wellbeing outcomes.

A series of subgroup analyses were then performed and only limited support for the model was found. As a preliminary step, the model was subjected to multigroup SEM using the Thriving and Getting By groups identified earlier. The model was found to be a good fit to the data for the Thriving group but not for the Getting By group. Significant differences in measurement parameter estimates and proportions of variance explained were found, which flagged two things: first, that the mental health measures may have different meanings to different people within the sample, and second, different mechanisms may be at play for different subgroups. To investigate these issues with more rigour, mixture SEM was employed, which is an advanced, hybrid technique that combines SEM with latent class analysis at the same time. The mixture SEM results indicated that the proposed mediation model of stress and mental health was valid for just 40% of the full sample. In the other 60% of the sample, the variables manifest differently and/or basic psychological need satisfaction plays a different role in the relationship between stress and mental health.

In sum, these findings demonstrate that the interrelations of stress and mental health and related variables can vary substantially in the community, and it is overly simplistic to assume a homogenous population. Instead various subgroups or subpopulations appear to exist that differ with respect to the measurement of mental
health and the structural relations among mental health and related variables. The current analyses also highlight that the subgroups are not always identifiable using single observed variables but may be readily identified using a small number of latent classes or profiles.

By exploring latent class membership and differences in regression relationships among stress, mental health and related variables, this study provides evidence that hypotheses concerning the structural relations between mental health and related factors (i.e., models of mental health) should be tested with statistical techniques that (a) account for heterogeneity and (b) identify differences in measurement and structural relations between subgroups.

Even though this has been an exploratory study, so replication with an independent data set is needed to confirm these findings, the current findings strongly support the assertion that it is overly simplistic to assume a homogenous population (Tueller & Lubke, 2010), especially in the field of mental health. This has direct implications for theory development, program development and evaluation.

The next chapter presents a detailed discussion of the findings in relations to the research questions and hypotheses. Implications for theory, practice and policy are considered as well as limitation and directions for future research.
Chapter 7 Discussion and Conclusion

This doctoral research began by asking the question: how well are we doing in the mental health sector and how can we do it better? These questions are commonplace in business management circles and lie at the heart of quality improvement programs, however they have yet to become a routine part of practice in the mental health sector. The motive for asking such questions is to pause and assess what plans, strategies, and processes are working well and what are not, and then identify what can be improved. When such questions are asked on a regular basis, they help drive quality improvement and innovation (U. S. Department of Health and Human Services, 2011; World Health Organization, 2003).

With this broad, strategic intent in mind, this thesis firstly reviewed the effectiveness and efficiency of national mental health programs in Australia. The review found that while the funding, scope and reach of mental health programs has expanded considerably over recent years, prevalence rates for common mental health disorders (such as anxiety and depression) remain high and stable. The review found that most of the national programs had demonstrated efficacy in pilot studies (i.e., they achieve desired outcomes under controlled conditions) but evidence of effectiveness post-implementation was rare and efficiency reports were practically non-existent. Based on current access and efficacy rates, it appears that just one in five people with a mental disorder in Australia is likely to be successfully treated at present. The need for system reform and quality improvement across the sector is clear.

The Australian National Mental Health Commission recently identified a range of structural issues and information gaps that contribute to this very modest treatment rate and have proposed significant system reform. Changes include major restructuring of how mental health services are funded, implementation of a stepped care approach, and greater emphasis on prevention. Findings from the current review support such reforms but also raise questions around the role psychological theory, research and practice may play in the limited effectiveness of the sector: Exactly how accurate are current models of mental health? How effective are the interventions, and how can they be improved?

To explore these questions, key psychological perspectives of mental health were initially reviewed. The review found that, by and large, all the psychological theories, their model(s) of change and associated interventions were well-supported by empirical evidence. In fact, recent meta-analyses have shown that there is little
difference between treatment approaches, in terms of their efficacy when differences in sample sizes are controlled for. Whilst this is consistent with clinical observations, such that some interventions help some people, some of the time, and not others, it is curious that such diverse and sometimes contradictory models and interventions yield such similar results. As the sector currently lacks the ability to predict who will benefit from which intervention, finding the right treatment for clients “remains an art that depends considerably on trial and error” (McMahon, 2014, p.455). Arguably such factors compromise effectiveness and efficiency in the mental health sector too.

If common mental health problems are to be prevented and the effectiveness of treatment interventions is to be improved, then an accurate understanding of the phenomena is needed. Accordingly, Chapter 4 reviewed the current state of knowledge regarding the developmental aetiology of common mental health problems. A stress-diathesis framework was used to synthesise recent findings and integrate them with knowledge accumulated from psychology research and practice. The review found that some variables (e.g., specific gene alleles, social determinants, personality traits) and some process mechanisms apply to some people and not others, even though they may share the same diagnoses. Evidently, just as some psychological models fit or apply to some people and not others, the same occurs with bio-medical models.

Reflecting on all the literature reviewed, two key points emerged: one pertains to how mental health is conceptualised and operationalised, and the other pertains to how mental health and related data are typically analysed in research and evaluation. That is, mental health is commonly defined and assessed in psychiatry and clinical psychology using a medical or pathogenic approach (i.e., number and severity of clinical symptoms over a certain period; Coulombe et al. 2015; Fava et al., 2007). However, this is at odds with the international standard definition of mental health established by the WHO (2004, 2014), which asserts that mental health is more than just the absence of disease or disorder; it includes wellbeing, functioning and dimensions that make life worth living. It was hypothesised that taking a fresh look at mental health data using this type of balanced approach may provide valuable insight into how we can conceptualise and operationalise mental health and illness in a way that improves our ability to screen for mental health problems and better target interventions. It may also shed light on the mixed findings in the literature.

To investigate this hypothesis, a series of latent profile analyses were run with measures of positive and negative mental health and controlling for a large range of
related variables known to influence mental health and wellbeing. Five distinct patterns of positive and negative mental health were found. Each pattern related to a subgroup of people within the non-clinical sample of Australian adults. Characteristics of each subgroup, the extent to which the subgroup profiles reflect risk of common mental health problems and the best predictors of subgroup membership were examined. The results from this analysis support the contention that symptoms are just one part of mental health and that both positive and negative dimensions are important for conceptualising and operationalising mental health (Keyes, 2005, 2007).

With regards to how mental health and related data are usually analysed, it was noted that the vast majority of mental health and related research employs regression-based techniques. These techniques are based on the general linear model, which assumes homogeneity (i.e., everyone in a population can be described by a single probability distribution). However in reality there are considerable differences between individuals, which implies heterogeneity. The mixture modelling results in this study clearly showed that the population was heterogenous and comprised of a mixture of distributions. Each distribution representing a different subgroup, each with its own features and characteristics.

Next, the potential importance of heterogeneity to model development and testing was examined. This was done through a series of SEM analyses examining the impact of the latent subgroups on traditional regression-based modelling techniques. The first step involved testing a novel mediated model of stress and mental health using data from the full sample. Results indicated strong support for the model. In the second step, the model was re-tested using multigroup analysis. The multigroup results indicated that the model was a reasonable fit and valid for the Thriving subgroup but not the Getting By subgroup due to problems with the measurement model. More specifically, there were problems modelling mental health as a higher-order latent variable with the Getting By subgroup, indicating that the model variables relate to each other in ways that are different from the Thriving group. There were also issues with the autonomy scale, such that some of the items meant different things to different people, therefore it is not valid to compare scores on that scale across subgroups. Even when these measurement issues were resolved and the structural model was re-tested, there was no evidence of the mediated relationship in the Getting By subgroup; only direct relationships were found between stress, basic psychological needs, and mental health. Given that the Getting By subgroup represents more than 30% of the sample, these
multigroup SEM results clearly demonstrate that the sample was not homogenous.

To examine if different models apply to different groups of people within the sample, a more advanced statistical technique, mixture SEM, was employed. As discussed in Chapters 4 and 5, mixture SEM integrates latent class analysis and SEM in the one step by looking for latent classes at the same time as it tests proposed models. The mixture SEM results were consistent with those from multigroup SEM with regards to identifying measurement non-invariance (i.e., the items mean different things to different people) for a subgroup of individuals in the sample. However, the mixture SEM results also extended the multigroup analyses by revealing that there were three distinct patterns of relationships between the variables within the model. For some people in the sample, the relationship between stress and mental health was mediated by basic psychological needs; for others, basic psychological needs did not mediate the relationship; and for the final group of people, stress was better modelled as an indicator of mental health than an antecedent. Rather than focussing on the content of these findings, what is important to note here is that these three patterns (or models), and the differences in measurement, were all present within the sample when traditional SEM was used with the full sample but were concealed. Taken together, these results clearly demonstrate that heterogeneity needs to be acknowledged and examined when analysing mental health and related data.

In sum, this thesis has examined effectiveness in mental health at the national level and the intervention level, and then drilled down to some conceptual and analytic factors that may be contributing to the modest intervention effects seen in practice. Five key findings have emerged from the reviews and study undertaken as part of this program of research. First, evidence for the effectiveness and efficiency of mental health programs at the national level is limited and corresponds with prevalence rates remaining high and stable. Second, the effectiveness of available treatments for anxiety and depressive disorders are roughly equivalent, regardless of the theoretical models underpinning them. Furthermore, there is often little difference between treatment programs and active control groups in terms of the amount of change produced. Third, national mental health plans, strategies, and outcome measurement in research and practice focus heavily on psychopathology rather than mental “health” per se. This bias is inconsistent with the international standard definition of mental health (i.e., WHO, 2004, 2014) and yields an incomplete view of mental health. Fourth, the assumption of homogeneity is not appropriate when modelling mental health and related data. Fifth,
when the appropriate statistics are used (which do not assume homogeneity) and mental health is operationalised in line with the standard definition of mental health, results strongly support a dual dimensional model of mental health and reveal subgroups that differ markedly from those solely based on symptom severity. These five findings have implications for mental health theory, research and practice.

This final chapter discusses each of these findings in relation to the aims and context of this research. Implications for theory and research, programs and services, and policy are considered, along with the limitations of the current study and directions for future research. The thesis concludes by summarising the contribution of this research and reiterating the key recommendations for improving effectiveness in the mental health sector.

**Key Finding #1: Limited evidence for the effectiveness and efficiency of mental health programs at the national level**

As just noted, the review of national mental health prevention programs in Australia (reported in Chapter 2) found that evidence for the effectiveness and efficiency of the programs at the national level is limited. There is reasonably strong evidence from pilot studies to support the efficacy of most of the programs but evidence demonstrating effectiveness (ability to achieve planned outcomes under normal conditions) is thin, and efficiency or cost-effectiveness analyses (to ascertain the level of resources needed to produce the benefit) are scarce. With just one in five people (18.40%) with a mental disorder in Australia being successfully treated (based on the current access rate of 46% and efficacy rates of around 40%; Cuijpers et al., 2011; Hunsley et al., 2013; Whiteford et al., 2014), these findings help explain why the prevalence rates for common mental health disorders remain high and steady.

Such figures and findings are not widely discussed. Within the mental health sector and the broader community, there are lots of discussions about unmet mental health needs and shoring up funding for services (APS, 2015; Mitchell, 2015; Patty, 2016). Far less has been said about how the money is being spent, whether it represents value for money, or ensuring that it is having an impact and making a significant difference to the populations’ mental health. Even within the psychology profession, the focus of program evaluations has tended to be on process (what was provided and how) and short-term outcomes (immediately post-treatment) rather than on quality, effectiveness and impact over the medium to longer-term (e.g., Bassilios et al., 2014; Kenter, Cuijpers, Beekman, & van Straten, 2016; Mackey, 2012; Mackey et al., 2016;
The current findings support calls from population health experts who argue that greater attention and investment needs to be placed on prevention (through risk modification) and improving the quality of treatment provided, not just increasing the availability of treatment, if we are to successfully address the high and stable prevalence rates in high income countries such as Australia (e.g., Jorm, 2014; Jorm et al., 2017; WHO, 2014).

The fact that there is limited evidence confirming the effectiveness and efficiency or cost-effectiveness of the national mental health programs represents an important gap in knowledge and program management (P. C. Smith, Mossialos, Papanicolas, & Leatherman, 2009). It also represents a missed opportunity to promote quality improvement and greater transparency and accountability within the sector (WHO, 2003). These points will be discussed later in this chapter within the implications for strategy, programs and services section.

**Key Finding #2: Approximate equivalence of mental health treatments**

The review of key psychological perspectives of mental health, their model(s) of change and associated interventions confirms that there is abundant evidence from systematic reviews to show that the interventions “work” in research and treatment settings. That is to say, they benefit a statistically significant portion of individuals within the samples studied, although the size of that portion varies across samples and studies.

The current review found convincing evidence from good quality meta-analyses (e.g., Shinohara et al., 2013; van Zoonen et al., 2014) that the different therapeutic approaches are approximately equivalent in terms of effectiveness, and there is often little difference between treatment programs and active control groups in terms of the amount of change produced. However, the actual success rate of specific interventions, the degree to which individuals are helped, and whether those figures are clinically significant and meaningful to consumers and carers was not clear.

The finding of approximate equivalence of psychological therapies is an interesting one. It is consistent with common factors theory (Wampold, 2001, 2015), which proposes that there are common factors that account for much of the effectiveness of a psychological treatment. Rosenzweig (1936) raised this idea early last century while discussing some of the therapies of his time. He observed that proponents of different approaches could all point to notable successes and therefore implied that their ideology was true. However, he asserted that “More detached observers, on the
other hand, surveying the whole field tend, on logical grounds, to draw a very different conclusion” (p.412). He went on to argue that such theoretically conflicting procedures, even if they yield success, cannot be a reliable indicator of the validity of theory. He proposed that, irrespective of the model of change proposed, the factors actually operating across therapies were likely to be the same. Forty years later, the idea that all psychotherapies are effective became known as the Dodo bird verdict (referring to a scene from Alice in Wonderland that Rosenzweig had cited in his original article).

More recently, Wampold and colleagues have championed the common factors theory (e.g., Laska, Gurman, & Wampold, 2014; Wampold, 2001, 2015). After extensive comparative, dismantling, and constructive analysis studies, Wampold and colleagues concluded that adding or removing components of treatment did not change the effects of the core treatment (Ahn & Wampold, 2001) and that therapist-related factors are more important than specific therapeutic approach for producing psychotherapeutic change (Wampold, 2010, 2007, 2001). In combination with individual client factors and environmental factors (each accounting for up to 20% of the variance in treatment outcomes; e.g., Beidas et al., 2015), therapist and process-related factors could theoretically account for approximate equivalence and thereby help explain why there is often little difference between treatment programs and active control groups in RCTs in terms of the amount of change produced (e.g., Goodyer et al., 2016; Honyashiki et al., 2014; Shinohara et al., 2013; van Zoonen et al., 2014).

Some authors dispute common factors theory and the approximate equivalence of different treatment models (e.g., Asnaani & Foa, 2014), often believing particular approaches (especially CBT) are superior to others. However, this belief is not substantiated by findings from the current literature review, which indicate that such differences vanish when meta-analyses correctly control for differences in sample size (e.g., Shinohara et al., 2013; van Zoonen et al., 2014).

Nevertheless, two things remain unclear: first, how common factors interact with individual factors and “the host of other moderating variables in psychotherapy” (Beutler, 2014, p.496); and, second, whether it is the same group or type of people that benefit from mental health interventions irrespective of the theoretical approach taken or whether there are distinct subgroups of people for which the specific approach or technique plays a part. Uncovering such patterns may help with efforts to predict treatment outcomes.
Key Finding #3: Mental health is routinely operationalised in terms of psychopathology rather than mental “health” per se

As discussed in Chapter 4, over the past century, mental health has been widely conceptualised using a medical (deficits) model. This approach conceptualises and operationalises mental health in terms of clinical symptoms, dysfunction and disease (Coulombe et al., 2016; Fava et al., 2006). The implicit assumption is that health equates to an absence of disease or dysfunction. In contrast, the WHO’s (2004; 2014) definition of mental health implies that there are two, equally important, dimensions within mental health – wellbeing and dysfunction.

Results from this study support the dual dimensional model of mental health. The results also indicate that the relationship between positive and negative dimensions of mental health are not strictly linear. On the one hand, the results highlight the inverse relationship between the positive and negative dimensions of mental health, such that: as negative affect and anxiety increases, quality of life and functioning decreases; and, as positive affect decreases, life satisfaction decreases and depressive symptoms increase. These findings are consistent with expectations and results from recent meta-analyses (e.g., Hofmann, Wu, & Boettcher, 2014; Hofmann, Wu, Boettcher, & Sturm, 2014; Riihimäki et al., 2016) as well as numerous epidemiology and longitudinal studies, across settings and populations (e.g., D'Avanzato et al., 2013; Ohaeri, Awadalla, & Gado, 2009; Shrestha et al., 2015).

On the other hand, the current results indicate that even with significant symptoms of anxiety and depression, individuals can vary considerably in terms of their wellbeing. For example, the current analyses found that an individual who scored a 6 on both the HADS anxiety subscale and the depression subscale could be Thriving (Low risk), Getting By (Marginal risk), Struggling (Moderate risk) or Floundering (High risk). This occurs because there is a wide range of symptom scores present within each of these groups (see Table 18 in Chapter 6). What differs between the groups is the strength of their positive mental health wellbeing relative to their symptoms. Evidently, it is the combination of positive and negative elements that is important to mental health, not just the dysfunction and symptoms of psychopathology.

To a large extent these findings are consistent with the positive psychology approach to mental health, which focuses on people’s strengths, not just symptoms or problems, to help people achieve a better quality of life (M. Slade, 2010). Results from the SEM analyses support assertions that some of the processes that affect positive
mental health are distinct from those affecting mental ill-health (e.g., Winzer et al., 2014; Huppert & Whittington, 2003), for example, satisfaction of basic psychological needs consistently mediated the relationship between stress and life satisfaction (an indicator of positive mental health) but not stress and anxiety (an indicator of negative mental health). This illustrates that different variables and processes involved in positive mental health can differ from those that are important for symptoms of psychopathology (Keyes, 2005b; Provencher & Keyes, 2011; Westerhof & Keyes, 2010).

At the same time, the current data did not support modelling mental health as two high-order latent variables: one for positive mental health and one for negative mental health, which one might expect if (positive) mental health constitutes a distinct entity (Diener & Emmons, 1984; Schlosser, 1990). Instead the results suggested that it was better to model the various measures of mental health separately. This is consistent with the argument that mental health might be better modelled as a formative latent variable, rather than a reflective one (as discussed in Chapter 5).

**Key Finding #4: The assumption of homogeneity is not appropriate**

As discussed in Chapter 4, traditional variable-oriented analytic strategies, which are based on correlations between variables, are useful for seeing the big picture of how specific variables relate to each other at the group level. Such analyses are based on the assumption that everyone in a population can be described by a single probability distribution and, therefore, it is commonly assumed that a good fitting model applies to everyone within the sample. But what if the basic underlying assumption is wrong? What if a single distribution over-simplifies matters and misses important differences that exist? It was hypothesised that these differences could be the key to understanding why some mental health models fit or apply to some people but not others and, in turn, why some interventions benefit some people but not others even though they may have the same presenting problem or diagnosis.

The results were clear. The community sample of Australian adults could not be adequately represented by a single distribution (i.e., a one-class model), rather it contained a mixture of five distributions (i.e., a five-class model). Each of the five distributions represented a different pattern of responding to mental health and wellbeing measures. The unobserved patterns across these variables indicate qualitative differences that exist between people, and hence need to be identified and accounted for when modelling mental health and related data.

Further confirmation of this came from the results of the mixture SEM analyses,
which provided a much more rigorous examination of heterogeneity in the sample. The results highlighted that people within the sample respond to measures in different ways (i.e., measurement non-invariance) and that three models would be needed to accurately represent the different ways that the stress and mental health variables in the model relate to each other.

The most surprising finding was that the original mediation model was valid for just 39.47% of the sample. It was surprising because the SEM analyses with the full sample had rendered strong support for the model and, ordinarily, it would have been enough to indicate that the model reflected an important mediational mechanism – one that could be potentially targeted through intervention to help improve mental health. Yet mixture SEM showed that the model was not accurate for a large part of the sample (just over 60%). This indicates that the assumption of homogeneity can severely compromise the accuracy and specificity of research results and subsequent conclusions.

Identifying latent classes that are qualitatively different from each other mirrors trends in other areas of psychology where LVMM has been employed (e.g., lifestyle and chronic disease management (Hardie et al., 2015; Mccarthy et al., 2015); attachment (Olsen, 2013); perinatal mental health (Postpartum Depression: Action Towards & Treatment, 2015); and dual diagnoses (Salom et al., 2016). Within these contexts, subtypes or subgroups that are qualitatively different from one another have also been identified, each with distinct risk profiles and characteristics. This has enabled more tailored and specific intervention recommendations to be made for each subtype/group.

To date, such recommendations have been mostly based on the latent class analysis or LPA rather than specific models or mechanisms identified and refined for each of the latent classes. For this, mixture SEM (Tueller & Lubke, 2010; Jedidi et al., 1997) or Bayesian finite mixture models (e.g., Yuan & Bentler, 2010) would be required. Such analyses are sometimes performed in epigenetic and neurobiological modelling, but to date they have not been common in psychology and mental health-related research. As previously mentioned, this is probably due to the large sample sizes needed to achieve adequate power and, in part, because of the level of expertise needed to competently employ this type of statistical analyses. Such analyses are considered to be advanced and are not routinely taught in graduate courses for mental health professionals. However, given the pressing need to improve model accuracy and intervention effectiveness and efficiency, it seems prudent to find a way of overcoming
these obstacles.

**Key Finding #5: Unobserved mental health subgroups**

The five latent subgroups identified in the current study were formed on a combination of positive and negative mental health (i.e., positive and negative affect, quality of life, life satisfaction, and symptoms of common mental health problems) and were labelled on the basis of their mental health profile: Thriving, Getting by, Struggling, Floundering, and Languishing. This section discusses each of the subgroups in turn.

Individuals in the largest subgroup (Thriving, 35.47%) reported strong positive mental health and few negative symptoms, which are characteristics commonly associated with people who are flourishing (Seligman, 2012). Current results indicate that individuals in this subgroup were more likely to be married, have lower perceived stress, and greater optimism and satisfaction of basic psychological needs for autonomy and competence, relative to the other subgroups. They reported using much less avoidant coping (particularly mental distraction, self-blame, using substances and denial) than other individuals in preference for more adaptive strategies like positive reframing, humour and seeking emotional support. These findings are consistent with past findings within the stress and coping literature, positive psychology, and research into resiliency (e.g., Akin & Akin, 2015; Faulk, Gloria, & Steinhardt, 2013; Seligman, 2008).

The second biggest subgroup (31.73%) in the sample reported elevated anxiety symptoms and were classified as Getting By. Compared to those who were thriving, those Getting By were much less likely to have used illicit drugs in the past but report experiencing significantly greater perceived stress and lower optimism and sense of competence. A smaller subgroup of individuals who were classified as Struggling (8.80%) reported similar levels of anxiety symptoms compared with those Getting By but they reported concurrent depressive symptoms, with low positive affect and poorer quality of life. This is consistent with the anhedonic nature of depression and captures the common phenomena of concurrent and mixed anxiety and depression. Membership in this group was best predicted by the combination of higher perceived stress, lower optimism, and low autonomy.

Around 20% of the sample seemed to be ‘floundering’ with significant negative affect, elevated depressive symptoms, and anxiety symptoms in the clinical range. Compared to people who were thriving, those floundering were much more likely to
have a history of mental illness and report high stress with low levels of autonomy and competence. They were also far less likely to be optimistic and far more likely to employ unhelpful coping strategies such as using substances, self-blame, denial, distraction or disengage from the situation. Individuals who were floundering were much more likely to spend time planning how to resolve their problems but they were far less likely to act to solve the problem(s) compared to others who were thriving. This behavioural pattern is consistent with clinical experience in which “planning” sometimes verges on rumination or procrastination - whilst making a plan is an important step in the problem-solving process, if the plan is not enacted, then repetitive thinking about the problem can become unproductive (Aldao, 2014).

Around 5% of the adults sampled were found to be languishing with markedly impaired functioning and diminished wellbeing and at high risk of comorbid depressive and anxiety-related disorders. Even though this subgroup of people reported more symptoms and lower wellbeing than individuals in the Floundering group, individuals in the Languishing group were much less likely to have a history of mental illness and less likely to drink alcohol. However, they were more likely to have used illicit drugs in the past than individuals in the Floundering group. Membership in the Languishing group was best predicted by the combination of very high levels of perceived stress, anxiety and depressive symptoms.

In the current sample, individuals who frequently use unproductive coping strategies, such as blaming themselves, disengaging and/or using substances to cope with problems were three to four times more likely to be languishing than thriving. Conversely, individuals who frequently seek emotional support, and use positive reframing and humour have two to four times the reduced risk of languishing. These findings reiterate the intimate connection between stress, coping and mental health.

The mental health subgroups also indicate that the relationship between positive and negative dimensions of mental health is not linear nor uniform. Ad hoc analyses revealed that if participants had been classified just on the basis of their self-reported symptoms of psychopathology, then some of the individuals in the Thriving, Getting By, and Struggling subgroups would fit in the clinical range (5.3%, 58.0%, and 54.6% respectively). This pattern is important because it implies that symptoms do not have to dictate a person’s mental health status and wellbeing. It also suggests that symptom scores may not be the most accurate indicators of mental health status - they are only one part of a much bigger picture.
The current mental health subgroups are reminiscent of Keyes’ six states of complete mental health, but only to an extent (Keyes, 2005b, 2007; Keyes et al., 2010). Based on a large, nationally representative, study of adults in the United States (known as the Midlife in the United States study; n = 3,032), Keyes (2005, 2007) proposed six states based on combinations of positive mental health (i.e., flourishing, moderate mental health, and languishing) and either the presence or absence of mental illness. Table 32 displays a comparison of the six states and their prevalence rates with the subgroups identified in the current study. Apart from the obvious differences in sample nationality and measures used, a key difference between the studies is that Keyes operationalised mental illness as a dichotomous variable (i.e., individuals either have a mental illness or they don’t) whereas the current study employed continuous measures, in recognition of the fact that symptoms exist on a continuum. This is a critical difference because it means that the current subgroups take symptom severity into account and potentially reflect the dimensional nature of mental health problems more accurately.

### Table 32

**Comparison of Mental Health Subgroups and Prevalence**

<table>
<thead>
<tr>
<th>Subgroup</th>
<th>Current study</th>
<th>Keyes (2005, 2007)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Portion</td>
<td>Subgroup</td>
</tr>
<tr>
<td>Thriving</td>
<td>35%</td>
<td>Absence of mental illness and flourishing</td>
</tr>
<tr>
<td>Getting by</td>
<td>32%</td>
<td>Absence of mental illness and moderate mental health</td>
</tr>
<tr>
<td>Struggling</td>
<td>9%</td>
<td>Absence of mental illness and languishing</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Presence of mental illness and flourishing</td>
</tr>
<tr>
<td>Floundering</td>
<td>20%</td>
<td>Presence of mental illness and moderate mental health</td>
</tr>
<tr>
<td>Languishing</td>
<td>4%</td>
<td>Presence of mental illness and languishing</td>
</tr>
</tbody>
</table>

Unlike Keyes (2005, 2007), the current analyses did not identify a separate subgroup of individuals with a diagnosable mental illness but who were flourishing nonetheless. This could be an artefact of sample size, given the very low prevalence rate of that subgroup (1%) in Keyes’ (2005) national study. In the current study, there were only three individuals who met that criteria (i.e., symptoms in the clinical range but
flourishing) and they were classified in the Thriving subgroup. Similarly, the current analyses did not identify a separate subgroup of depressed individuals without anxiety either. Given that the prevalence rate of pure depression is around 1% (e.g., Das-Munshi et al., 2008), replication of these LVMM analyses with clinical samples and/or much larger community samples is needed to be able to identify and study these smaller subgroups. This could be important as these individuals are likely to have quite different needs to others in the Thriving subgroup and may benefit from different interventions.

It is worth reiterating that the current study employed very different measures to those used by Keyes’ (2005, 2007) and yet the subgroups are remarkably similar. The combination of measures used in the current study included: positive and negative affect (as measured by the PANAS), symptoms of anxiety and depression (as measured by the HADS), life satisfaction, and health-related quality of life, which incorporated indicators of social and emotional functioning and vitality (as measured by the SF-36 MCS). In contrast, Keyes’ (2005) study used the Composite International Diagnostic Interview Short Form (CIDI-SF) scales (Kessler, DuPont, Berglund, & Wittchen, 1999) to diagnose mental illness, Ryff’s (1989) scales of psychological wellbeing, Keyes’ (1998) scales of social wellbeing, and a selection of novel measures, including: a limitations of activity of daily living scale, a 6-item scale of positive affect, a single-item life satisfaction question, two items about helplessness, two items assessing resilience, and an item about intimacy. Given the differences in measures used, the fact that the subgroups identified in the current study are so similar to those found by Keyes and colleagues lends support to Keyes’ research and findings regarding the existence of these groups across nations and cultures (see Keyes, 2013). The similarities also attest to the impact that conceptualising and operationalising mental health based on a dual continuum model can have on research outcomes, as compared to other studies that group people based solely on symptoms and severity (e.g., ABS, 2008).

In sum, when appropriate statistics are used and mental health is operationalised with measures of the positive and negative aspects of mental health, subgroups emerge that differ markedly from those just based on symptom severity. The potential utility and predictive capacity of these subgroups, however, needs further investigation.

**Implications for Theory.**

Having discussed the key findings in the context of previous research, this section discusses their implications for theory. It begins by discussing the issue of conceptualising mental health. It considers the criteria for a scientific theory and then
argues that an overarching theoretical framework for mental health could help make sense of the diverse (and sometimes contradictory) theories and findings in mental health. The discussion then specifically looks at the dual continua model of mental health and its specific implications for program development and evaluation.

**Unifying diverse approaches to mental health.**

As previously stated, given the diverse and sometimes contradictory nature of the psychological models and interventions, it is curious that they are all supported by empirical evidence and the interventions are approximately equivalent in terms of effectiveness (Hunot et al., 2013; van Zoonen et al., 2014). How can all the different conceptualisations and theories about anxiety and depression be accurate? The simple answer is that they may not be. This links back in with Rosenzweig’s (1936) assertion that success of an intervention does not mean that the theory is accurate, as there may be other underlying factors and mechanisms at play. The implicit assumption that because there is evidence to support one theory, other theories must be wrong, is flawed.

From a scientific stand point, a theory must be able to make falsifiable or testable predictions of phenomena with consistent accuracy across a broad area of scientific inquiry (National Academy of Sciences, 2008; Reynolds, 2007; Winther, 2016). It may be modified over time if it does not fit with new findings, but the strength of a theory is related to the diversity of phenomena it can explain, its capacity to withstand rigorous scrutiny, and the likelihood that no new evidence is likely to alter it substantially (National Academy of Sciences, 2008).

Comparing each of the psychological perspectives of mental health to this definition, it becomes clear why CBT claims to have the strongest evidence base. It readily offers predictions about mental health outcomes based on cognitions and behaviour that have been rigorously tested experimentally, and the theory has evolved as new findings have emerged (e.g., D. A. Clark & Beck, 2010). In contrast to CBT, it is difficult to make specific and accurate predictions based on unconscious processes, such as those that underpin psychodynamic theory, or experiential phenomena such as empathy and existential issues, which are central to humanistic theory. The individual tailoring of psychodynamic and humanistic interventions during the course of therapy also means that they are not easily standardised, which makes it difficult to develop the protocols needed for rigorous experimentation and clinical trials. Hence, it is not surprising that CBT is commonly held up as the gold standard for mental health treatment (NIMH, 2013; NMHC, 2014a) based on the rigour with which it has been
researched.

However, CBT does not work for everyone and the fact that there is substantial evidence to support other psychological theories and interventions cannot be ignored. If CBT theory is entirely accurate, then one might expect that its application (through interventions) would help everyone (except for the odd anomaly; Rosenzweig, 1936). Yet CBT has an average efficacy rate of 40 – 60% (e.g., Twomey et al., 2015), which means that 40 – 60% of people are not helped by it. Whilst some of this ineffectiveness undoubtedly stems from implementation issues, these rates indicate that CBT does not apply to everyone and its model of change is not universal. The same can be said for the other psychological approaches to mental health.

Baddeley (2012) offers a helpful way to think about this, which he articulated following many years of working in the field of working memory: “a distinction needs to be made between the overall theoretical framework, which [needs to] remain relatively stable, and the attempts to build more specific models within this framework” (p.1). As such, the various psychological approaches to mental health reviewed in this thesis can be seen as attempts to build specific models. Each one has merit but focuses on slightly different mechanisms. What is missing is the overarching theoretical framework that can pull them all together and explain the plethora of biopsychosocial and ecological variables associated with mental health; the different relationships known to exist between these variables (including direct, moderated and mediated pathways); and, the diverse features and symptoms of mental health and illness.

A diathesis-stress model, like the one discussed in Chapter 4, could function as the overall theoretical framework. At its core, it posits that a person’s vulnerabilities (diathesis) must interact with environmental risk factors or stressful life events to trigger mental health problems (Borba & Druss, 2009). According to the model, the greater a person’s diathesis for a disorder, the less environmental stress is needed for the person to become ill.

Whilst the model illustrated in Chapter 4 (Figure 4) is somewhat limited in the variables and pathways pictured, it could be readily expanded to accommodate the host of biopsychosocial and ecological variables known to influence mental health and the different relationships between these variables. The diathesis-stress model can also accommodate the diverse psychological theories reviewed here. For example, stressful early life experiences (e.g., insecure attachments, parental mental illness, violence or abuse, etc.) interact with genetic predispositions and can lead to varying degrees of
vulnerabilities or predispositions for developing mental disorders. The mechanism for this predisposition could be maladaptive schemas or core beliefs (a hypothesis of cognitive theory) or dysfunctional learnt behaviours (a hypothesis of behavioural theory), or an underdeveloped ability to self-soothe and regulate one’s emotions (a hypothesis of psychodynamic theory and a key factor in transdiagnostic approaches to prevention and treatment; Aldao et al., 2010). In this way, the diathesis-stress model provides a framework for thinking about mental health that is flexible enough to accommodate current evidence-based theories as well as emerging findings from biomedical research. It could also facilitate the development of testable predictions about how variables interact with each other and impact mental health, as well as how mental health feedbacks and increases or decreases stress and vulnerabilities.

The diathesis-stress model was originally developed by Zubin and Spring (1977) to explain some of the causes of schizophrenia but, as discussed in this thesis, it applies equally to a wide range of mental health phenomena, including common mental health problems such as depression and anxiety. This indicates that the model has broad applicability.

The model is also compatible with the 4Ps framework (Havighurst & Downey, 2009) used by mental health clinicians in case formulations (e.g., predisposing factors equate to one diathesis/vulnerability factors and precipitating factors are found in the form of environmental stressors), which attests to its potential utility in practice too.

In sum, the diathesis-stress model could be a useful overarching theoretical framework for thinking about the diverse models of mental health. In this way, each of the key psychological perspectives of mental health could be seen as offering specific models and mechanisms, which apply in particular circumstances. The challenge is to accurately identify those circumstances, and develop new models and applications to better meet the needs of those people who are not helped by the current suite of models. As this study has shown, a key to refining existing models and developing new ones may be to ensure that mental health is conceptualised and operationalised in a way that acknowledges the dual dimensions of mental health (not just psychopathology) and accounts for heterogeneity and individual differences.

**The dual-continua model.**

Results from this study offer strong support for the dual-dimensions model of mental health and echo calls for a paradigm shift away from the classic medical model of pathology to a more balanced perspective of ‘health’. As mentioned in Chapter 4, the
classic medical model focuses on disease, pain, or defects, waits for dysfunction to emerge, diagnoses the problem, and then treats it (Clare, 1980). More recently, Shah and Mountain (2007) have sought to update the definition, proposing that “the ‘medical model’ is a process whereby, informed by the best available evidence, doctors advise on, coordinate or deliver interventions for health improvement” (p. 375). This is more consistent with a dual continua model of mental health as it opens the door for psychosocial and ecological variables to be considered as part of case formulations and it is broad enough to accommodate prevention efforts. However, the definition falls short of acknowledging wellbeing and the worthy goal of taking action to help people thrive, not just relieve symptoms.

To some people this distinction may seem trivial but, in practice, when a paradigm shift, so does the focus. The metrics and measures used to monitor and evaluate outcomes also change. For example, under the current medical model, the K10 (a 10-item measure of psychological distress; Kessler & Mroczek, 1994) is often used in primary care to screen and measure changes in mental health (e.g., DoHA, 2016; Kessler et al., 2003). It says little of whether that level is normal for the individual, how the individual copes with it or how it impacts their wellbeing. Likewise, someone with low symptoms could be struggling. Nevertheless, it is often used as a key indicator measure of treatment success. According to the mental health subgroups and profiles found in the study, someone with high levels of symptoms could be Thriving, Languishing or anywhere in between, depending on their quality of life and wellbeing. Hence, measures of positive mental health are needed also to more accurately gauge an individual’s mental health.

The dual continua model of mental health discussed in this thesis is not new; it has been discussed extensively by Keyes and colleagues (e.g., Keyes, 2002, 2005b; Keyes et al., 2010; Keyes & Lopez, 2002) and proponents of positive psychology (e.g., Provencher & Keyes, 2011; Seligman & Csikszentmihalyi, 2000; M. Slade, 2010). However, the current study adds to this discussion by explicitly illustrating some of the differences that emerge in research results and conclusions when mental health is operationalised with measures of positive mental health as well as symptoms of psychopathology.

**Heterogeneity.**

Complementing the call to (a) conceptualise mental health using a diathesis-stress model, and (b) operationalise mental health using measures of positive and
negative mental health and wellbeing, is (c) the importance of assuming heterogeneity in samples and analysing it. This is particularly relevant to theory development and testing.

As previously mentioned, homogeneity is one of the basic assumptions that underpin the general linear model and associated statistical analyses, such as those based on regression. However, the current study clearly showed that a model developed and tested on a full sample does not necessarily apply to everyone in the sample. In this study, it was valid for less than 40% of the sample and two different models were needed to adequately represent the remaining 60% of the sample. This merits further discussion because it illustrates a systemic problem in mental health and related research where regression-based, full sample analyses are commonplace.

These findings suggest that full sample regression analyses may be like using a hack saw when a scalpel is needed: both tools cut, but one is rough and crude while the other enables precise and accurate cuts. In this case, mixture modelling techniques may be the scalpel needed to help researchers dissect heterogeneity in the sample while testing their hypothesised models.

If the current findings are replicated in further studies, then serious questions need to be raised about the utility of traditional (full sample) SEM and regression analyses in mental health and related research. It would also cast a long shadow of doubt over the accuracy and specificity of past findings arising from regression-based analyses (including SEM) with full samples. Precisely, how many individuals within the sample did the model apply to?

Based on the findings of this research, it is recommended that heterogeneity (rather than homogeneity) be assumed and routinely investigated in mental health research and program evaluation. If heterogeneity is assumed a priori, researchers can employ appropriate statistical methods and test various models to identify what model fits whom. Once that is clarified, then more informed choices can be made about what type of interventions may be most appropriate.

One of the sources of heterogeneity could be variations in people’s risk (diathesis) and protective factors. Drawing on the diathesis-stress model discussed in Chapter 3, individuals differ in terms of predisposing factors (e.g., one’s genome, temperament, emotionality, early life experiences of violence and abuse or parental mental illness) and environmental factors, and these interact with protective factors (e.g., economic and biopsychosocial resources). The actual combination of vulnerability
and protective factors, and the ways in which these interact are likely to account for significant individual differences and underpin much of the complexity of mental health presentations. Accordingly, individual differences need to be acknowledged, identified and incorporated into mental health research and evaluation.

The next section discusses how this specifically relates to program development and evaluation.

Specific implications for program development and evaluation.

In the early chapters of this thesis, two different approaches to improving treatment effectiveness and efficiency were outlined: personalised medicine (e.g., Insel, 2014) and the transdiagnostic approach (e.g., Barlow et al., 2004). The former depends on improving intervention outcomes starting with an accurate understanding of what variables and processes are important for each individual. From this understanding, theoretical models and interventions can be developed and refined. This approach implicitly assumes heterogeneity and that analysing it can lead to the identification of important subgroups that have different key variables, resources and mechanisms of change. Once identified, these can inform the theory of change for each subgroup and, from there, interventions can be developed, tested and refined accordingly to maximise efficacy. It is anticipated that when such factors are more clearly understood, practitioners will be in a much better position to predict treatment outcomes and tailor interventions to individuals. Conversely, the transdiagnostic approach focusses on those variables and processes that are common across mental health problems and disorders. It does not assume heterogeneity nor is it typically analysed. Both approaches have merit but, at present, it is unclear who would potentially benefit from which approach.

Although the current study did not analyse intervention outcomes, the principles used in this study could be applied to program development and evaluation. Specifically, if heterogeneity is assumed (rather than homogeneity), then researchers and evaluators can employ hybrid mixture modelling techniques to identify potentially important subgroups that might respond differently to interventions.

With regards to the tailoring process, it is worth noting that efforts to tailor interventions are already occurring in some online treatment programs (e.g., eCouch, My Compass), where it is done quite easily and efficiently using a series of questions and measures that assess peoples’ needs and preferences. Participants’ responses then guide what modules or sub-programs will be included in their treatment program. Similar programs (e.g., MindSpot, This Way Up) also enable participants to choose
whether they want to their treatment to be therapist-assisted (e.g., weekly emails and phone calls) or fully self-guided online. Although these initiatives yield a high degree of consumer satisfaction for those who complete the programs (Clarke et al., 2014; Donker et al., 2013; A. Mackinnon, Griffiths, & Christensen, 2008; Titov et al., 2015), the tailoring process has yet to translate into higher treatment success rates (e.g., average pooled effect size = .36, which translates approximately to NNT ratio of 1:4.49 or a success rate of approximately 22.27%; Twomey & O’Reilly, 2016). Although this could be linked to the very low completion rates, which average around 30% (Donker et al., 2013) but often drop below 10% (Twomey & O’Reilly, 2016), another explanation could be that the measures used to tailor the package are largely treated individually (e.g., high anxiety scores indicate that certain modules are needed). Perhaps analysing people’s response patterns across all of the psychosocial measures would yield some different insights. This could be done with latent class and mixture modelling techniques.

Similarly, there have been efforts to identify predictors of treatment outcome for MoodGYM also (Calear, Christensen, Mackinnon, & Griffiths, 2013) but these have been limited to regression-based analyses with observed variables also. For example, Calear (Calear et al., 2013) found that regional and remote, young Australian men were most likely to benefit from the program. LVMM could be employed in this situation to extend the findings and examine if this demographic group correlates to a particular mental health profile and whether that (latent) profile corresponds to people who are most likely to complete the program and benefit from it.

In sum, it is recommended that subgroup analyses be routinely conducted when developing models and evaluating programs to more accurately identify who the intervention worked for and who it did not. Examining these subgroups quantitatively and qualitatively may yield further insight into how interventions can be modified to better meet their needs and keep them engaged in the program.

**Specific implications for reporting program evaluations and research**

While developing algorithms to predict treatment outcomes is still some way off, there is one change that could help with intervention selection - change the way that efficacy and effectiveness results are typically reported. While undertaking the literature reviews for this thesis, it was observed that there is a strong tendency to report and focus on effect sizes rather than clearly stating what portion of people were helped by the intervention(s). For example, efficacy studies commonly report effect sizes using
Pearson’s correlations ($r$) or Cohen’s $d$ values. If a large effect size of .80 or more is obtained, authors often interpreted it as strong support for an intervention (e.g., Slee et al., 2009; Slee et al., 2012). However, if that effect size is translated into a need-to-treat (NNT) ratio, it equates to 1: 3.32, which means that 3.32 people need to be treated in order for one person to be successfully treated (Kraemer & Kupfer, 2006). In practical terms, it indicates that the intervention helped one out of three (30.12%) participants. Stating a 30% success rate would provide a much clearer picture of the intervention effectiveness in terms of practical significance.

Kraemer and Kupfer (2006) wrote about this over a decade ago in an article about the size of treatment effects and their importance to clinical research and practice. They concluded that the commonly used effect size metrics (and other related figures such as statistical significance, power, and meta-analyses) are limited in conveying clinical significance. Accordingly, they recommended three equivalent effect sizes be used: NNT, area under the receiver operating characteristic curve comparing treatment and control responses, and success rate difference. Of these three, the first and the last are the easiest to understand. If one of these metrics was routinely reported for interventions, then it would allow people to make comparisons between options and enable them to make more informed choices in treatment planning. As such, this represents a relatively easy change for researchers and scientist-practitioners to make, which would help improve the utility of research results published and improve transparency in the sector.

**Implications for Strategy, Programs and Services.**

As outlined in the introduction to this thesis, nation health programs succeed and are effective when there is (1) an evidence base for action; (2) a technical package of high-priority evidence-based interventions that together have a major impact; (3) effective performance management and program improvement; (4) strong partnerships and coalitions with public- and private-sector organizations; (5) accurate and timely communication across stakeholders in the health care community and government; and (6) sustained political commitment to providing the resources and support necessary for effective action. (Frieden, 2013). The reviews in this thesis have shown that: there is a clear and pressing need for action; there is a package of high priority and evidenced-based interventions in Australia, but they are not having a major impact on the national mental health needs and prevalence rates.

Although there are many reasons for this (NMHC, 2014), findings from the
current research highlight that a key reason is likely to be the dearth of effective performance management within the sector. Effective performance management is generally evidenced by rigorous and timely monitoring and evaluation of programs, services, and intervention, and the result directly inform quality improvement activities. The lack of evidence regarding the effectiveness and efficiency of national mental health programs in Australia suggests that there is a gap in this area.

Whilst this thesis did not formally review funding arrangements, cross sector partnerships, nor communication in the sector, it has been shown that there is continuous political commitment in Australia to provide resources and to support effective action in this area (e.g., DoHA, 2003, 2008, 2016). Taken together, these findings imply that good work is being undertaken in the mental health sector and progress is being made in terms of improving access to treatment, but further work is needed if we are to reduce the prevalence, impact and burden of mental disorders in the community (Jorm, 2014; Jorm et al., 2017). From a strategic point of view, this would entail: much greater emphasis to be placed on prevention; developing more effective interventions and programs; and, improving monitoring, evaluation, and quality improvement across the sector. Each of these will be considered in turn.

**Prevention.**

As discussed in Chapter 2, national mental health strategies in Australia have been designed with prevention in mind over the past 25 years (Australian Government Department of Health, 2016; Australian Health Ministers, 1992, 1998; Commonwealth of Australia, 2009a). However, despite the explicit emphasis on prevention, the vast majority of research and funding is still directed towards treating mental illness after it has emerged, not preventing it (AIHW, 2016b). Over this time, there has been little impact on the nation’s overall mental health needs, as evidenced by the high and stable prevalence rates for common mental disorders (Jorm et al., 2017; Patten et al., 2016) and increasing demand for treatment services (National Mental Health Commission, 2014a). It is highly questionable whether such a reactionary approach to service delivery will be sustainable into the future, especially during economic downturns when resources are restricted and demand increases (NMHC, 2014; Jorm, 2014). Furthermore, it is increasingly out-of-sync with public health models and policy directions that emphasise prevention and stepped care models of service delivery. Arguably, a change in paradigm is needed.

The incumbent paradigm needs to broaden the scope of assessment and
diagnosis to formally include positive mental health and wellbeing, in addition to psychopathology, and needs to put much greater emphasis on prevention – recognising that it is the key to reducing the prevalence, burden and impact of mental health problems in the community over the longer-term.

The following sections discuss different strategies for prevention and improving existing programs and services, in the light of the current finding.

Screening.

Current screening in mental health is typically based on two classes: those with symptoms above a clinical cut-off score compared to those below the cut-off; or, those with particular risk factors present compared to those without. These dichotomies are useful to the extent that they help identify the 15% to 20% of individuals who are experiencing significant symptoms of distress or risk but they are not particularly effective or efficient at identifying who will benefit from prevention interventions (Dowdy et al., 2015).

One reason for this could be that the screening tools (e.g., K10, DASS, CES-D) rarely take into account protective factors or an individual’s positive mental health and functioning. It may be the combination of positive and negative dimensions of mental health that is important to risk, recovery and response to interventions. This is consistent with clinical experience in which practitioners conducting risk assessments need to balance risk and vulnerability factors on the one hand and strengths and protective factors on the other. Extending this approach to screening protocols could provide a more nuanced and useful stratification of individuals into subgroups that extend beyond the typical low/moderate/high risk categories. This could be done in much the same way as the current study did, by operationalising mental health with measures of emotional wellbeing, functioning and quality of life. That said, including additional measures in a screening program invariably increases cost and participant burden in terms of time and effort. Hence, to optimise efficiency, screening tools ideally need to be low cost, fast, and accurate at predicting the target condition.

Of the six measures used in this study, the Perceived Stress Scale and the mental-health component summary (MCS) of the SF-36 distinguished between the mental health subgroups the best. This may be because the MCS is composed of four subscales that assess vitality, social and emotional functioning, and mental health (i.e., the absence of anxiety and depressive symptoms) and, together, they provide a more complete picture of mental health compared to the other measures. That is not to say
the other measures are not important in the assessment of mental health but, based on these findings, the SF-36 MCS appears to be the most discerning of these measures, with higher scores reflecting better mental health status and lower risk of mental illness.

The SF-36 MCS is also known as the SF-14 or Mental Health Questionnaire (MHQ-14; i.e., it comprises the 14 mental-health related questions of the SF-36 and excludes the items relating to physical health). Until recently, the SF-14 was employed as a standard outcome measure in Australia for the Private Hospital Mental Health Service Alliance, the Mental Health Nurse Initiative Program (MHNIP), and several private health insurance companies have required it for any mental health service claims. It has been widely used in research and practice around the world but rarely at the primary health level, which has tended to favour the K-10 or CES-D, at least in Australia (Mental Health National Outcomes and Casemix Collection, 2015). A comparative analysis of these three measures in terms of their sensitivity, specificity, and their ability to predict treatment outcomes could be a worthwhile avenue for future research into effective and efficient screening programs.

It is worth noting that while scores on the Perceived Stress Scale (S. Cohen & Williamson, 1988) in this study strongly predicted mental health status, there were problems with this measure when it was used in SEM with other indicators of mental health: it was not unidimensional and it confounded the effect of some other psychological variables in the model. Consequently, caution is recommended with the use of this measure in future research that involves regression-based analyses with multiple mental health and related variables.

**Interventions.**

The mental health subgroups identified in this research align with a stepped care framework for prevention and treatment. Informed by Professor Littlefield’s (2015) work, Table 33 maps the current subgroups to levels of care and provides examples of broad-based intervention strategies for each of the subgroups to improve mental health and prevent the progression of mental health problems.

Based on the current community sample, just over a third of individuals are thriving. Previous public health research into mental health prevention suggests that this group of people can benefit from general interventions designed to promote positive mental health and wellbeing. Such interventions can help reduce the risk of future mental health problems and increase life satisfaction (Albee, 1982; Graetz et al., 2008; M. Greenberg et al., 2015; WHO, 2004).
Another third of the population have some mental health problems and are typically characterised by higher levels of perceived stress, some symptoms of anxiety and perhaps depression, and reduced life satisfaction. This group of people, identified here as Getting By, function fairly well but are likely to benefit from some selective or early intervention to help improve their mental health literacy, strengthen their coping skills, and equip them to more effectively manage stress and anxiety. These skills serve as protective factors, promoting better emotional and social wellbeing, and can help prevent the onset of mental disorders. Follow-up screening of this subgroup (e.g., within 3 months) could be particularly beneficial as it could help detect any significant deterioration in mental health and enable timely support to be given to help the individual access appropriate pathways to care. Some of those pathways to care may include the interventions listed for individuals who are Struggling (e.g., bibliotherapy, refer to peer support group, online psycho-social program, counselling). Although there

<table>
<thead>
<tr>
<th>Subgroup</th>
<th>Risk category</th>
<th>Interventions</th>
<th>Examples</th>
</tr>
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<tbody>
<tr>
<td>1 Thriving</td>
<td>Low risk (35.47%)</td>
<td>Primary/universal prevention</td>
<td>Health promotion</td>
</tr>
<tr>
<td>2 Getting by</td>
<td>Marginal risk (31.73%)</td>
<td>Primary/selective prevention</td>
<td>Health and psycho-education Stress management; Mindfulness Skill development</td>
</tr>
<tr>
<td>3 Struggling</td>
<td>Moderate risk (8.80%)</td>
<td>Secondary/selective or indicated intervention</td>
<td>Bibliotherapy Address risk factors Refer to peer support group Online psycho-social program Counselling</td>
</tr>
<tr>
<td>4 Floundering</td>
<td>High risk (Clinical - Anxiety) (19.73%)</td>
<td>Tertiary/indicated intervention or treatment</td>
<td>Clarify predisposing, perpetuating and protective factors for the individual as well as their treatment preferences, then utilise new algorithms and technologies to tailor treatment</td>
</tr>
<tr>
<td>5 Languishing</td>
<td>Very high risk (Clinical - Comorbid) (4.27%)</td>
<td>Clinical assessment and treatment</td>
<td>As for Floundering, with strong consideration given to medical treatment and counselling (Goal: Reduction in relapse and recurrence)</td>
</tr>
</tbody>
</table>
would be additional costs to the health care system to provide this type of monitoring, such a proactive step to improve early detection and intervention is likely to facilitate faster access to treatment and faster recovery, which in turn would help reduce longer-term costs associated with untreated mental illness in the community. Certainly, cost could be kept to a minimum if it is delivered online or via an app.

Based on the current sample, around a quarter of the population is at high or very high risk of having a mental disorder. Clinical assessment and standard treatment is indicated for these individuals with the dual aims of restoring mental health and functioning and reducing the risk of relapse and future recurrence.

The intent of matching prevention and treatment efforts to mental health subgroups in this stepped way is to better match individuals’ needs with appropriate levels of intervention and thereby optimise resource usage (NMHC, 2014). By intervening early and with the least intensive options, mental health and wellbeing can be improved and the onset of common mental health problems and high prevalence mental disorders may be prevented. In the long term, it is anticipated that this type of approach could help reduce demand on treatment services for high prevalence disorders and free up capacity for clinical services to focus on more complex cases and severe psychiatric disorders (Littlefield, 2015; National Mental Health Commission, 2014a).

**Prevention through very early intervention**

Based on the developmental aetiology of common mental health problems (as discussed in Chapter 3), it is clear that prevention efforts need to start even before birth, with expectant parents and family (Buist et al., 1999; Ginsburg, Drake, Tein, Teetsel, & Riddle, 2015; Milgrom et al., 2008; T. Moore, McDonald, Carlon, & O'Rourke, 2015; Pollak, 2015). While little can be done (at present) about one’s genetic predisposition, the environment that parents create for infants/children in the first few years of life establishes many of the predisposing and protective factors for one’s mental health and developmental trajectory (Ozomaro, Wahlestedt, & Nemeroff, 2013). Therefore, it stands to reason that prevention in mental health needs to begin with very early intervention, ideally in the antenatal period (J. Barlow, 2014; Jacka & Reavley, 2014). There is strong evidence demonstrating that improving family dynamics (e.g., reducing parental stress, domestic violence, drug and alcohol abuse, and mental illness and improving communication, problem solving and conflict resolution skills) helps improve the environments children subsequently grow-up in (e.g., Albee, 1982; Pollak, 2015). For instance, if individuals see healthy and respectful relationships modelled and
experience them throughout childhood, then they are more likely to internalise them and reproduce them in the years to come, including when parenting their own children (Knight, Menard, Simmons, Bouffard, & Orsi, 2013; A. Lewis, Galbally, Gannon, & Symeonides, 2014; Prinz, Sanders, Shapiro, Whitaker, & Lutzker, 2009).

For this type of proactive, prevention approach to work, it is crucial that governments, local health networks, health service leaders and management value a proactive approach. There needs to be a strong desire to allocate resources to people before, not only after, they demonstrate overwhelming psychological need, and see the importance of focusing on positive mental health and wellbeing in addition to remediating distress and dysfunction. Only with strong leadership, monitoring and accountability is headway likely to be made in this area.

**Improving the effectiveness of programs and services.**

In addition to improving sustainability of programs and services by better matching the level of care and resources to people’s level of need, there are two interrelated areas of professional practice and service management that merit further discussion, in light of the current research findings. These are routine monitoring and evaluation, and quality improvement.

**Quality improvement.**

In the context of mental healthcare, quality improvement refers to the systematic and continuous actions that lead to measurable improvement in healthcare services and better outcomes for the targeted patient group (U. S. Department of Health and Human Services, 2011; World Health Organization, 2004). The National Standards for Mental Health Services (Australian Government Department of Health, 2010) in Australia refer to it throughout the foreword and under Standard 10.1, recognising it as an essential component of good governance in mental health services and critical to ensuring quality and safety for mental health consumers. The National Quality and Safety in Health Services framework (Australian Commission on Safety and Quality in Health Care, 2012) further highlights how vital such a system is for organisational learning and continual improvement, and reinforces why it is a requirement for all mental health services seeking accreditation in Australia.

Whilst it is crucial that the importance of quality improvement is recognised in policy and required under the national standards, an ongoing challenge seems to be the implementation of those standards outside of public health (i.e., in community managed organisations and private practice). Nevertheless, if patient safety and quality care are to
be ensured and effectiveness in mental health is to be improved at the national level, then implementing standards and strategies such as these across settings is likely to be an important step in the process.

**Routine monitoring and evaluation.**

The reviews conducted as part of this research found that the evidence base supporting the effectiveness and efficiency of current programs and services is rather sparse. This represents an important gap in knowledge and practice.

There are likely to be a number of reasons for this, such as the lack of infrastructure (e.g., appropriate integrated software solutions) and increased administrative costs, but it may be the case that the capacity of program administrators and service managers also needs to be built in the area of program evaluation, performance management, and quality improvement. These topics and skills are not routinely taught to mental health professionals. However, there is strong evidence showing that highly “competent managers are one of the key contributors to effective and efficient health service delivery” (Liang, Howard, Koh, Lee, 2013, p. 256). Hence, promoting a high standard of business acumen and professionalizing the leadership and management of mental health services represents an important opportunity to improve client care across settings, enhance efficiency and help ensure the best use of limited resources (Australasian College of Health Service Management, 2016).

It bears mentioning that routine reporting of financial and non-financial indicators is a fundamental principle of good governance and performance management and is now standard practice in most industries, including (physical) health care (Australian Institute of Company Directors, 2012). However, outside of hospital/inpatient settings, such business practices anecdotally appear to be rare in the mental health sector.

Improved monitoring and program evaluation, and making the results public could enable stakeholders to begin to do comparative analyses of effectiveness and efficiency. This will empower consumers and carers, clinicians, policy makers, funding bodies and administrators to make more informed strategic decisions based on the value for money each program or option represents. Such evidence is crucial in the face of competing needs and finite resources.

**Implications for Mental Health Policy and Planning**

The findings from this research have several implications for public policy
pertaining to mental health programs and research. Figure 25 outlines three suggested priority areas and associated actions that could complement the national mental health plan and strategies. Some of the actions stem entirely from the current reviews and empirical study, and others are informed by the larger corpus of research and clinical experience in mental health service administration and program evaluation. Together, they represent point for consideration and potential next steps as the sector moves to improve performance and achieve better outcomes for clients.

**Setting targets.**

Setting and monitoring targets is one way in which governments can provide leadership, guidance, and strategic direction for the health sector (Baars, Evers, Arntz, & van Merode, 2010; P. C. Smith et al.; van Herten & Gunning-Schepers). As previously discussed, there are increasing calls for targets to be set to reduce the prevalence of mental illness and thereby reduce the associated social and financial burden of mental health on individuals, families, and the community (e.g., Jorm et al., 2017; NMHC, 2014; Patten et al., 2016). Findings from the current research support this call and align with the larger population health literature that advocates for the use of targets to measure progress with, and success of, health policy implementation (Berry, Gardner, & Anderson, 2015; WHO, 2014; WHO & Wonca, 2008). Such activities increase transparency and accountability, which are known to help improve the efficient and effective use of resources and the delivery of quality programs and services (International Hospital Federation, 2015). However, what those targets should be and when and how they should be implemented and reported are topics for further research.
Figure 25. Suggested priority areas and actions to help improve effectiveness in the mental health sector.
Summary of Key Recommendations.

In sum, the current review of mental health prevention programs in Australia found that only a small portion of people with mental health problems in the community are successfully treated at present (i.e., around 20%) and that programs remain in place and are expanded despite a lack of compelling evidence to show their impact or relative efficiency. In order improve the effectiveness and efficiency of mental health prevention and treatment programs, the following strategies are recommended.

- Governments to improve the monitoring and evaluation of programs they fund and routinely publish the details. This will facilitate comparative analyses of effectiveness and efficiency, and promote transparency and accountability.

- Set targets to reduce the prevalence of common mental disorders such as anxiety and depressive-related disorders.

Secondly, based on the review of psychological theories and recent advances and insights into the aetiology of common mental health problems, the author recommends:

- Consideration be given to basing mental health research and intervention frameworks on a diathesis-stress model that is informed by a bio-ecological perspective of human development.

- Mental health intervention research and reports to routinely translate effect sizes into clinically meaningful terms such as NNT ratios and success rates.

Thirdly, based on the results of the empirical study, which were consistent with the dual continuum model of complete mental health, the author recommends:

- Mental health be operationalised (measured) in research and practice in accordance with the WHO’s (2014) standard definition, which includes positive mental health, functioning and wellbeing not just symptoms of distress and psychopathology.

Finally, based on the results of the empirical study, which found that empirically supported models probably only apply to a portion of the sample, the author recommends:

- Heterogeneity, not homogeneity, be assumed in mental health and related research.

- Mental health research and evaluation routinely investigate (unobserved)
heterogeneity and use statistical techniques that identify and model differences across latent classes (subgroups).

**Limitations**

Although this research makes a number of contributions to the field of mental health and associated literature, it has some limitations associated with the scope of the review, the cross-sectional design of the study, and the inherent limitations of latent class analysis. First, with regards to the scope of the review, one of the difficulties with considering broad strategic questions, such as how the field of mental health sector is performing at the moment or how can we improve effectiveness in mental health, is that there are so many potential avenues to explore. Therefore, to keep the scope of this project within reasonable limits, the decision was made to focus predominantly on the local context and look at mental health programs and progress within Australia. As different countries have different mental health policy and programs, it could be argued that focusing on one country limits the generalisability of the findings. However, other high income countries report similar outcomes at the national level, such that prevalence rates continue to be high and stable (Center for Behavioral Health Statistics and Quality, 2015; Ishikawa, Kawakami, & Kessler, 2016; McManus, Bebbington, Jenkins, & Brugha, 2016; Mental Health Commission of Canada, 2014), and the need for treatment far exceeds capacity (WHO, 2014). Despite the differences in policy and programs across the developed world, this thesis focussed on process-related issues (i.e., conceptualising, operationalising, and analysing mental health and related data) rather than content or implementation-related issues. The latter two are much more context specific, whereas process-related factors potentially apply to mental health research and practice anywhere. Similarly, the recommendations (e.g., assume sample heterogeneity rather than homogeneity; improve program evaluation, business analytics, and quality improvement practices within the industry) potentially reflect principles of good practice and are applicable across settings, sectors and borders.

Second, with regards to the current study, it was limited by its cross-sectional design. Even though this was an exploratory study, the subgroups and profiles identified in this study represent a static snapshot of a person’s mental health status at one point in time and do not provide information about the person’s journey or trajectory. For instance, someone identified as Struggling (with subthreshold symptoms) could conceivably be progressing towards the onset of a clinical disorder, in the process of recovering from a mental disorder or they may just always have that level of residual
symptoms. Such variation illustrates the need for further subgroup analyses to be explored with longitudinal designs.

Although the current sample size was sufficient to conduct latent profile analysis according to some guidelines (e.g., G. Williams & Kibowski), it was underpowered for multigroup SEM given the size of some of the smaller subgroups (i.e., \(n < 100\)). Ensuring adequate power is one of the challenges with multigroup analyses but it could be overcome in future studies by obtaining samples large enough to ensure that low prevalence subgroups are sufficiently big enough (i.e., with at least 100 in each subgroup).

The current study also collected data online. Whilst online research provides valid data and makes it possible to reach people who are dispersed geographically (Coulombe et al., 2016), future studies may benefit from supplementing online self-report measures of mental health with standardised diagnostic interviews to provide a more objective assessment of symptoms, and/or with family/carer perceptions of clients’ symptoms and wellbeing. This may provide richer insight into each of the mental health subgroups and even help widen the scope of potentially helpful interventions (e.g., relationship/family systems interventions).

Third, when analysing subgroups, this study initially employed the two-step approach (i.e., step one = conduct latent profile analysis, step two = conduct multigroup SEM analyses based on the latent classes identified in step one). Typically, multigroup analyses are conducted with known classes, that is, subgroups based on an observed variable (e.g., gender, socioeconomic status, diagnostic category; Görz, Hildebrandt, & Annacker, 2000). However, in this study, the subgroups were formed based on the posterior probability estimates for the latent profiles identified in step one. In this case, the posterior probability estimates all exceeded .85 and the entropy was above .70, which indicated good, crisp classification (B. O. Muthén, 2008). Nevertheless, because class membership is based on a probability, there is a risk that someone could be assigned to one subgroup when they ought to be in another one. Multigroup SEM does not account for this probability risk so, technically, mixture SEM would be the more appropriate statistical technique. This is because it combines steps and forms latent classes while conducting the SEM and therefore accounts for class membership probabilities.

However, mixture SEM relies on advanced statistical knowledge and software. Although there are a handful of articles referencing mixture SEM, clear user-friendly
instructions and/or training are not readily available. This severely restricts its use and puts it out of reach of most scientist-practitioners. This is unfortunate because it has the potential to substantially improve accuracy in model development and testing, and in turn improve our understanding of what intervention(s) might work for who and why. Clearly, further work in this area is needed to make this technique more accessible to researchers in mental health and related fields.

One of the main limitations of latent class and related analyses is that the number and nature of classes identified varies, based on the specific variables included in each analysis. Change the variables (including any covariates/auxiliary variables) and the results can change - to reflect the patterns that exist with that specific combination of variables and measures. Therefore, some variation in results across studies is to be expected, when different measures are used. This trend already occurs with regression-based modelling techniques, so it is not unique to LVMM, just something to keep in mind when designing research and evaluations, and comparing results across studies.

In sum, this study was exploratory. The above limitations are not unique to studies of this nature, nor do they compromise the integrity of the findings. Rather, they highlight areas for further investigation and development.

**Important Issues for Further Research**

This thesis has identified a number of process-related issues in research and evaluation that potentially undermine the effectiveness of the mental health sector, programs, and interventions. However, given the exploratory nature of the study and the limitations specified above, further research is certainly needed. Throughout the thesis specific recommendations for research have been noted but an inclusive outline of the key areas recommended as a focus for future investigations is presented below.

In the context of high and stable prevalence rates and treatment needs that exceed capacity throughout most of the developed world, a worthy long-term goal for public mental health would be to reduce the lifetime prevalence of common mental disorders and increase social and emotional wellbeing. To help achieve this, a three-pronged strategy is needed. First, substantially more research on prevention is needed that aims to help people avoid needing treatment in the first place. Successful prevention of mental health problems is likely to depend on identifying individuals who are at risk of mental health problems long before they even develop symptoms and then successfully intervening to reduce vulnerabilities and stress, and increase protective factors.
As discussed in the review chapters, it is well-established that modifiable predisposing factors can begin very early in life (i.e., from conception onwards) in the form of maternal health, stress, and wellbeing during pregnancy and beyond, paternal mental health, early attachment, and family dynamics, including parenting style, parental conflict and/or family violence. Hence, the perinatal period offers a crucial and promising opportunity for very early intervention and warrants further research to develop interventions that effectively and efficiently help parents and caregivers work through any pre-existing psycho-social issues, and support them to successfully navigate the challenges of early parenthood and particular social determinants of health that elevate risk. The latter necessarily involves a multi-level cross-sectoral approach, with governments and organisations addressing systemic issues and community groups helping to address local issues. This approach may lay more in the domain of public health rather than psychology or mental health per se, but it is in-line with Bronfenbrenner's (2005) bioecological model of human development and represents a crucial part of the plan to ensure that the contextual factors affecting people’s mental health are acknowledged and addressed. In sum, each of these areas (whether at the systemic, family or individual level) merit focussed effort and resources to help ensure that future generations have the best beginning possible, with a reduced risk of developing mental health problems.

Second, quality improvement projects are urgently needed that focus on determining the effectiveness and efficiency of existing prevention and early intervention programs and services, and then improving them. This would be helped by the establishment of best practice guidelines for monitoring and evaluation in mental health and related areas. Routine monitoring and evaluations highlight strengths and areas for improvement, and potentially increasing transparency and accountability. Accordingly, targeted research into the development and implementation of such guidelines and tools is needed to determine how best to implement them across sectors and settings, encourage uptake, set appropriate targets and benchmarks for prevention programs and treatment services that are realistic and useful.

Moving focus from the sector level down to the intervention level, this thesis has shown that many questions remain regarding the extent to which existing psychological models and interventions apply to individuals within any given sample. Re-analysis of existing models and data with latent mixture modelling techniques could provide a better insight into what specific models apply to what subgroups. Once clarified, such
insight would help services and practitioners as they seek to tailor interventions to individual clients.

Replication of the latent mixture modelling presented in this study is also prudent. The mental health subgroups identified in this study are promising, and provide an example of how an alternate mental health classification system could be developed, which better integrates the positive dimensions of mental health with the negative. However, the capacity of the mental health subgroups to predict future mental health status or differences in intervention outcomes needs to be thoroughly investigated and will give a better indication of their potential usefulness – lest we find ourselves back in the position of having diagnostic manuals that are unable to guide treatment selection for any given individual with accuracy and reliability.

Based on the current findings, best practice in mental health and related research, program evaluation, and quality improvement is likely to include subgroup analyses. However, it is worth noting that the issue of unobserved heterogeneity has been periodically raised since the 1960’s (Collins & Lanza, 2010; Goodman, 1974; Lanza & Rhoades, 2013; Lazarsfeld & Henry, 1968; Velicer, Martin, & Collins, 1996) but it has not penetrated mental health research and evaluation to the extent that is needed. To overcome this, further research and resources are needed to build the capacity of scientist-practitioners to analyse data in this way, and to spread the message.

Finally, future work should aim to extend the application of person-oriented data analysis techniques to intervention studies as it could provide valuable insight into what variables predict treatment completion and outcomes. In addition to using measures of both positive and negative dimensions of mental health, further insights might also be gained by including a measure of readiness for change and ascertaining people’s intervention preferences (e.g., mode of delivery, type and nature of intervention). At the individual level, such information could help practitioners tailor prevention or treatment interventions; at the group level, it may help us to identify gaps in knowledge and services for those whose needs and preferences are not being met currently and who are typically lost to attrition. Such information has the potential to improve intervention effectiveness and efficiency and move us closer to personalised prevention and treatment.

**Concluding Comments**

This thesis began by asking the question: how well are we doing in the field of mental health? A review of the academic and grey literature, combined with experience
in the sector, indicates that there is enormous good will from stakeholders across the board. Clients and carers value therapy and support; clinicians want the best for their clients; families and communities value healthy, contributing lives; and, many governments provide considerable support to facilitate treatment and recovery for those affected by mental illness. However, despite the substantial goodwill and investment into mental health programs and research, prevalence rates remain high and steady, intervention effects are modest, and efficiency is rarely analysed or reported.

Much like a rope that is made up of many individual strands twisted together to make a strong, cohesive whole, this research has covered a broad range of issues, theories and research that intertwine and ultimately lead to the conclusion that we need to revise how we conceptualise, operationalise, and analyse mental health and related data. Ideally it needs to be in a way that is not constrained by paradigms, practices and assumptions of the past that are no longer relevant, instead it needs to be in a way that acknowledges and values individual differences and can accommodate both positive and negative dimensions of mental health.

This doctoral research project has sought to (a) critically review the evidence base for program effectiveness and efficiency in mental health in Australia; (b) identify and examine alternate ways to conceptualise, operationalise and analyse mental health in a way that might improve our ability to screen for mental health problems and target interventions; (c) identify and profile latent subgroups that may account for some of the inconsistencies seen in research and practice; and, (d) demonstrate the importance of considering latent subgroups in model testing rather than just evaluating theoretical models and mechanisms using whole samples. In doing so, this thesis contributes to the literature by offering a strategic analysis of factors that may be limiting the effectiveness and efficiency of mental health programs in general, rather than focussing on a particular program or setting.

Importantly, this research found that the way mental health is commonly operationalised and analysed in research and practice does not adequately capture the complexity and heterogeneity in mental health. These common practices undoubtedly contribute to the modest intervention effectiveness and efficiency rates seen in practice today.

Based on the findings of this research, it is strongly recommended that heterogeneity be assumed in mental health related research and practice. It needs to be routinely accounted for in model development, intervention trials, and program
evaluation. Additionally, more rigorous monitoring and evaluation of programs post-implementation are urgently needed. These changes are essential if we are to improve our capacity to tailor interventions to the needs of individual consumers and improve the effectiveness and efficiency of prevention and treatment programs locally, nationally and internationally.
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Appendices

Appendix A: Certificate of Ethics Approval

From: Resethics <Resethics@groupwise.swin.edu.au>
Sent: Tuesday, 20 September 2011 11:36 AM
To: Cunningham, Everarda; Nicholls, Jennifer
Cc: Ann Gaeth; Theiler, Stephen; White, Nadine
Subject: SUHREC Project 2010/041 Ethics Clearance for Modified/Extended Project (2)

To: Assoc Prof Everarda Cunningham/Ms Jennifer Nicholls, FHEL

Dear Arda and Jennifer

SUHREC Project 2010/041 Promoting wellbeing to prevent disorder: Preliminary examination of measures and a proposed model
A/Prof Everarda Cunningham, FHEL; Ms Jennifer Nicholls, A/Prof Stephen Theiler
Approved duration Extended To 31/03/2012 [Modified March 2011; September 2011]

Thank you for the progress report for the above project, emailed 16 September 2011, which included a request with documentation to modify the approved protocol and extend project duration. The report and request documentation, in this instance, was put to the Chair of SUHREC for consideration and feedback sent to you on 16 September 2011. I acknowledge receipt today of updated consent instruments in response to the feedback.

I am pleased to advise that, as modified to date, the project may continue in line with standard on-going ethics clearance conditions previously communicated and reprinted below.

Please contact the Research Ethics Office if you have any queries about on-going ethics clearance, citing the SUHREC project number. A copy of this clearance email should be retained as part of project record-keeping.

As before, best wishes for the project.

Yours sincerely

Keith Wilkins
Secretary, SUHREC & Research Ethics Officer
Swinburne Research (H68)
Swinburne University of Technology
P O Box 218
HAWTHORN VIC 3122
Tel +61 3 9214 5218
Fax +61 3 9214 5267
Dear Arda and Jennifer

SUHREC Project 2010/041 Promoting wellbeing to prevent disorder: Preliminary examination of measures and a proposed model
A/Prof Everarda Cunningham, FHEL; Ms Jennifer Nicholls, A/Prof Stephen Theiler
Approved duration Extended To 31/12/11 [Modified March 2011]

Thank you for the annual report for the above project, emailed 15 March 2011, which included a request with documentation to modify the approved protocol and extend project duration. The report and request documentation, in this instance, was put to the Chair of SUHREC for consideration.

I am pleased to advise that, as submitted to date, the modified project may continue in line with standard on-going ethics clearance conditions previously communicated and reprinted below.

Please contact the Research Ethics Office if you have any queries about on-going ethics clearance, citing the SUHREC project number. A copy of this clearance email should be retained as part of project record-keeping.

As before, best wishes for the project.

Yours sincerely

Keith Wilkins for
Ann Gaeth, Secretary, SHESC3
*******************************************

Dear Associate Professor Cunningham and Ms Nicholls,

SUHREC Project 2010/041 Promoting wellbeing to prevent disorder: Preliminary examination of measures and a proposed model
A/Prof Everarda Cunningham FHEL Ms Jennifer Nicholls
Approved duration: 28/04/10 To 28/04/11 [adjusted]

Ethical review of the above project protocol was undertaken on behalf of Swinburne's Human Research Ethics Committee (SUHREC) by a SUHREC Subcommittee (SHESC3) at a meeting held 16 April 2010. Your responses to the review emailed on 22 April 2010 clarifying some detail was put to the Chair/delegates of SUHREC (SHESC3) for consideration and, I am pleased to advise, approved and the project may therefore proceed in line with what follows.

- All human research activity undertaken under Swinburne auspices must conform to Swinburne and external regulatory standards, including the current [National Statement on Ethical Conduct in Human Research] and with respect to secure data use, retention and disposal.

- The named Swinburne Chief Investigator/Supervisor remains responsible for any personnel appointed
to or associated with the project being made aware of ethics clearance conditions, including research and consent procedures or instruments approved. Any change in chief investigator/supervisor requires timely notification and SUHREC endorsement.

- The above project has been approved as submitted for ethical review by or on behalf of SUHREC. Amendments to approved procedures or instruments ordinarily require prior ethical appraisal/clearance. SUHREC must be notified immediately or as soon as possible thereafter of (a) any serious or unexpected adverse effects on participants and any redress measures; (b) proposed changes in protocols; and (c) unforeseen events which might affect continued ethical acceptability of the project.

- At a minimum, an annual report on the progress of the project is required as well as at the conclusion (or abandonment) of the project.

- A duly authorised external or internal audit of the project may be undertaken at any time.

Please contact me if you have any queries about on-going ethics clearance. The SUHREC project number should be quoted in communication. Chief Investigators/Supervisors and Student Researchers should retain a copy of this email as part of project record-keeping.

Best wishes for project.

Yours sincerely,

Ann Gaeth
Secretary, SHESC3

*******************************
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Appendix B: Preliminary analyses Psychometric analyses of selected measures.

A number of preliminary steps were taken to ascertain the validity and reliability of the measures. First, confirmatory factor analysis (CFA) was performed on each measure. The appropriateness of items to each latent construct was primarily evaluated in terms of: the Satorra-Bentler re-scaled chi-square ($\chi^2$) test, which is an index of exact fit adjusted for non-normality; the Comparative Fit Index (CFI), which compares the hypothesized model to a model perfectly fitting the data; and, the Standardised or Weighted Root Mean Square Residual (SRMR/WRMR), which estimates the degree to which residual variance (error) contributes to model misspecification with continuous or categorical variables respectively (Bentler, 2007, 2010; Iacobucci, 2010). As noted in the previous chapter, model fit was assessed using the following criteria for good model fit: $\chi^2$ with $p \geq .05$, CFI $\geq .95$, RMSEA $\leq .06$, and either SRMR $\leq .08$ for continuous variables or WRMR $\leq .10$ for categorical observed variables (Muthén & Muthén, 2002).

Where model misspecification was evident (i.e., items did not adequately represent the construct they were supposed to measure), the items were checked for unidimensionality using scree plots and eigenvalues greater than one as per the criteria for Cronbach’s alpha reliability coefficient. Items were removed one at a time based on the standardised residuals and modification indices in Mplus, in order to establish simple structure and parsimonious one-factor congeneric models. These were assessed for model fit and proportion of variance explained, prior to being assessed for reliability. Reliability was estimated using Cronbach’s alpha via the reliability analysis function in IBM SPSS Statistics 24. Streiner and Norman (2008) recommend that alpha values should exceed .70 but be no higher than .90 as very high values of alpha may indicate redundancy of some items.

Coping measure.

As noted in Chapter 5, the Brief-COPE comprises 14 pairs of items, which are designed to assess 14 different coping responses. A second order principal components analysis (PCA) with varimax oblique rotation was performed in Mplus. A scree plot of the subscale scores suggested the presence of four components, which was consistent with the number of eigenvalues greater than one. The four components reflected Ebert, Tucker, and Roth’s (2010) groupings: Approach (Acceptance, Positive Reframing, Humour, Planning, and Taking Action); Avoidant (Self-blame, Behavioural Disengagement, Denial, Mental Distraction and Substance Use); Support Seeking (Seek Emotional Support, Instrumental Support, and Venting); and, Religion. In the current
study, Denial and Mental Distraction cross-loaded with the Religion and Approach factors respectively.

Results from a second order confirmatory factor analysis supported the modelling of Avoidant coping as a higher-order factor reflected by the five coping strategies: Behavioural Disengagement, Blame Self, Denial, Substance Use, and Self-distraction (Satorra-Bentler $\chi^2(5) = 5.68$, $p = .339$, CFI = 1.00, RMSEA = .02 [90% CI: .02, .04], SRMR = .02). Notably, Self-distraction and Substance Use only correlated with the higher-order factor .27 and .34 respectively and the associated R-square estimates were .07 and .12, which suggests that those two strategies may not be empirically useful indicators of avoidant coping and are not well represented by the Avoidant latent variable. Similar patterns were found for both Approach coping and Support Seeking latent variables but rather than excluding all the low correlating strategies to achieve acceptable reliability coefficients, the decision was made to form weighted composites for use in the mixture SEM.

**Basic psychological needs.**

A three-factor CFA of the satisfaction of basic psychological needs measure was a poor fit to the data (Satorra-Bentler $\chi^2(186) = 689.12$, $p < .001$, CFI = .78, RMSEA = .09 [90% CI: .08, .13], SRMR = .07). Inspection of the scree plots for each of the subscales indicated that they were multidimensional. All items of the scale were subjected to exploratory PCA. This revealed complex structure with several items cross-loading on two factors. Problematic items were removed one at a time in accordance with the modification indices and with consideration given to the standardised parameter estimates, normalized residuals and variance explained. The best fitting model (Satorra-Bentler $\chi^2(24) = 63.00$, $p < .001$, CFI = .92, RMSEA = .07 [90% CI: .052, .10], SRMR = .05) included three indicators for each of the three subscales: Autonomy (items 1, 8 & 17), Competence (items 3, 5 & 19), and Relatedness (items 2, 9 & 12). The revised subscales were unidimensional with reliability coefficients of .71 for Autonomy, .72 for Competence, and .69 for Relatedness. Correlations between the subscales ranged from .57 (Autonomy with Competence) to .79 (Autonomy with Relatedness). Scale scores were subsequently calculated using the summed means of the relevant items and modelled as three unidimensional indicators of the latent variable, satisfaction of basic psychological needs.
Mental health and wellbeing measures.

*SF-36.*

The four domains of the SF-36 mental health summary component (MCS) demonstrated unidimensionality on individual scree plots. However, a four-factor CFA of the items indicated that it was not a good fit to the data ($\chi^2(71) = 381.84, p < .001$, CFI = .86, RMSEA = .11 [90% CI: .10, .12], SRMR = .06). High standardised residuals were found between several of the vitality (VT) and mental health (MH) items, and also the social functioning (SF) and role limitations due to emotional problems (RE). To further investigate the discriminant validity of these subscales, a four-factor EFA was run. The resultant factor structure is presented in Table A1. Note that the two SF items failed to load on the same factor, let alone their own factor, and the reverse scored MH items load on a factor with some of the VT items. Such complex structure indicated a lack of discriminant validity between subscales.

### Table A1

*Four-factor EFA Factor Structure of the Mental Health-Related Subscales of the SF-36*

<table>
<thead>
<tr>
<th>SF-36 Subscale and Item No.</th>
<th>Factor 1</th>
<th>Factor 2</th>
<th>Factor 3</th>
<th>Factor 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>RE-SF05A</td>
<td><strong>0.80</strong></td>
<td>0.38</td>
<td>0.40</td>
<td>0.23</td>
</tr>
<tr>
<td>RE-SF05B</td>
<td><strong>0.79</strong></td>
<td>0.38</td>
<td>0.43</td>
<td>0.27</td>
</tr>
<tr>
<td>RE-SF05C</td>
<td><strong>0.77</strong></td>
<td>0.34</td>
<td>0.42</td>
<td>0.25</td>
</tr>
<tr>
<td>SF-SF06r</td>
<td><strong>0.70</strong></td>
<td><strong>0.50</strong></td>
<td><strong>0.60</strong></td>
<td>0.32</td>
</tr>
<tr>
<td>SF-SF10</td>
<td><strong>0.50</strong></td>
<td>0.48</td>
<td><strong>0.57</strong></td>
<td>0.23</td>
</tr>
<tr>
<td>VT-SF09A-r</td>
<td>0.47</td>
<td><strong>0.85</strong></td>
<td><strong>0.53</strong></td>
<td>0.43</td>
</tr>
<tr>
<td>VT-SF09Er</td>
<td>0.39</td>
<td><strong>0.84</strong></td>
<td>0.38</td>
<td><strong>0.50</strong></td>
</tr>
<tr>
<td>VT-SF09G</td>
<td>0.33</td>
<td>0.42</td>
<td>0.46</td>
<td><strong>0.77</strong></td>
</tr>
<tr>
<td>VT-SF09I</td>
<td>0.32</td>
<td>0.43</td>
<td>0.33</td>
<td><strong>0.83</strong></td>
</tr>
<tr>
<td>MH-SF09B</td>
<td>0.31</td>
<td>0.30</td>
<td><strong>0.60</strong></td>
<td>0.31</td>
</tr>
<tr>
<td>MH-SF09C</td>
<td>0.48</td>
<td>0.48</td>
<td><strong>0.87</strong></td>
<td>0.32</td>
</tr>
<tr>
<td>MH-SF09D-r</td>
<td>0.36</td>
<td><strong>0.71</strong></td>
<td><strong>0.56</strong></td>
<td>0.36</td>
</tr>
<tr>
<td>MH-SF09F</td>
<td><strong>0.50</strong></td>
<td>0.49</td>
<td><strong>0.87</strong></td>
<td>0.37</td>
</tr>
<tr>
<td>MH-SF09H-r</td>
<td>0.48</td>
<td><strong>0.77</strong></td>
<td><strong>0.67</strong></td>
<td>0.26</td>
</tr>
</tbody>
</table>

*Note.* RE = Role limitations due to emotional problems, SF = Social functioning, VT = Vitality, MH = Mental Health, and r = reverse scored item. $N = 375$.

Without an acceptable measurement model for the four subscales, it was not
feasible to investigate the constructs separately. Nevertheless, the SF-36 is a widely-used, well-validated measure of quality of life, particularly when the standardised mental health component summary (MCS) and physical health component summary (PCS) scores are used. Therefore, to overcome the lack of discriminant validity between the subscales and to be consistent with its use in the wider literature, the standardised component summary scores were calculated using Australian population norms (ABS, 2003) for subsequent analyses. A comparison of the means and standard deviations for the current sample compared to the Australian population is presented in Table A2.

Table A2

<table>
<thead>
<tr>
<th>Component</th>
<th>Australian Population</th>
<th>Current Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
</tr>
<tr>
<td>Mental Health</td>
<td>50.1</td>
<td>10.0</td>
</tr>
<tr>
<td>Physical Health</td>
<td>49.8</td>
<td>10.2</td>
</tr>
</tbody>
</table>

Note. N = 375.

A comparison of the means indicates that the current sample have marginally better physical health overall than the general Australian population. Conversely, the MCS mean in the current sample is almost one standard deviation lower than the mean of the general population. This indicates that the current sample has poorer mental health and wellbeing overall, compared to the general population. These findings are consistent with the broader literature and research involving university students and community members who voluntarily participate in mental health and related research, who often have slightly better physical health than the general population (as a function of age) and significantly higher prevalence rates of mental health problems (e.g., Stallman, 2010).

**HADS.**

Both scales from the Hospital Anxiety and Depression Scales (HADS) were unidimensional, with Cronbach’s alpha reliability coefficients of .85 and .82 for the Anxiety and Depression scales respectively. These coefficients are approximate to the average alphas reported in Bejelland and colleagues’ (2002) review of the reliability and validity of the HADS. Model fit statistics for a two-factor CFA indicated a good fit to
the data (Satorra-Bentler $\chi^2(76) = 143.13, p < .001, \text{CFI} = .96, \text{RMSEA} = .05 [90\% \text{CI}: .04, .06], \text{SRMR} = .04$). The correlation between the anxiety and depression factors was .62, which indicates that there is some overlap of the constructs.

**SWLS.**

The five-item Satisfaction with Life Scale (SWL) clearly demonstrated unidimensional structure in the scree plot. Internal consistency was .89, which is comparable to the alpha of .85 reported by Pavot, Diener, Colvin, and Sandvik (1991). Results of the one-factor congeneric model indicated a good fit to the data (Satorra-Bentler $\chi^2(5) = 14.95, p = .011, \text{CFI} = .98, \text{RMSEA} = .07 [90\% \text{CI}: .03, .12], \text{SRMR} = .03$).