Emotional and Social Loneliness as Mediators of Chronic Conditions and Depression in Older Adults in Aotearoa

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Thomas Nicholson

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Abstract

Background and Objectives: Aotearoa New Zealand is experiencing an acceleration in its ageing population that will present economic and health challenges for its people and healthcare systems. Modern changes in healthcare enable people to live longer but have come with increased chronic conditions. Adding to this burden, older adults are vulnerable to psychological problems such as depression, itself often considered a chronic condition. Searching for ways to understand and prevent depression in older adults, researchers discovered connections with both chronic conditions and loneliness. The relationship between chronic conditions, loneliness, and depression is complex and not well understood. While considerable research suggests that these components are related, a dearth of research addresses all three components concurrently. Given that chronic conditions are potential risk factors for both depression and loneliness and that loneliness may predict depression, it is conceivable that loneliness may mediate the relationship between chronic conditions and depression. Consequently, it may be possible to prevent or alleviate depression in older adults experiencing chronic conditions by addressing loneliness.

Method: Analyses used survey data from 3,011 participants aged 55-91 years taken from two waves of the New Zealand Health, Work and Retirement Study. Two structural equation models tested the relationship between chronic conditions and depression, between multimorbidity and depression, and whether emotional or social loneliness mediated the relationships. Covariates included age, ethnicity, gender, partner status, and SES measured as living standards.

Results: SEM analyses found that sleep disorder and multimorbidity predicted depression and that sleep disorder predicted social and emotional loneliness while multimorbidity predicted emotional loneliness. Additionally, SES predicted depression and both types of loneliness. However, loneliness did not mediate either relationship.

Conclusion: The current study supports prior research findings that sleep disorder and multimorbidity predict depression. This study further provides a valuable contribution to the literature investigating the relationship between SES when measured as living standards and depression in older people and aligns with the considerable research on the importance of inequalities and their negative impact on health outcomes.

Keywords: chronic conditions, depression, living standards, loneliness, older adults

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1. Introduction: Chronic Conditions and Depression in Older Adults

People live longer today due to public health, medical, and socioeconomic improvements (Remm et al., 2023). The World Health Organization (WHO; 2020) estimates the global population of people aged 60+ to be approximately 13.5%, slightly more than 1 billion people. The WHO expects this number to increase to about 2.1 billion by 2050, representing nearly 20% of the population. Aotearoa New Zealand is experiencing a similar acceleration in its ageing population. While those aged 65+ numbered approximately 842,000 in 2022, Statistics New Zealand Tatauranga Aotearoa (SNZTA; 2022) projects this number to reach 1 million by 2028. Moreover, SNZTA estimates that one in fifty people in Aotearoa are currently 85+ years old, increasing to around one in twenty after 2040.

Along with increased age, modern changes correlate to an increasing number of older people living with chronic conditions (Maresova et al., 2019; Remm et al., 2023), which are recurrent or long-term conditions that can significantly affect people's lives (National Advisory Committee on Health and Disability, 2007). Often considered a chronic condition, depression is one of the most common forms of mental distress in older adults (Zhao et al., 2023) and is characterised by empty, sad, or irritable mood in conjunction with somatic and cognitive changes that appreciably affect the ability to function (American Psychiatric Association, 2022). Gaining an understanding of its prevalence and risk factors is crucial to enable early detection, treatment, and possibly prevention (Cai et al., 2023). Considerable research supports an association between chronic conditions and the decline in the mental wellbeing of older persons (Remm et al., 2023), particularly for depression (Cai et al., 2023; Huang et al., 2010; Maresova et al., 2019; Zenebe et al., 2021).

Chronic conditions and depression present challenges for the individual as well as for Aotearoa. According to the 2014 Report on the Positive Ageing Strategy (Ministry of Social Development Te Manatū Whakhiato Ora, 2015), health is a key theme among services for older adults, and society benefits when populations age positively and in a healthy manner that puts less demand on public health systems. Looking to understand and hopefully prevent depression in older adults, past research associated geriatric depression with many different factors, including both chronic conditions as previously discussed and loneliness (Cohen-Mansfield et al., 2016; Zenebe et al., 2021). Unfortunately, research on loneliness as a determinant of health has been neglected until relatively recently (Griffin et al., 2024; World Health Organization, 2021). Nevertheless, research does link chronic conditions with loneliness and loneliness with depression (Lim et al., 2020).

The precise relationship between chronic conditions, loneliness, and depression and how they interrelate is complex and not well understood. Given that chronic conditions are potential risk factors for both depression and loneliness and that loneliness may predict depression, it is conceivable that loneliness may mediate the relationship between chronic conditions and depression. Therefore, it may be possible to prevent or alleviate depression in older adults experiencing chronic conditions by addressing loneliness.

1.1. Chronic Conditions

1.1.1. Prevalence of Chronic Conditions in Older Adults

Using longitudinal data from the WHO 2007 Study on Global Ageing and Adult Health, Oduro et al. (2023) reported the global rate of chronic conditions in people 50 years and older to be 81.5%, ranging from 58.6% in the Russian Federation to 94.0% in Ghana. Research in Aotearoa NZ and Australia showed similar results, with 51% and 63% of the population reporting at least one chronic condition, respectively, and most experiencing more than one chronic condition concurrently (Aspin et al., 2010). Aspin and colleagues further reported that chronic condition rates increased with age, noting research showing that all participants 85+ years of age in their study reported at least one chronic condition, with most facing multiple concurrent chronic conditions, defined as multimorbidity (Marengoni et al., 2011). Longitudinal research in Aotearoa by Aminisani et al. (2019) reported multimorbidity incidence of 68.5 per 1,000 person-years over 10 years of study participants initially aged 55-70 years.

The increasing incidence and prevalence of chronic conditions is a current health concern worldwide (Maresova et al., 2019), particularly with rising rates of multimorbidity (Aspin et al., 2010; Marengoni et al., 2011). According to a review by Gifford et al. (2021), such conditions constitute 70% of global deaths and lead to 88% of health loss in Aotearoa NZ (Ministry of Health Manatū Hauora, 2016b; World Health Organization, 2017). Furthermore, Māori face higher rates of both chronic conditions (Ministry of Health Manatū Hauora, 2015) and multimorbidity (Aminisani et al., 2019), as well as worse outcomes due to chronic conditions than non-Māori (Gifford et al., 2021). The increasing incidence of multimorbidity also puts pressure on healthcare systems. Research in Aotearoa NZ shows the costs to the public health system of experiencing two or more non-communicable conditions concurrently is super-additive for most combinations of conditions studied, increasing the total cost to an amount that is more than what would be expected from experiencing the same conditions independently (Blakely et al., 2019). In fact, the excess costs attributed to multimorbidity that went beyond the cost of the individual conditions themselves comprised 23.8% of all healthcare expenditures from 1 July 2007 to 30 June 2014 (Blakely et al., 2019; New Zealand Institute of Economic Research, 2022). Additionally, recent research indicates that multimorbidity in older people contributes significantly to a reduced quality of life (Maresova et al., 2019; Yeung et al., 2022), an increased risk of disability, hospitalisation, institutionalisation, and mortality (Quiñones et al., 2016), and a decline in psychological wellbeing (Remm et al., 2023).

1.1.2. Research on Chronic Conditions in Older Adults

The research on chronic conditions is heterogeneous, with a significant amount focusing on single conditions. Common conditions studied include cardiovascular and metabolic conditions such as cardiovascular disease, chronic obstructive pulmonary disease (COPD), diabetes, hypertension, and the like (Ng et al., 2018), respiratory conditions such as asthma (Aspin et al., 2010), stroke (Maresova et al., 2019), arthritis (Birk et al., 2019), and cancers (Silva et al., 2022), among others. Additional research focuses on those experiencing two conditions in which one is treated as the index condition and the other is viewed as secondary, known as comorbidity (Suls et al., 2016), and on multimorbidity (Tazzeo et al., 2023). Research on multimorbidity is also highly varied, with considerable heterogeneity in methodologies used to identify groups of chronic conditions, with many focusing on common traits or the total number of chronic conditions per individual (Ng et al., 2018).

1.1.3. Summary

Aotearoa is experiencing a rapidly growing ageing population. Chronic conditions in this population are prevalent globally and in Aotearoa. The number of older adults with multiple chronic conditions is likewise growing. Accordingly, the increasing incidence of chronic conditions in older adults is a current public health concern that puts increased costs and pressure on the nation's health systems. Furthermore, chronic conditions lead to poor outcomes in older adults that disproportionately affect Māori. One such potential outcome is depression, a potentially preventable chronic condition.

1.2. Depression

1.2.1. Prevalence of Depression in Older Adults

Prevalence data for depression in older people vary in the literature. The WHO (2023) estimates that 3.8% of the worldwide population experiences some level of depression, including 5.7% of adults aged 60+. A recent systematic review and meta-analysis examining the worldwide prevalence of depression in older adults (Cai et al., 2023) from 55 studies covering 59,851 participants reported the pooled prevalence of depression in older adults was 35.1%, though this declined with age. Zhao et al. (2023) reported similar numbers in their literature review of late-life depression, indicating an average prevalence of late-life depression of 31.8%, as did Zenebe et al. (2021), who reported an average depression rate of 31.74% among older adults in their systematic review and meta-analysis. Zhao and colleagues analysed evidence that suggests depression is higher in developing countries than in developed, 40.78% and 17.05%, respectively. Regrettably, the authors reported no data for Aotearoa; however, Western countries indicated a smaller percentage of depressed older adults, 19.47%, and in Australia, the rate was reported to be 9.8%. Zenebe and colleagues reported similar numbers in their breakdown, indicating an average prevalence of 7.7% in Australian older adults while providing evidence that suggests depression is underdiagnosed in older individuals. The review authors stated that different levels of prevalence data were discovered based on differences in clinical and demographic characteristics, including sample size, study sampling method employed, and assessment tools used (Cai et al., 2023; Zenebe et al., 2021; Zhao et al., 2023). Additionally, Haigh et al. (2018) noted in their review of the literature on depression in older adults that much depends on how depression is conceptualised and defined. The authors found similar prevalence data as described previously until studies assessed specific diagnoses such as major depressive disorder, at which point prevalence rates consistently ranged from 0.4% to

10.2%, variable by country. Haigh and colleagues concluded that while older adults do experience significant rates of clinical depressive symptoms, the rates of older adults experiencing diagnosed depression were lower than that found for younger adults.

Specific to Aotearoa NZ, the Ministry of Health Manatū Hauora (MoH; 2021) provides an interactive tool for searching and investigating the NZ Health Survey data from 2017 – 2020. Pooled year data indicate that 13.9% of respondents aged 65+ previously received a depression diagnosis. The number of females diagnosed with depression in this age group was considerably higher at 17.0% versus 10.4% for males, a consistent pattern across the ethnic groups reported, including Asian, Māori, Pacific, and European/Other. The MoH discontinued the diagnosed depression indicator in recent survey data in favour of a general psychological distress indicator, making recent comparisons of older adults specifically diagnosed with depression difficult. However, previous survey data indicated a slight decline since the 2014-2017 survey of 14.5% and an increase since the 2011 – 2014 survey of 13.1%. Additional research suggests that depression rates in older adults are increasing. The Association of Salaried Medical Specialists Toi Mata Hauora (2021) estimated the number of adults in Aotearoa diagnosed with depression in 2019 to be 16.5%, an increase of 32% since 2011 and one of the highest in the countries that comprise the Organisation for Economic Cooperation and Development (OECD). Further research by Tapsell et al. (2018) compared the rates of new adult admissions to mental health services for major depressive disorder (MDD) in 2014 by ethnicity using a Ministry of Health national database. The authors reported the incidence of new inpatients for Māori and non-Māori to be 25.8 and 18.4 per 100K, respectively. They further reported the incidence of new clients referred to NZ mental health services with MDD to be 41.5 and 51.1 per 100K for Māori and non-Māori, respectively. The general mental wellbeing of older people living in Aotearoa has also declined in recent years. SNZTA (2022b) reported a significant decline in mental wellbeing from 2018 to 2021 based on the 2021 General Social

Survey for several age groups, including a 7.1% decline in older adults aged 55 to 64 years, 1.7% aged 65-74, and 5.3% for those aged 75+.

1.2.2. Depression as Public Health Concern

Depression leads to potentially poor consequences in older people, including a general decline in physical health (Cai et al., 2023), wellbeing, and functioning (Remm et al., 2023), a higher chance of disability (Wu et al., 2022) and mortality (Birk et al., 2019; Wu et al., 2022), recurring cardiovascular incidents and reduced quality of life (Pan et al., 2023). Research from Aotearoa indicates that depressive symptoms account for a reduction in life expectancy of up to 25 years for those with severe mental distress (He Ara Oranga, 2018) and 9.7% of all years lived with a disability, a metric used to estimate the level of health loss due to a specific condition (The Royal Australian & New Zealand College of Psychiatrists, 2016). Likewise, the WHO (2017) estimates that depression is the greatest contributor to global non-fatal health loss.

Accordingly, depression in older adults results in increased health service usage, including hospitalisation and outpatient care (Zhao et al., 2023), and contributes substantially to the global disease burden (Zenebe et al., 2021). The Royal Australian & New Zealand College of Psychiatrists (2016) noted in their report on the cost of mental distress and comorbidities in NZ and Australia that there are very few cost-of-illness studies for mental distress in Aotearoa. Indeed, Doran and Kinchin (2019) reviewed the literature on the economic impact of mental distress in Aotearoa, Australia, Canada, and the UK, which included a single study from Aotearoa concerning impacts due to mental distress in young adults aged 18-25 years in 2010 and none for depression specifically, in sharp contrast to the other countries reviewed. Nevertheless, research on the costs of mental distress in general has been conducted in Aotearoa since the review. Research by Lockett et al. (2018) using data from the Ministry of Health NZ Health Survey (2016) found that those adults indicating internalising disorders such as depression were significantly more likely to use primary health services, including after-hours medical centres. The authors reported odds ratios for those adults experiencing an internalising disorder versus those that were not between 1.43 for after-hours medical centres and 3.02 for GP visits. From their inquiry into mental health and addiction, the NZ government further estimated the public sector cost due to the burden of serious mental distress in Aotearoa to have been approximately $1.4 billion in 2016/17 (He Ara Oranga, 2018).

1.2.3. Summary

Depression is one of the most common forms of mental distress in older adults. The literature reports heterogeneous rates globally, dependent on how depression is defined and conceptualised. In Aotearoa, the overall mental wellbeing of older adults has declined in recent years, and evidence exists to suggest that depression rates in older adults are on the rise, disproportionately impacting females and Māori. The increasing depression rate is unfortunate, as depression in older adults is associated with increased health service usage and poor outcomes. Research supports an association between this decline in the mental wellbeing of older persons, particularly depression, with chronic conditions.

1.3. Chronic Conditions and Depression

A recent umbrella review by Wu et al. (2022) investigated the risk factors for depression in older persons in the literature and evaluated the credibility of the evidence presented for each risk factor. The authors reviewed 22 meta-analyses and three qualitative reviews that included over 1.1 million participants and 82 distinct risk factors. While Wu and colleagues judged the majority of studies to be of low quality, the authors determined the evidence for many chronic conditions as risk factors for depression to be convincing and generally moderate to strong. Likewise, Zenebe et al. (2021), in their systematic review and meta-analysis of the determinants of depression in older people, concluded that chronic conditions exhibited a positive and strong association with depression in old age.

Cross-sectional research consistently demonstrates an increased incidence of depression following the onset of chronic conditions in older adults (Birk et al., 2019). Additionally, longitudinal research by Wicke et al. (2022) provided support for chronic conditions as risk factors and predictors of depression, particularly when multimorbid. The authors concluded that multimorbidity predicted incident depression, a worsening of depressive symptoms, and a lower chance of remission. In their scoping review, Birk et al. (2019) presented evidence indicating that people with multimorbidities are twice as likely to be depressed as those without and that depression is the most common comorbid condition in older people.

Despite the evidence supporting chronic conditions as risk factors for depression in older individuals, the research in this area is equivocal, and the relationship is complex. In their recent integrated literature review, Li et al. (2019) highlighted the evidence for a bidirectional relationship between depression and chronic conditions. In their scoping review, Birk et al. (2019) also pointed to evidence supporting a bidirectional relationship, having noted complex patterns of chronic conditions associated with ensuing depression as well as depression with impending incidence of chronic conditions. Furthermore, the authors discussed research that described depression and multimorbidity covarying in a dose-dependent manner where the larger the number of comorbid conditions, the greater the odds of depression.

1.3.1. Summary

Chronic conditions and depression are recognised as major health concerns globally. Evidence suggests that the combination of the two leads to poor quality of life, compromised self-management, and diminished life expectancy (Li et al., 2019), life satisfaction, daily functioning, and wellbeing (Cai et al., 2023; Remm et al., 2023) which in turn lead to greater healthcare costs (Sporinova et al., 2019). Moreover, longitudinal research by Wicke et al. (2022) suggests that multimorbidity in older adults predicts a worsening of depressive symptoms and reduced probability of remission. Given current evidence, it is plausible that loneliness may mediate the relationship between chronic conditions and depression.

1.4. Loneliness

Historical research often treated loneliness as an epiphenomenon of, or as a concept synonymous with, other concerns such as social isolation and depression (Lim et al., 2020). However, more current evidence supports the conceptualisation of loneliness as a separate, unique construct (Cacioppo et al., 2006). Loneliness has been explained in bidimensional terms as the subjective feeling resulting from the lack of a desired intimate relationship, so-called emotional loneliness, or from the longing for a broader social network, known as social loneliness (Gierveld & Tilburg, 2006). Although the two dimensions are frequently correlated, evidence supports unique risk factors for each, though researchers do not often differentiate between them even when using a bidimensional scale (Dahlberg et al., 2022).

1.4.1. Vulnerability to Loneliness

It has been proposed that older adults may be vulnerable to both types of loneliness for a variety of reasons. Older adults are more likely to go through the loss of a partner, family members, and friends, lower socioeconomic status (SES), increased financial concerns, loss of social roles due to retirement, declining health, decreased mobility and functioning, and relocation (Cohen-Mansfield et al., 2009, 2016; Lim et al., 2020; Luhmann et al., 2022). Additionally, because older people are more likely to experience the passing of aging partners and friends, the probability of maintaining an existing or obtaining another intimate relationship decreases with age (Luanaigh & Lawlor, 2008).

Here again, the research shows heterogeneity in results and conclusions. Considerable research supports an association between loneliness and age in a U-shaped manner, with people of younger and older aged groups showing higher loneliness rates than middle-aged groups (Lim et al., 2020; Solmi et al., 2020; World Health Organization, 2021) with a significant increase in loneliness for those aged 80+ (Luhmann et al., 2022). In their integrative review of research on older adult loneliness in Aotearoa, Wright-St Clair et al. (2017) noted research indicating that adults 65 – 74 years of age reported the lowest rates of loneliness of any age group. However, the authors also reported that older adults living with economic hardship had greater loneliness rates than younger individuals who indicated comparable levels of economic hardship and that Māori aged 55 – 70 were more likely to indicate feeling lonely. On the other hand, further research, including a meta-analysis of longitudinal studies, found no significant relationship between loneliness and age (Luhmann et al., 2022), while others suggested a steady decrease in loneliness with age (Barreto et al., 2021).

1.4.2. Prevalence of Loneliness in Older Adults

Estimates of the prevalence of loneliness in older individuals are sparse and highly variable in the literature. A recent systematic review and meta-analysis (Surkalim et al., 2022) investigated the global incidence of loneliness in 113 countries. The authors noted the scarcity of data outside of Europe for every age group other than adolescents. The authors reviewed research showing estimations of loneliness prevalence in older adults between 4.2% and 24.2% across European countries. Additionally, the authors of a recent umbrella review of observational studies examined research in North America that indicated a wide range between 17% to 57% (Solmi et al., 2020). In contrast, researchers in a review of the UK literature presented evidence that indicated rates from 5% to 43% (Paul et al., 2021). While noting the scarcity of research on estimates of loneliness in older people, the WHO nevertheless maintains that enough is known to conclude that loneliness is likely widespread among older adults in most regions of the world (World Health Organization, 2021) and may in fact be underreported due to stigma (Cohen-Mansfield et al., 2016).

Wright-St Clair et al. (2017) indicated in their research review on older adult loneliness in Aotearoa that 13% of those aged 75+ and 10% of adults between 65 to 74 years acknowledged feeling lonely most, all, or some of the time in the previous four weeks. The Ministry of Health Manatū Hauora (2021) reported smaller percentages in survey data from 2017, ranging from 2.5% to 8.2% for those aged 55+ who reported being lonely all, most, or some of the time in the past four weeks. Survey data from 2023 indicated increases for all ethnic groups surveyed, including Asian, European/Other, Māori, and Pacific, and for both genders. In that year, percentages ranged from 2.9% to 11% for the same categories, with the largest percentages for Māori and Pacific peoples and larger percentages for females than males. While some evidence exists to suggest that rates of loneliness in older adults are on the rise, the evidence is mixed (Holt-Lunstad, 2017; Luhmann et al., 2022; World Health Organization, 2021), with some suggesting rates may be declining (Surkalim et al., 2023). Moreover, while a good deal of the research suggests that older adults experiencing loneliness are more likely to be female, Māori, or a member of another marginalised ethnicity (Cohen-Mansfield et al., 2016; Solmi et al., 2020; Wright-St Clair et al., 2017; Yang, 2018), others found no association with gender (Maes et al., 2019).

1.4.3. Loneliness as Public Health Concern

Loneliness is increasingly recognised as a public health concern globally (Lim et al., 2020) and for older adults in Aotearoa (Wright-St Clair et al., 2017). Substantial evidence from meta-analyses and longitudinal studies exists to indicate that loneliness in older adults is a risk factor for poor outcomes, including all-cause mortality, low quality of life, adverse physical, mental, and cognitive health conditions, and physiological decline (Cohen-Mansfield et al., 2016; Hawkley & Cacioppo, 2007; Kraav et al., 2021; Lim et al., 2020; Mihalopoulos et al., 2020; Wang et al., 2023; Wright-St Clair et al., 2017). Once again, the research is equivocal. For instance, Lim et al. (2020) noted research in their review that found no significant relationship between loneliness and mortality, and others that suggested the relationship could be better explained by social isolation. However, the authors noted that this could have been due to methodological differences concerning how the two constructs were measured.

While the evidence concerning the consequences of loneliness is growing, the literature on the economic costs of loneliness is scarce (World Health Organization, 2021) due to the challenge of identifying and quantifying healthcare costs attributable solely to loneliness (Kung et al., 2021). Nevertheless, some research on the costs of illness attributable to loneliness exists, with most studies completed in European countries and the United States (Mihalopoulos et al., 2020). Mihalopoulos and colleagues noted in their review that research found increased healthcare and long-term care costs due to loneliness. These increased costs may be directly or indirectly attributed to loneliness due to increased GP visits, hospital admissions, and through accessing mental health services (Meisters et al., 2021). For example, research has found that lonely older adults were more likely to visit their GP for social contact in the United States and China, which increased costs (Gerst-Emerson & Jayawardhana, 2015; Zhang et al., 2018).

1.4.4. Summary

Loneliness may be conceptualised in bidimensional terms, with emotional loneliness arising from the absence of desired intimate relationships and social loneliness resulting from the longing for more social connections. Prevalence estimates of loneliness in older individuals are mixed; however, loneliness is increasingly recognised as a public health concern. Research indicates a relationship between loneliness and chronic conditions in older people.

1.5. Chronic Conditions and Loneliness

Decades of research link chronic conditions with loneliness. Multiple meta-analyses and literature reviews support a strong association between loneliness and various chronic conditions (Cohen-Mansfield et al., 2016; Lim et al., 2020; Paul et al., 2021). Furthermore, studies support a positive relationship between the number of chronic conditions and higher loneliness scores (Theeke, 2010; Theeke & Mallow, 2013). Longitudinal research further offers compelling evidence for chronic conditions and multimorbidity as predictors of loneliness (Cohen-Mansfield et al., 2009; Deckx et al., 2014; Havens et al., 2004; Lim et al., 2020; Theeke, 2009). Additionally, evidence suggests that chronic conditions and multimorbidity may exacerbate feelings of loneliness (Dahlberg et al., 2022; Deckx et al., 2014; Trtica et al., 2023). However, not all of the research suggests a unidirectional relationship between chronic conditions and loneliness. Research evidence exists to support loneliness as a risk factor for chronic conditions (Bu et al., 2020; Shankar et al., 2011), suggesting a potentially bidirectional relationship (Paul et al., 2021).

1.6. Chronic Conditions, Loneliness, and Depression

1.6.1. Relationship Between Loneliness and Depression

The relationship between depression and loneliness in the literature is ambiguous. In their longitudinal study of Finnish older men followed up over 23.2 years on average, Kraav et al. (2021) found a strong bidirectional association between loneliness and depression. Another longitudinal study of older adults in the UK found that depression, in addition to several factors, was significantly related to future loneliness (Pikhartova et al., 2016). In their literature review of the correlates and risk factors of loneliness, Lim et al. (2020) examined the evidence that suggested developing comorbid depression with loneliness exacerbated loneliness but noted that most studies were cross-sectional and, therefore, could not infer causality. Furthermore, the authors investigated additional evidence that implicated loneliness as a risk factor for changes in later depressive symptoms and that higher loneliness levels predicted an increase in depressive severity. In a later systematic review of longitudinal research on risk factors for loneliness in older adults, Dahlberg et al. (2022) reviewed the evidence. They concluded that while few factors showed evidence for a strong longitudinal association with loneliness, depression and increases in depressive symptomatology were relatively consistent in their association with loneliness. On the other hand, 12-year longitudinal research by Lee et al. (2021) of older adults in the UK and five-year longitudinal research by Cacioppo et al. (2010) of older individuals in Chicago, USA, found that loneliness predicted depressive symptomatology and not the reverse regardless of other sociodemographic factors. Other researchers explored the relationship between living alone and depression and obtained results that suggested loneliness was a strong mediating factor (N. S. Park et al., 2017).

1.6.2. Relationship Between Chronic Conditions, Loneliness and Depression

Research addressing all three components concurrently and how they interrelate is limited. Wright-St Clair et al. (2017) reviewed the research examining loneliness of older adults in Aotearoa. The authors discussed evidence that indicated loneliness was negatively associated with poor physical and mental health and that loneliness, in turn, was related to depression. Kirkland et al. (2023) studied loneliness in older Canadian adults during the COVID-19 pandemic using data from the Canadian Longitudinal Study on Aging. The authors found an association with loneliness and pre-pandemic loneliness, female gender, number of chronic conditions, and depression but could not define a direction for these latter relationships due to study limitations. Researchers in multiple reviews reported separate evidence that associated chronic conditions with loneliness and evidence that associated loneliness with depression (C. Park et al., 2020; Zenebe et al., 2021). In an umbrella review of observational studies of loneliness, Solmi et al. (2020) reviewed evidence that associated chronic conditions with loneliness and longitudinal evidence that suggested loneliness increased depression risk. Similarly, Hodgson et al. (2020) performed a synthesis of the literature on loneliness, social isolation, cardiovascular disease, and mortality in UK adults, in which they noted that loneliness was associated with a variety of chronic conditions and increased depression rates. The authors further noted the interdependence between loneliness and depression. In their longitudinal study of loneliness in older adults using data from the Survey of Health, Age, and Retirement in Europe over seven years, Lundmark et al. (2023) found that chronic conditions and depression, in addition to female gender and lack of cohabitant partner, predicted loneliness.

1.6.3. Theoretical Explanations for the Relationships

Given the heterogeneity and complexity of the relationships between chronic conditions, loneliness, and depression found in the literature, researchers have put forward a multitude of theoretical explanations for each relationship.

1.6.3.1. Chronic Conditions and Depression

Theoretical explanations in the literature often recognise the complex relationship between chronic conditions and depression, with an emphasis on biopsychosocial models which accentuate the multifaceted and often unclear interplay between various biological, psychological, and social factors (Zenebe et al., 2021). In their review of longitudinal studies examining risk factors for depression in older persons, Maier et al. (2021) developed and evaluated a conceptual framework based on the diathesis-stress model. In their model, stressful life events and individual vulnerabilities combine to form a precondition for the development of depression. Maier and colleagues presented evidence showing that chronic conditions are one of the many vulnerabilities for late-life depression. The overall model proposes that various developmental, genetic, psychosocial and sociodemographic factors in addition to impairment, mental and physical health status, and relationship qualities may influence depression vulnerability. Moreover, the authors maintained that any of these potentially interrelated factors could influence the etiology of depressive disorders directly or by moderating the effects of an individual’s life stressors. During evaluation of their conceptual framework against the longitudinal evidence reviewed, much of the literature suggested heterogeneous results; however, chronic conditions, insomnia, and physical health had the strongest results as factors that increase the risk of depression in older adults.

Further related to models of stress, other researchers conceptualise chronic conditions as a factor that leads to suffering, which is likely to create a source of enduring stress and impede the older adult’s ability to function (Theeke, 2009), which in turn affects biological systems that lead to depression. Stress is known to impact the underlying biological mechanisms purported to influence late-life depression. Zhao et al. (2023) reviewed evidence associating depression in older adults with DNA methylation of brain-derived neurotrophic factors, reducing the ability to guard against defects in the brain’s plasticity caused by stress, along with impaired regulation of the stress-response system through the Hypothalamic-Pituitary-Adrenal (HPA) axis (Dunlavey, 2018). Alternatively, some researchers propose that the association between chronic conditions and depression may result from symptom overlap, such as depression’s somatic symptoms and common symptoms of many chronic conditions, including anhedonia, appetite disturbance, fatigue, loss of concentration and energy, reduced physical activity, and sleep disturbance (Kerahrodi et al., 2019; Wicke et al., 2022).

1.6.3.2. Chronic Conditions and Loneliness

Researchers have proposed a variety of theoretical explanations for the relationship between chronic conditions and loneliness in older individuals. Theeke (2009) proposed that suffering from chronic conditions will likely impair the older person's ability to function over time and create a source of enduring stress, both of which impede the individual's ability to socialise. Theeke and Mallow (2013) expanded this conceptualisation using the psychoneuroimmunology (PNI) paradigm. Here, the authors proposed that loneliness leads to further stress, adding to the stress from chronic conditions, which produces neuroendocrine and immunological responses in the individual, leading to or exacerbating further chronic conditions and impeding the individual's control over them. Similarly, Havens et al. (2004) proposed that chronic conditions hinder the person's ability for socalisation, which can lead to loneliness. Alternatively, loneliness is posited to increase stress levels in older adults, which can compromise physiological resilience, and loneliness may interfere with the capacity to engage in pro-health behaviours, including exercise, healthy eating, and not smoking, all of which may lead to chronic conditions (Bu et al., 2020; Paul et al., 2021).

1.6.3.3. Loneliness and Depression

Historically, researchers conceptualised loneliness and depression as overlapping unpleasant and aversive states (Cacioppo et al., 2010). Indeed, some researchers used social models of depression to conceptualise the experiences of loneliness and identify risk factors for loneliness previously identified for depression (Victor et al., 2005). Current research has begun to separate the two constructs. Paul et al. (2021) presented research that took a biopsychosocial approach to conceptualise the relationship. Researchers began with the observation that humans are social by nature and that human contact is necessary for survival. Consequently, social isolation is perceived as a danger and a threat, which in turn triggers psychological mechanisms through biological pathways leading to depression. Others took a decidedly evolutionary approach to explaining the relationship between depressive symptoms and loneliness. Cacioppo et al. (2015) theorised that loneliness increases depressive symptomatology as an adaptive response to signal the need for social connection and support.

1.6.4. Summary

Researchers have developed multiple theoretical explanations for the relationships between chronic conditions, loneliness, and depression. Research on loneliness as a determinant of health is starting to develop, though theoretical explanations involving loneliness lag. In their scoping review of interventions for loneliness and social isolation used in primary care, Galvez-Hernandez et al. (2022) concluded that the research suggested no theoretical consensus in theories developed to examine loneliness in older adults. Moreover, just one-third of the articles reviewed provided a clear theoretical framework for their research. Nevertheless, conceptual explanations for the relationship between chronic conditions, loneliness, and depression do exist, and researchers have created several theoretical models.

1.7. Theoretical Models

Theoretical models explaining the relationship between chronic conditions, depression, and loneliness tend to be complex, reflecting the nature of the relationship. Moreover, these models include a variety of factors in addition to chronic conditions that may impact loneliness and depression. Hawkley et al. (2008) employed a filtration model in which distal demographic factors operate through proximal structural factors such as education and income that in turn operate through stress, social roles, and health factors, including chronic conditions, that are more directly related to relationship quality and social network size. The authors operate under the assumption that the quality of social relationships and the frequency and number of social contacts exert the largest influence on loneliness. Therefore, the extent to which the distal factors filter down to influence social connections and relationship quality ultimately affects loneliness. Hawkley and colleagues further pointed to research that found loneliness predicted depression but did not explicitly include depression in their model. This filtration model emphasises social loneliness and does not directly address emotional loneliness. While the model provides a framework to conceptualise loneliness and the factors leading to it, it is not considered a causal model (Hawkley et al., 2022).

Alternatively, Lim et al. (2020) synthesised the literature to offer a conceptual model of loneliness that highlights interactions among known and emerging associations and risk factors of loneliness. In their model, significant life events or life stage transitions act as triggers that interact with correlates and risk factors of loneliness, such as chronic conditions and other health factors, demographic factors, and socio-environmental factors to initiate loneliness. The model states that triggers do not lead directly to loneliness as individuals hold a personal level of risk to loneliness; rather, the two interact to initiate loneliness. In this model, risk factors may interact with each other and may also be consequences of loneliness, represented bidirectionally, with depression and chronic conditions being some of the many potential correlates and risk factors for loneliness and vice versa. This conceptual model of loneliness defines loneliness in terms of social loneliness, the subjective feeling arising from the difference between actual and desired levels of social relationships, though the model could likely be adapted to include emotional loneliness as well. Additionally, the model does not address depression directly but includes mental health as a potential risk factor and correlate of loneliness, again as a potential bidirectional relationship. Ultimately, the conceptual model of loneliness is solution-focused rather than causal, though the authors maintain that causal factors may be investigated within each level.

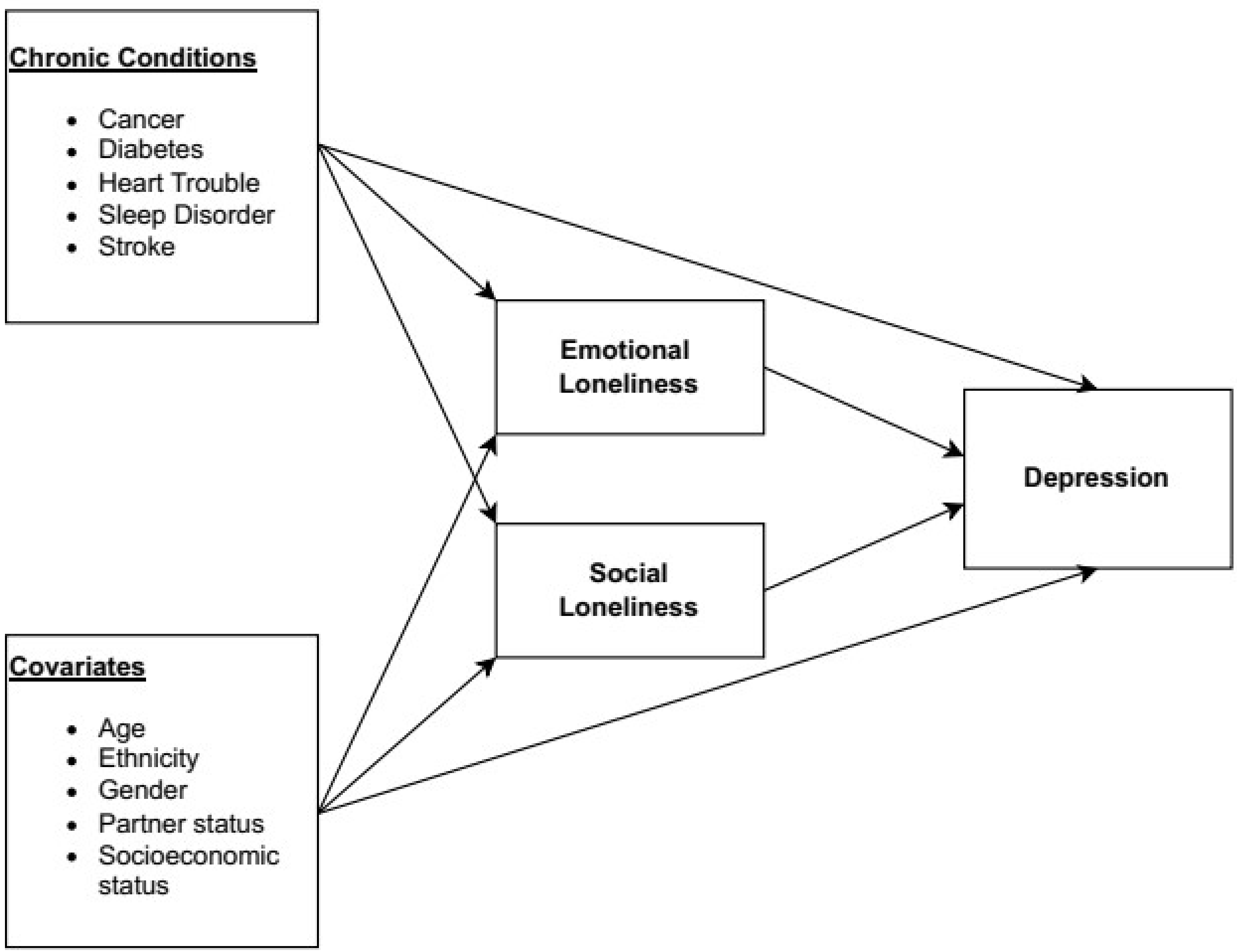
1.7.1. Model of Depression and Loneliness (MODEL)

This study conceptualised the relationship between chronic conditions, loneliness, and depression using the Model of Depression and Loneliness (MODEL; Cohen-Mansfield & Parpura-Gill, 2007). Having recognised the lack of a comprehensive theory of loneliness for older adults, Cohen-Mansfield and Parpura-Gill designed MODEL to investigate predictors of loneliness in older persons. Grounded in Cognitive-Behavioural Theory and Socioemotional Selectivity Theory (Carstensen, 1992), MODEL conceptualises behaviour as the result of interactions between various cognitive processes and environmental events, focusing on the factors likely to occur prior to loneliness. The model considers that many older adults build social skills around a core network of friends, family, and coworkers. Circumstances and events common in old age, such as chronic conditions, can interrupt or disrupt these important relationships by limiting the person's ability, motivation, and resources to develop and maintain social relationships, with the decline in social interactions potentially resulting in social skills deficits. MODEL conceptualises these circumstances and events as barriers that prevent establishment or maintenance of relationships and groups them into four distinct factors, that of environmental, health, psychosocial, and stressful life events. Any of these factors can influence loneliness which, as a robust predictor of depressed affect according to research, will in turn affect depression. This study focused on chronic conditions as a key factor, with other important factors considered as covariates. An adapted model based on this framework for this study is shown in Figure 1.

MODEL benefits from empirical support. After testing MODEL, Cohen-Mansfield and Parpura-Gill (2007) found that the framework explained a significant percentage of the variance of depressed affect and loneliness. Additionally, the authors found loneliness to be the strongest predictor of depression. In later research using MODEL as a theoretical framework to examine longitudinal determinants of loneliness in older individuals (Cohen-Mansfield et al., 2009, 2016), researchers found the health factor domain, including chronic conditions and comorbidity, predicted loneliness, particularly in unmarried individuals. Additional research supported some of the other domains in MODEL, including environmental, psychological, and stressful life events (Yu et al., 2023).

Figure 1

Theoretical Model Depicting Relationships



Note. Adapted from “Loneliness in older persons: A theoretical model and empirical findings,” by J. Cohen-Mansfield and A. Parpura-Gill, 2007, *International Psychogeriatrics*, *19*(2), p. 282. Copyright 2007 by International Psychogeriatric Association.

Of the conceptual models discussed, the weight of the evidence supported MODEL as a good fit and was therefore used for this study. MODEL is a causal model of depression and loneliness in older adults. The framework recognises the potential impact of health factors such as chronic conditions and multimorbidity on loneliness, acknowledges the experience of both social and emotional loneliness, and explicitly includes depression (Cohen-Mansfield et al., 2009).

2. Current Study

As people live longer, the prevalence of chronic conditions and multimorbidity in older adults is on the rise. The mental wellbeing of older people in Aoteaora, on the other hand, has declined in recent years, and considerable research suggests an association between chronic conditions and depression. A review of the literature found evidence of a relationship with loneliness, suggesting a potential mediator effect. Yet, few studies examined the relationship between chronic conditions, depression, and loneliness. Furthermore, from the existing literature, there is little consensus concerning the direction of the relationships between the three constructs. In the aggregate, this suggests a need for further research, particularly from the viewpoint of Aotearoa. Fortunately, theoretical explanations for the relationships have been proposed in the literature. The MODEL framework conceptualises the relationship between chronic conditions, depression, and loneliness, among other factors that commonly covary, providing a guide for this research.

2.1. Chronic Conditions and Covariates

This study focused on chronic conditions previously found to be robustly associated with loneliness and depression in the literature. These conditions include cancer, diabetes, heart trouble, sleep disorder, stroke, and multimorbidity (Birk et al., 2019; Cai et al., 2023; Griffin et al., 2024; Lim et al., 2020; Maresova et al., 2019; Wu et al., 2022; Zenebe et al., 2021). Other variables research previously found to be consistently associated with depression and loneliness in older adults and frequently controlled for in studies include female gender, higher age, lack of a partner, lower SES, and Māori ethnicity (Cohen-Mansfield et al., 2016; Griffin et al., 2024; Wright-St Clair et al., 2017). These covariate variables were controlled for in this study.

2.2. Hypotheses

This study aimed to employ the MODEL framework to investigate correlational and prospective relationships between chronic conditions (including multimorbidity) and loneliness (emotional and social) in 2020 (T1) and depression in 2022 (T2) among a sample of older New Zealanders. Covariates found in the literature were also examined. The second aim was to examine whether the relationships between chronic conditions and depression and that of multimorbidity and depression were mediated by emotional and social loneliness. This study made the following predictions.

H1 Chronic conditions (cancer, diabetes, heart trouble, sleep disorder, and stroke) and multimorbidity at T1 will be positively associated with emotional and social loneliness at T1.

H2 Chronic conditions (cancer, diabetes, heart trouble, sleep disorder, and stroke) and multimorbidity at T1 will be positively associated with depression at T2 (controlling for depression, age, ethnicity, gender, partner status, and SES at T1).

H3 Emotional and social loneliness at T1 will be associated with depression at T2.

H4 Emotional and social loneliness at T1 will mediate the relationship between chronic conditions (cancer, diabetes, heart trouble, sleep disorder, and stroke) at T1 and depression at T2 (controlling for depression, age, ethnicity, gender, partner status, and SES at T1).

H5 Emotional and social loneliness at T1 will mediate the relationship between multimorbidity at T1 and depression at T2 (controlling for depression, age, ethnicity, gender, partner status, and SES at T1).

3. Method

This research used observational data collected from two waves of the New Zealand Health, Work, and Retirement Study (HWR; 2024) led by the Health & Ageing Research Team at Massey University (HART; 2024) and funded by the Ministry of Business, Innovation and Employment Hīkina Whakatutuki (Phillips, 2021, 2022). Launched in 2006, HWR seeks to support healthy ageing in Aotearoa by providing information on issues relevant to older adults, including health, housing, retirement, and work (Allen et al., 2023; Massey University, 2024).

3.1. Participants and Procedure

Data was collected through a biennial postal survey with participants drawn from a random sample of adults 55+ years of age from the electoral roll, which contains 97.6% of eligible voters in this age group. The target sample size was based on established guidelines detailed in the technical reports (Phillips, 2021, 2022) that reference the size of the populations of interest according to the 2013 New Zealand census and recognise lower Māori response rates. Therefore, the surveys over-sampled Māori to represent the population sufficiently. Participants from previous waves were surveyed in both years if not excluded due to overseas relocation, withdrawal from the study, non-response over the last two waves, lost contact, or being deceased. Additionally, both years contain a refresh recruitment of additional individuals aged 55-65 to maintain a representative sample of participants and to ensure sufficient representation of the Māori population.

The response rate in 2020 for the existing cohort was 75.4%, with a lower response rate for Māori (67.1%) than for non-Māori (80.8%) and little difference in the response rate for females (76.0%) and males (74.8%). Response rates for the refresh cohort in 2020 were smaller, with an overall response rate of 24.5%, again lower for Māori (20.0%) than non-Māori (30.4%), and higher for females (26.3%) than males (22.7%). Response rates in 2022 were similar to those from 2020, with an overall response rate for the existing cohort of 78.7%, slightly lower for Māori (72.0%) than for non-Māori (83.0%), though with no difference in response rates for females (78.6%) and males (78.6%). Although refresh cohort response rates for 2022 were published, only those participants who answered the variables of interest from the surveys in both years were included in this study. Surveys received were excluded where there was a mismatch between demographic data reported in the current and prior waves, with 10 participants excluded in 2020 and 20 in 2022. The final number of participants was 4,351 in 2020 and 5,514 in 2022 (Phillips, 2021, 2022).

3.1.1. Exclusion Criteria

See Table 1 for exclusion criteria numbers specific to this study, which included participants who missed any covariate, all depression items in either year, or any loneliness item, as a participant's loneliness scores are not calculated when missing any item scores (Gierveld & Tilburg, 2010). Additionally, one participant who indicated gender-diverse was excluded as this was determined to be an insufficient number for analysis. Person-level missingness greater than 30% of the study variables was used as recommended by Kline (2023) and Newman (2014); however, no participants reached this threshold.

Table 1

Participant Exclusion Criteria

Exclusion Criteria		*N*	%
Indicated gender-diverse [a]		1	0.0
Missed all depression items in T1		33	0.8
Missed all depression items in T2		824	19.0
Missed any covariate	Age	0	0.0
	Ethnicity	37	0.9
	Gender	0	0.0
	Partner Status	54	1.2
	SES	214	4.9
Missed any loneliness item [b]		164	3.8
Missed greater than 30% of study variables [c]		0	0.0
Total [d]		1,095	25.2

[a] Due to insufficient number for analysis.

[b] Per scoring criteria from Gierveld and Tilburg (2010).

[c] As recommended by Newman (2014) and Kline (2023).

[d] Total does not sum due to criteria overlap.

3.1.2. Present Sample

Final study numbers appear in Table 2, and descriptive statistics in Table 3. The final sample size following all exclusion criteria was 3,011. The sample contained approximately 29.2% of participants identifying as Māori, as compared to 10.1% of the total population aged 55+ from the 2023 NZ Census (Statistics New Zealand Tatauranga Aotearoa, 2024), likely due to the previously described objective to over-sample the population. The sample contained more females (56.7%) than males (43.3%), differing slightly from the 2018 census data of 52.4%

Table 2

Demographic Numbers

Variable	*N*	%	Variable	*N*	%
Total Sample	3,011	100	Multimorbidity		
Age			0	1,828	60.7
55 - 64	1,330	44.2	1	902	30.0
65 - 74	1,229	40.8	2	239	7.9
75 - 84	446	14.8	3	40	1.3
85+	6	0.2	4	2	0.1
Chronic Conditions			Partner Status		
Cancer	487	16.2	Partnered	2,307	76.6
Diabetes	267	8.9	Single	704	23.4
Heart Trouble	367	12.2	SES		
Sleep Disorder	348	11.6	Severe hardship	24	0.8
Stroke	39	1.3	Significant hardship	46	1.5
Ethnicity			Some hardship	102	3.4
Māori	878	29.2	Fairly comfortable	225	7.5
Non-Māori	2,133	70.8	Comfortable	464	15.4
Gender			Good	1,125	37.4
Female/Wāhine	1,706	56.7	Very good	1,025	34.0
Male/Tāne	1,305	43.3			

Table 3

Descriptive Statistics

Measure	Range	*M*	*Mdn*	*SD*	α		Skew	Kurtosis
					Raw	Std		
Age	55 - 91 [a]	67.03	66	6.95			0.50	2.55
Depression (T1)	0 - 24	5.13	4	3.92	0.80	0.81	1.00	3.88
Depression (T2)	0 - 25	5.24	4	4.11	0.82	0.83	1.03	4.01
Loneliness (Emotional)	0 - 3	0.48	0	0.76	0.54	0.60	1.69	5.41
Loneliness (Social)	0 - 3	0.88	0	1.12	0.77	0.77	0.85	2.21
Loneliness (Overall)	0 - 6	1.36	1	1.54	0.70	0.72	1.13	3.60
Multimorbidity	0 - 4	0.50	0	0.70			1.33	4.36
SES	0 - 31	25.82	27	4.86	0.86	0.88	-1.53	5.69

[a] Rounded to the nearest year

females aged 55+ (Statistics New Zealand Tatauranga Aotearoa, 2018). A clear majority of participants were partnered, approximately 76.6%, somewhat higher than the 2018 census data indicated for those aged 55+ who indicated they were partnered or married (66.3%).

Most participants (85%) were under 75 years, and the bulk (60.7%) indicated no chronic conditions. While just six participants were aged 85+ years, and only two indicated the presence of four chronic conditions, excluding them did not change the data distribution and were retained. Furthermore, the most common chronic condition in this sample was cancer (16.2%), while only 39 participants (1.3%) indicated stroke. Most participants rated their living standards as fairly comfortable to very good (86.8%), whereas a smaller proportion (5.7%) indicated a level of hardship. In the 2021 report on the material wellbeing of NZ households (Perry, 2021), the New Zealand Ministry of Social Development (MSD) Te Manatū Whakahiato Ora reported that 4% of those aged 65+ experienced material deprivation using the Material Wellbeing Index, which replaced the SES proxy used in this study in 2013.

3.1.3. Ethics

Both of the HWR project waves were reviewed and approved by the Massey University Human Ethics Committee: Southern A, Application 22/23; Health, Work and Retirement Study 2022 (Phillips, 2022) and Southern A Application – 20/07; Health, Work and Retirement Study 2020 (Phillips, 2021).

3.2. Measures

The HWR surveys relied on various measures to gather data on issues important to older adults. Table 4 illustrates the variables and their measures from the survey used in this study, and Table 3 shows their descriptive statistics.

3.2.1. Chronic Conditions and Multimorbidity

The HWR survey asked participants to indicate if a health professional had ever told them they had any of the specific chronic conditions listed in the survey (Phillips, 2021, 2022). For each chronic condition, participants chose from three options, including “yes, in the last 12 months”, “yes, prior to the last 12 months”, or “no”. This study included participant responses for the five chronic conditions of interest, as indicated in Table 2. Variables for each condition were dichotomised to Yes (coded 1) for either the yes options or No (coded 0). In addition, participants who missed answering a chronic condition question (n = 179) were categorised as not having the condition, and participants who stated they did not have cancer or who missed answering the question but provided a cancer type (n = 37) were categorised as having had cancer. The number of chronic condition variables indicating Yes were summed to represent multimorbidity (range = 0 – 4).

Table 4

Study Variables and Measures

Variable	Measure
Age	Date of Birth
Chronic Conditions	Cancer, Diabetes, Heart Trouble (e.g., angina or heart attack), Sleep Disorder, Stroke
Depression	Center for Epidemiologic Studies Depression Scale Short Form (CESD-10)
Ethnicity	Māori, New Zealand European, Samoan, Cook Island Māori, Niuean, Chinese, Indian, Tongan, Other specified
Gender	Tāne/Male, Wāhine/Female, Gender Diverse
Loneliness	The 6-item De Jong Gierveld Loneliness Scale
Partner status	Married, Civil Union/De Facto/Partnered, Divorced/Separated, Widow/er, Single
Socioeconomic status	Economic Living Standards Index Short Form (ELSI-SF)

3.2.2. Demographic Variables

Age was computed from an individual's date of birth. Participants self-reported their ethnicity, gender, and partnership status by choosing from several options, as listed in Table 4. Ethnicity in this study was dichotomised to include those who indicated Māori (coded 1) and non-Māori (coded 0) ethnicity. Partner Status was dichotomised as Single (coded 1), which consisted of participants who indicated they were single, widowed, or divorced, and Partnered (coded 0), which included participants who indicated they were married or in a civil union. Gender remained unchanged as the variable was dichotomised in the data set (Wāhine/Female coded 2, Tāne/Male coded 1).

3.2.3. Depression

Depression was measured with the Center for Epidemiologic Studies Depression Scale short form (CES-D-10), a short version of the 20-item Center for Epidemiologic Studies Depression Scale (CES-D; Andresen et al., 1994). The CES-D-10 is used to screen for symptoms of depressed mood during the previous week and meets the criteria for inclusion in surveys, according to the authors. Participants indicate the frequency of each symptom on a four-point Likert scale, ranging from 0 (rarely or none of the time) to 3 (all of the time). Eight of the items focus on positive symptoms of depression, while the remaining two consist of negative symptoms. Scores for items indicating positive mood are reverse-scored, and item scores are then summed to get a total score ranging from 0-30, with higher scores representing greater levels of depressed mood (Mohebbi et al., 2018).

The CES-D-10 has strong psychometric properties, and research supports its use with older adults. The short form's predictive accuracy compares favourably to the well-established CES-D (α = 0.97) when tested with a sample of 1,206 older adults in the US (Andresen et al., 1994). Andresen and colleagues reported an overall correlation between the two instruments of r = .71. Mohebbi et al. (2018) completed a large study of 19,114 community-dwelling older adults in Australia and the US with results that suggested high internal consistency (Cronbach's alpha of 0.70 and composite reliability of 0.72) and factor analyses that indicated a unidimensional structure. Additionally, Mohebbi and colleagues assessed the validity of the CES-D-10 across age, gender, language, race, and ethnic groups with findings that supported the measure's construct and convergent validity.

As the HWR depression item data ranged from 1 to 4, the items for this study were transformed to adhere to formal scoring procedures by subtracting 1 from each item, and appropriate items were reverse-coded. Consistent with other research on depression and loneliness using CES-D measures, the item that asks participants if they felt lonely was removed from this study to circumvent overlap with the loneliness measure (Cacioppo et al., 2010; Griffin et al., 2024). Research by Lee et al. (2021) demonstrated that removing this item did not have a large impact on the internal consistency of the measure, reducing the alpha coefficient from 0.78 when tested with the item to 0.76 without the item. Alpha coefficients for both years in this study ranged from 0.81 – 0.84 with the loneliness item included and 0.80 – 0.83 when excluded, suggesting comparable and acceptable reliability (Streiner, 2003). The nine items were summed to obtain participants' overall depression scores at T1 (M = 5.13; SD = 3.92; range = 0 – 24) and T2 (M = 5.24; SD = 4.11; range = 0 – 25). As noted in Table 3, the measures of central tendency for depression scores in both waves were fairly low and very similar, suggesting a low overall rate of depression in this sample on average and a very small increase in depression over this period.

3.2.4. Loneliness

Loneliness was measured with the 6-item De Jong Gierveld Loneliness Scale, a short version of the 11-item De Jong Gierveld Loneliness Scale (Gierveld & Tilburg, 2006). The scale measures emotional, social, and overall loneliness and is easy to use in surveys. The scale includes three negatively worded items and three positively worded items. Participants indicate each item by selecting "Yes", "More or less", or "No". Summing positive and neutral answers to negatively worded items provides an emotional loneliness score, while summing negative and neutral answers to positive items assigns a social loneliness score, both ranging from 0 to 3, with higher scores signifying higher loneliness. Combining the subscale scores provides an overall loneliness score ranging from 0 to 6 (Gierveld & Tilburg, 2010).

The 6-item measure has good psychometric properties and compares positively to the reliable (internal consistency of .81) and validated 11-item measure when used with older adults (Gierveld & Kamphuls, 1985; Tilburg & Leeuw, 1991; Van Baarsen et al., 2001). Gierveld and

Tilburg (2006) reported correlations between the two measures ranging from .93 to .95. The authors tested the short version on 9,448 participants over two surveys in the Netherlands and found that Cronbach's α coefficients ranged from 0.70 to 0.76, including for those aged 65+, and verified the existence of two factors of loneliness through confirmatory factor analysis. The authors tested congruent validity for both subscales, compared against the subscales from the longer form, and found correlations between .88 and .93. A recent systematic review by Alsubheen et al. (2023) evaluated the measurement properties of both forms for adults and assessed the quality and evidence of the research on them. They determined that moderate to high-quality evidence supported the measures' high internal consistency and structural validity. The authors further maintained that while the evidence supported high test-retest reliability, construct validity, and content validity of both versions, they judged the evidence to be of low to very low quality and recommended more research in this area.

In this study, the loneliness items were transformed according to the previously described scoring procedures. Alpha coefficients for emotional loneliness ranged from 0.54 to 0.60, suggesting questionable reliability (Streiner, 2003), while alpha coefficients for social loneliness were higher at 0.77 raw and standardised, indicating questionable reliability. Overall loneliness coefficients ranged from 0.70 to 0.72, suggesting overall questionable reliability. Items for emotional loneliness were summed to obtain an emotional loneliness score (*M* = 0.48; *SD* = 0.76; range = 0 - 3), and items for social loneliness were summed to obtain a social loneliness score (*M* = 0.88; *SD* = 1.12; range = 0 – 3). The emotional and social loneliness scores were then summed to obtain an overall loneliness score (*M* = 1.36; *SD* = 1.54; range = 0 - 6). As described in Table 3, the measures of central tendency for all three types of loneliness were fairly low, suggesting that, on average, participants were not lonely.

3.2.5. Socioeconomic Status

SES was assessed with the Economic Living Standards Index Short Form (ELSI-SF; Jensen et al., 2005), the short version of the Economic Living Standards Index (ELSI; Jensen et al., 2002). Both versions are survey tools developed as part of the MSD research programme on living standards to measure an individual's economic standard of living. The measure conceptualises economic standard of living as varying along a continuum, from those with a very low standard of living characterised by the inability to socialise with others, need to economise on daily activities, and limited access to resources, to a high standard of living typified by having the ability to socialise in many ways, little need to economise on daily activities, and unlimited access to resources. The measure assesses four domains, including limitation of possessions (ownership restrictions), limitation of social participation due to income (social participation restrictions), reduction of spending on daily needs and activities (economising), and perception of individual standard of living. Items are scored on a Likert scale ranging from three to five points. Outliers are truncated by assigning a score of 10 to any score less than 10, and items are summed to provide a total score ranging from 0 to 31, with higher numbers indicating higher living standards. To ensure that participants with the lowest possible living standard have a final score of zero, 10 is subtracted from the total score. The final score falls into one of seven standard ranges that describe the individual's economic standard of living, ranging from severe hardship to very good.

Jensen et al. (2005) provided evidence that the measure is highly correlated with the larger ELSI scale ($\alpha = 0.79$), with r values between .98 and .99, broken down by age, ethnicity, and partnership groupings. They further found that the ELSI-SF had good internal consistency ($\alpha = 0.88$). Concerning validity, Jensen and colleagues provided evidence that, like the larger ELSI, the measure correlated with variables that one can expect to be associated with living standards, such as financial and stress-related variables.

This study used estimated ELSI-SF scores (M = 25.82; SD = 4.86; range = 0 - 31) based on imputed data from prior studies (Jensen et al., 2005). The HWR data manager provided a data set that included the items used to compute scores at a later point. The items from this data set were merged with the previous data set, and alpha coefficients ranging from 0.86 to 0.88 were computed, suggesting acceptable reliability (Streiner, 2003). As described in Table 3, measures of central tendency for SES were fairly high, adding to the previous discussion of demographics that indicated a relatively high standard of living for most participants.

3.3. Data Analysis

3.3.1. Data Preparation

Comma-Separated Values (CSV) and IBM SPSS Statistics (SAV) files were securely provided by the HWR Data Manager following agreement to the data access and conditions of use policy. Files were loaded into RStudio version 2024.04.2+764 (Posit Software, 2024), Jamovi version 2.3.28 (Jamovi, 2024), and Microsoft Excel 2021 for analysis. All analyses were completed using the R programming language version 4.4.0 (R Core Team, 2024), and diagrams were created with the draw.io application version 24.7.8 (JGraph Ltd, 2024). See Appendix A for the R code for all analyses.

Participants matching the exclusion criteria (n = 1,095) were removed, appropriate measurement items were reverse-scored or transformed, specified variables were dichotomised, and scores were computed for the depression and loneliness measures and multimorbidity variable as previously described. Based on box plots, histograms, and visual examination of the data and standard deviations in Rstudio and Excel, the data contained no obvious univariate or multivariate outliers or overly consistent responding. To programmatically detect the existence of multivariate outliers, an analysis using the Mahalanobis distance

(Mahalanobis, 1930) was applied to the study variables using the MASS package (Ripley et al., 2024). Multivariate outliers were excluded (*n* = 241; 7.4%) based on a conservative level of statistical significance, chi-square *p* < .001, recommended by Kline (2023) and Leys et al. (2018). Logistic regression analyses performed with a dichotomised dependent variable (1 = outlier, 0 = non-outlier) before exclusion showed that the outliers were more likely to have indicated a lower standard of living, a higher number of chronic conditions, a higher depression score in either wave and a higher emotional loneliness score. The presence of stroke could not be analysed via regression due to extremely low variability, as shown in Table 2. Examining this variable separately revealed that 64.2% (*n* = 68) of participants indicating stroke were removed.

The data were further checked for multivariate normality to inform later decisions concerning method and statistical test selection (Kline, 2023). A Mardia's Test (Mardia, 1970) was performed using the MVN package (Korkmaz et al., 2021) that indicated multivariate non-normality of the items. Similarly, outcome variables indicated moderate skew and kurtosis using the moments package (Komsta & Novomestky, 2022), as displayed in Table 3. The data set was additionally inspected for extreme multicollinearity by checking for high bivariate correlations of predictor variables. As there is no gold standard for a cutoff, this study checked the correlation thresholds suggested by Kline(2023), including *r* > .90 and *r* > .80. No extreme correlations were found using these standards. The data set was further checked and met assumptions for a positive definite matrix using the matrixcalc package (Novomestky, 2022) and for homoscedasticity and linear relationships between variables where appropriate with plot diagrams and a linear regression model.

3.3.2. Missing Data

An analysis of missing data was completed along with data preparation. The total missing data across all study variables was very low (0.3%), as displayed in Table 5.

Depression at T1 had the highest rate of missing data (0.5%) across the nine CES-D items used in the study. Missing data for depression at T2 was also low (0.3%) across the items for the time period. As participants who missed any loneliness items or covariates were previously excluded, the expected number of missing items is zero.

A Little MCAR Test (Little, 1988) was performed using the naniar package (Tierney et al., 2024) to determine the type of missing data in the sample. A significant result was obtained ($p < .05$), thereby rejecting the hypothesis that the missing data were missing completely at random (MCAR). The test assumes homoscedasticity and multivariate normality unless the sample is large in size (The R Project for Statistical Computing, 2024). Though the data previously indicated non-normality, the sample size ($n = 3,252$) at this point in the analysis was assumed to be sufficiently large. As no particular test provides evidence for data missing at random (MAR) or missing not at random (NMAR; Kline, 2023), the missing data were assumed to be MAR.

Table 5

Missing Data After Exclusions

Variable	*N*	%
Covariates	0	0.0
Depression (T1) [a]	140	0.5
Depression (T2) [b]	85	0.3
Loneliness	0	0.0
Total Missing Data [c]	315	0.3

[a] Across depression items at T1, excluding loneliness item.

[b] Across depression items at T2, excluding loneliness item.

[c] Across all study variables.

The multivariate expectation-maximization (EM) imputation method was selected to impute the missing data using the Amelia package (Honaker et al., 2024). In a simulation study, Scheffer (2002) found that EM allowed reasonably trustworthy inferences about data means and variances when the overall percentage of missing data was under 5%. All study variables were used in the imputation process as recommended by Newman (2014) and Dong and Peng (2013).

3.3.3. Correlation Analysis

A Pearson's r correlation matrix was produced using the psych package (Revelle, 2024) to analyse associations among the main study variables. The correlation matrix addressed whether the chronic conditions of interest and multimorbidity were associated with emotional and social loneliness at T1 (H1) and depression at T2 (H2), and whether emotional and social loneliness at T1 was associated with depression at T2 (H3).

3.3.4. Structural Equation Modeling

Structural equation modeling (SEM) using the lavaan package (Rosseel et al., 2024) was the main method used to test the hypotheses that emotional and social loneliness at T1 mediated the relationship between the chronic conditions of interest and depression at T2 (H4) and between multimorbidity and depression at T2 (H5). SEM provided additional analyses to test for the relationships of chronic conditions and multimorbidity with emotional and social loneliness at T1 (H1) and with depression at T2 (H2), and emotional and social loneliness at T1 with depression at T2 (H3). SEM was selected to estimate the direction and magnitude of the postulated effects predicted by the theoretical model and the relationships among the model's hypothetical constructs represented by latent variables. SEM further supports parallel mediation, allowing for simultaneous examination of the effects of both types of loneliness.

All models in this study employed the diagonally weighted least squares with robust standard errors estimator (WLSMV) suggested by Kline (2023). The WLSMV estimation method was designed for categorical data and does not assume normality of observed variables, assuming instead that a continuous, normal distribution exists in the population (Li, 2016). The method further performed better in computer simulations of large sample sizes (*N* = 500) than the robust maximum likelihood method (MLR; Li, 2021), another option recommended for estimation with categorical data (Kline, 2023).

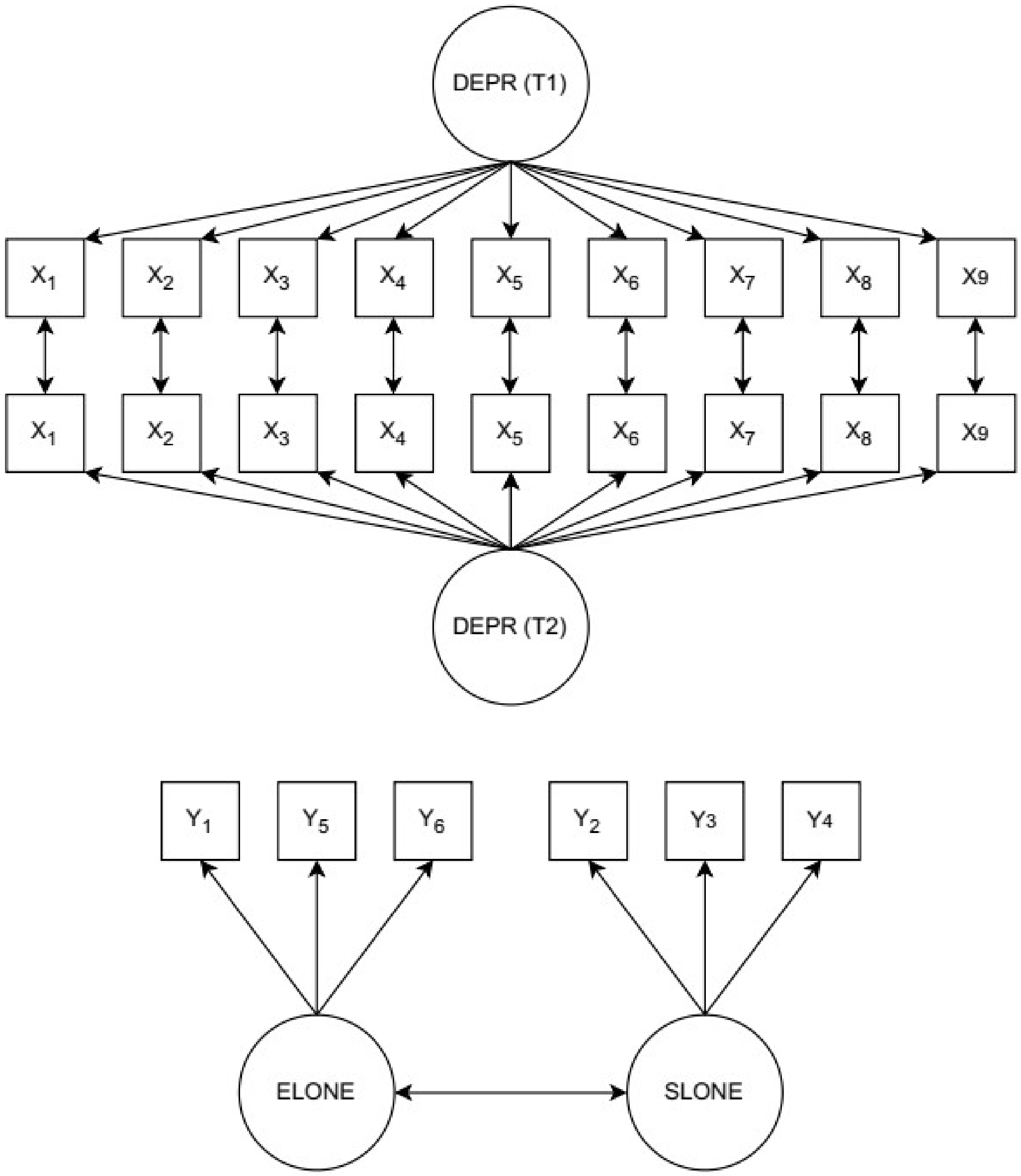
3.3.4.1. Confirmatory Factor Analysis

A confirmatory factor analysis (CFA) was completed using Muthén's continuous/categorical variable methodology (CCVM; Muthén, 1984) as recommended by Kline (2023) to assist with fitting models containing Likert variables consisting of two to four categories. As shown in Figure 2, a measurement model was created that included latent variables for depression at T1, depression at T2, emotional loneliness, and social loneliness from their respective items, the observed variables. Given the modest correlation between emotional and social loneliness (r = .31), these variables were allowed to covary. Error covariances for depression items measured at different time points were also allowed to covary.

The CFA supported the two-factor structure of the loneliness measure and single-factor structure of the CES-D-10 measured at T1; however, local model fit for a single-factor structure at T2 was poor. See Table B1 and Table B2 in Appendix B for global fit indices and residuals, respectively. According to Kline (2023), absolute residual values that surpass .10 may suggest poor fit between model and data, though researchers lack consensus regarding the number of values that signify a concern. As more discrepancies provide evidence of worse fit, the large number of problematic residuals found during analysis led to further exploration of the measurement model. Examining the residuals and modification indices indicated the potential

Figure 2

Initial Measurement Model



Note. DEPR (T1) = Depression at T1; DEPR (T2) = Depression at T2; ELONE = Emotional Loneliness; SLONE = Social Loneliness; X and Y represent items for the CES-D-10 and 6-item De Jong Gierveld Loneliness Scale, respectively; double-headed arrows indicate items or factors allowed to covary.

for two factors for the depression measure, with the second factor comprising the two positive affect (PA) items. Research exists to support the two-factor structure of the measure based on the separation of the PA and remaining depressive affect/somatic retardation (DA/SR) items (Bradley et al., 2010; A. Lee & Chokkanathan, 2008; B. Lee, 2019). As shown in Figure 3, the model was respecified to include two-factor latent depression variables consistent with these findings, which improved global and local fit, as can be seen in Table B3 and Table B4 of Appendix B, respectively. Although the measurement model failed the exact fit chi-square test, as is common with large samples (Kline, 2023), the approximate fit indices were within acceptable thresholds, and local fit was considered acceptable. Additionally, factor loadings for the depression and loneliness measures were acceptable, as shown in Table 6 and Table 7, respectively. Consequently, the measurement model was retained.

3.3.4.2. Path Analysis

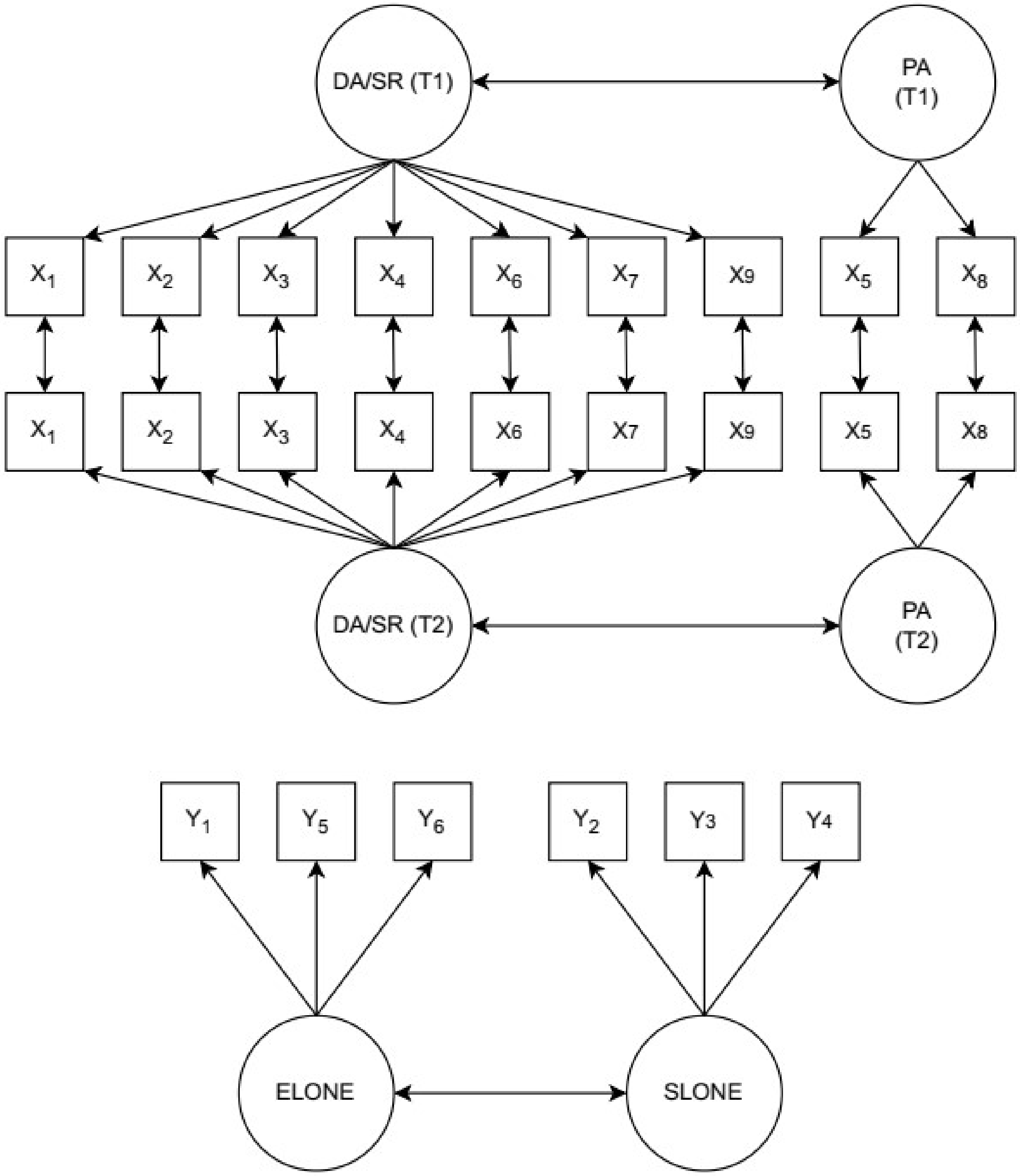
Two parallel mediation path analysis models were created to test the hypotheses, one for the effect of chronic conditions and the other for multimorbidity. In both models, the measurement model was carried forward from the CFA.

Regression paths were created for the structural portion of the models to represent the structure shown in Figure 1. Observed variables included the chronic conditions of interest, the items that make up the latent variables, and the covariates previously specified, with the latter as control variables.

Regarding the chronic conditions model, the chronic conditions, covariates, and the two-factor depression T1 latent variables defined in the measurement model were regressed onto both the emotional and social loneliness endogenous latent variables in two separate regressions. Additionally, these same variables, plus the emotional and social loneliness variables now considered intervening (intermediate) variables in this context, were regressed

Figure 3

Final Measurement Model



Note. DA/SR = Depressive Affect/Somatic Retardation Depression Factor; PA = Positive Affect Depression Factor; T1 = Time 1; T2 = Time 2; ELONE = Emotional Loneliness; SLONE = Social Loneliness; X and Y represent items for the CES-D-10 and 6-item De Jong Gierveld Loneliness Scale, respectively; double-headed arrows indicate items or factors allowed to covary.

Table 6

Standardised Depression Instrument Factor Loadings

Parameter	DA/SR (T1)	DA/SR (T2)	PA (T1)	PA (T2)
X_1	0.670	0.729		
X_2	0.684	0.738		
X_3	0.816	0.832		
X_4	0.744	0.772		
X_6	0.670	0.730		
X_7	0.479	0.450		
X_9	0.729	0.724		
X_5			0.644	0.682
X_8			0.874	0.848

Note. DA/SR = Depressive Affect/Somatic Retardation Depression Factor; PA = Positive Affect Depression Factor; T1 = Time 1; T2 = Time 2; X represents measurement items for the CES-D-10.

Table 7

Standardised Loneliness Instrument Factor Loadings

Parameter	ELONE	SLONE
Y_1	0.968	
Y_5	0.488	
Y_6	0.857	
Y_2		0.876
Y_3		0.873
Y_4		0.906

Note. ELONE = Emotional Loneliness; SLONE = Social Loneliness; Y represents measurement items for the 6-item De Jong Gierveld Loneliness Scale.

onto the endogenous latent depression T2 variables. The model initially failed to converge due to the extremely low variability of the stroke variable. See Table 2 for details. Consequently, stroke was excluded from the chronic conditions model analysis. Additional parameter labels were included to capture the direct, indirect, mediational, and total effects of the variables of interest.

The multimorbidity model operated similarly, substituting the continuous multimorbidity variable for the individual chronic condition variables. The multimorbidity model did not exclude those who indicated having had a stroke, as these participants were previously included in the summing of the variable. Further, the model was tested with a dichotomised multimorbidity variable with two or more chronic conditions (coded 1) or less than two (coded 0); however, this did not change the overall results, and the continuous variable was retained.

Following model creation, both models were fitted and correlation residuals computed with code adapted from Kline (2023). Additionally, unstandardised and standardised parameter estimates were obtained to evaluate the hypothesised effects and relationships. As Kline noted, mediation analysis generally requires temporal precedence, i.e., that hypothesised causes precede effects. However, mediation in a cross-sectional design generally includes variables measured concurrently, violating the temporal precedence requirement. In such cases, Kline maintained that strong theory containing a conceptual time-ordering of cause, mediator, and outcome can support directionality. It was assumed that MODEL satisfied this requirement as the causes were stated to exist conceptually before the mediators and outcome. This study further assumed local independence (of errors), that there were no unmeasured confounders following covariate selection from the literature or unobserved confounding of the mediator variables, that all exogenous variables were measured without error, and that the model is properly specified as is typical for SEM and mediation analyses (Kline, 2023).

4. Results

4.1. Correlations

The matrix of Pearson's r bivariate correlation coefficients for the main study variables is shown in Table 8. Using industry-standard benchmarks from Cohen (1988), as displayed in Table 9, support for the hypothesised relationships of H1 – H3 was mixed. Emotional loneliness indicated a medium positive and significant relationship with depression at T2, while social loneliness indicated a small positive and significant relationship with depression at T2. Of the chronic conditions, only sleep disorder showed a small positive but significant relationship with depression at T2 and with emotional loneliness and a significant but negligible positive association with social loneliness. While the remaining chronic conditions showed some statistically significant relationships with some of the remaining variables, the strength of their correlations was negligible. Multimorbidity indicated a small positive and significant association with depression at T2 and a significant but negligible positive correlation with emotional and social loneliness.

Other statistically significant relationships of note include a medium positive relationship between emotional and social loneliness and medium negative correlations between SES and emotional loneliness and depression in both years. Higher SES further exhibited a small negative correlation with diabetes, sleep disorder, multimorbidity, and social loneliness. Female gender indicated a small negative association with heart trouble, multimorbidity, and social loneliness. Age showed a small positive relationship with heart trouble, cancer, and multimorbidity. Māori ethnicity indicated a small positive relationship with diabetes and small negative relationship with SES. Being single showed a small negative relationship with SES and small positive association with emotional loneliness. Multimorbidity demonstrated a large

Table 8

Pearson's r Correlation Matrix of Main Study Variables

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Gender	------													
2. Age	-0.08***	------												
3. Ethnicity	0.01	-0.07***	------											
4. Partner Status	0.17***	0.11***	0.08***	------										
5. SES	-0.04*	0.07***	-0.14***	-0.23***	------									
6. Diabetes	-0.05**	0.02	0.15***	0.05**	-0.14***	------								
7. Heart Trouble	-0.11***	0.15***	0.07***	0.04*	-0.06***	0.07***	------							
8. Sleep Disorder	-0.07***	0.05**	0.04*	0.04*	-0.13***	0.06**	0.06***	------						
9. Stroke	-0.03	0.06***	-0.02	0.02	0.01	0.00	0.07***	-0.02	------					
10. Cancer	-0.02	0.13***	-0.07***	0.03	0.01	-0.02	0.07***	0.02	0.01	------				
11. Multimorbidity	-0.12***	0.18***	0.07***	0.07***	-0.14***	0.45***	0.57***	0.51***	0.19***	0.56***	------			
12. Depression (T1)	0.04*	-0.03	0.08***	0.09***	-0.39***	0.07***	0.05**	0.24***	-0.04*	0.01	0.16***	------		
13. Depression (T2)	0.04*	0.02	0.08***	0.07***	-0.36***	0.06***	0.05**	0.24***	-0.03	0.03	0.17***	0.66***	------	
14. Emotional Loneliness	-0.02	-0.04	0.04*	0.1***	-0.31***	0.05**	0.01	0.14***	-0.03	-0.01	0.08***	0.46***	0.37***	------
15. Social Loneliness	-0.11***	-0.08***	0.01	0.06***	-0.26***	0.03	0.02	0.08***	-0.02	-0.04*	0.04*	0.34***	0.28***	0.31***

Note. α = .05; * p < .05; ** p < .01; *** p < .001

Table 9

Cohen's Benchmarks for Interpreting Pearson's r Correlation Coefficients

Effect Size	*r*
Small	.10
Medium	.30
Large	.50

positive association with heart trouble, sleep disorder, and cancer, a medium positive association with diabetes, and a small positive association with stroke. Finally, depression at T1 and T2 exhibited a large positive relationship, and both types of loneliness indicated a medium positive correlation with depression at T1.

4.2. SEM Analyses

4.2.1. Model Fit

Global fit statistics for the chronic condition and multimorbidity models are shown in Table 10. Consistent with Kline (2023), the model and baseline chi-square (Jöreskog, 1969) statistics and three approximate fit indices are reported, including the Root Mean Square Error of Approximation (RMSEA; Steiger, 1990) with 90% confidence intervals, Bentler Comparative Fit Index (CFI; Bentler, 1990), and Standardized Root Mean Square Residual (SRMR; Jöreskog & Sörbom, 1981). Overall results suggest questionable global fit of the models to the data. A significant chi-square result for both models rejected the null hypothesis that the data fit the population perfectly, and scaled CFI < 0.95 suggested poor fit (Boateng et al., 2018). Alternatively, the models' RMSEA values with confidence intervals between 0.043 – 0.051

suggested a close fit for the chronic conditions model and a fair to close fit for the multimorbidity model, and all SRMR values met the threshold (≤ 0.08) for acceptable fit (Boateng et al., 2018).

Latent variable residuals used to describe local fit for the chronic condition and multimorbidity models are found in Table B5 and Table B6 of Appendix B, respectively. The relatively few residuals exceeding the .10 threshold endorsed by Kline (2023) in both models of this study suggested reasonable local fit and led to the retention of both models.

Table 10

Model Global Fit Statistics

Fit index	Chronic Conditions Model		Multimorbidity Model	
	Standard	Scaled [a]	Standard	Scaled [a]
Model chi-square				
chi_M	2,842.070	3,126.077	2,566.296	2,927.083
p	0.000	0.000	0.000	0.000
df_M	408	408	348	348
Scaling correction factor		0.940		0.903
Approximate fit				
RMSEA [90% CI]	.045 [.043, .046]	.047 [.046, .049]	.046 [.044, .048]	.050 [.048, .051]
CFI	.963	.908	.968	.915
SRMR	.041	.041	.041	.041
Baseline model				
chi_B	65,766.336	29,683.400	69,255.134	30,563.133
p	0.000	0.000	0.000	0.000
df_B	276	276	276	276
Scaling correction factor		2.227		2.278

[a] Scaled indexes are adjusted to account for non-normality.

4.2.2. Model Results

The results of the regression equations for the chronic conditions and multimorbidity models are shown in Table 11 and Table 12, respectively. Support for H1 and H2 was mixed with small coefficients when significant. Multimorbidity and sleep disorder were significantly positively related to both depression factors at T2. Sleep disorder was significantly positively related to both types of loneliness. Multimorbidity was significantly positively related to emotional loneliness but not social loneliness. Emotional loneliness was significantly positively related to both depression factors at T1 in both models but not with either depression factor at T2. Social loneliness was significantly positively related to the PA depression factor at T1 in both models but not to DA/SR at T1 or either depression factor at T2.

Direct and indirect effects for the chronic conditions and multimorbidity models are displayed in Table 13 and Table 14, respectively. Path diagrams denoting standardised estimated parameters for the chronic conditions and multimorbidity models are displayed in Figure 4 and Figure 5, respectively. The direct effects of sleep disorder and multimorbidity on depression at T2 were significant but small, as was the total direct effect of all chronic conditions. None of the indirect effects through either loneliness type reached significance, providing no support for H4 or H5. Total effects were significant but small, and both models' computed mediation and indirect effect sizes were small. In general, R^2 values were high for both models, indicating that the models accounted for a substantial proportion of variance in the endogenous variables (Cohen, 1988).

Table 11

Chronic Conditions Model Regressions

Regression	*B*	*β*	*SE*
ELONE ~ Diabetes	-0.029	-0.008	0.101
ELONE ~ Heart Trouble	-0.073	-0.022	0.097
ELONE ~ Sleep Disorder	0.492***	0.147***	0.083
ELONE ~ Cancer	-0.029	-0.010	0.086
ELONE ~ DA/SR (T1)	0.784***	0.461***	0.084
ELONE ~ PA (T1)	0.468***	0.261***	0.093
SLONE ~ Diabetes	-0.062	-0.019	0.072
SLONE ~ Heart Trouble	0.027	0.010	0.064
SLONE ~ Sleep Disorder	0.159*	0.055*	0.062
SLONE ~ Cancer	-0.102	-0.041	0.056
SLONE ~ DA/SR (T1)	0.114	0.077	0.071
SLONE ~ PA (T1)	0.538***	0.344***	0.077
DA/SR (T2) ~ Diabetes	0.023	0.009	0.050
DA/SR (T2) ~ Heart Trouble	0.018	0.008	0.044
DA/SR (T2) ~ Sleep Disorder	0.472***	0.198***	0.048
DA/SR (T2) ~ Cancer	0.055	0.027	0.039
DA/SR (T2) ~ SLONE	0.030	0.036	0.025
DA/SR (T2) ~ ELONE	0.061	0.085	0.046
DA/SR (T2) ~ DA/SR (T1)	0.693***	0.572***	0.057
DA/SR (T2) ~ PA (T1)	-0.048	-0.038	0.044
PA (T2) ~ Diabetes	-0.089	-0.037	0.053
PA (T2) ~ Heart Trouble	0.072	0.034	0.047
PA (T2) ~ Sleep Disorder	0.173**	0.080**	0.057
PA (T2) ~ Cancer	0.064	0.034	0.042
PA (T2) ~ SLONE	0.024	0.033	0.029
PA (T2) ~ ELONE	0.018	0.027	0.056
PA (T2) ~ DA/SR (T1)	0.101	0.092	0.062
PA (T2) ~ PA (T1)	0.635***	0.548***	0.061

Note. * $p < .05$; ** $p < .01$; *** $p < .001$; *B* = Estimated Coefficient; *β* = Standardised Coefficient; *SE* = Standard Error; ELONE = Emotional Loneliness; SLONE = Social Loneliness; DA/SR = Depressive Affect/Somatic Retardation Depression Factor; PA = Positive Affect Depression Factor; T1 = Time 1; T2 = Time 2; ~ indicates variable regressed.

Table 12

Multimorbidity Model Regressions

Regression	*B*	*β*	*SE*
ELONE ~ MM	0.097*	0.065*	0.042
ELONE ~ DA/SR (T1)	0.799***	0.479***	0.083
ELONE ~ PA (T1)	0.454***	0.258***	0.092
SLONE ~ MM	0.001	0.000	0.029
SLONE ~ DA/SR (T1)	0.117	0.080	0.071
SLONE ~ PA (T1)	0.537***	0.348***	0.077
DA/SR (T2) ~ MM	0.136***	0.127***	0.022
DA/SR (T2) ~ SLONE	0.028	0.035	0.025
DA/SR (T2) ~ ELONE	0.069	0.096	0.047
DA/SR (T2) ~ DA/SR (T1)	0.708***	0.593***	0.057
DA/SR (T2) ~ PA (T1)	-0.058	-0.047	0.044
PA (T2) ~ MM	0.061**	0.063**	0.023
PA (T2) ~ SLONE	0.025	0.034	0.029
PA (T2) ~ ELONE	0.012	0.019	0.056
PA (T2) ~ DA/SR (T1)	0.099	0.091	0.063
PA (T2) ~ PA (T1)	0.639***	0.558***	0.061

Note. * $p < .05$; ** $p < .01$; *** $p < .001$; *B* = Estimated Coefficient; *β* = Standardised Coefficient; *SE* = Standard Error; ELONE = Emotional Loneliness; SLONE = Social Loneliness; DA/SR = Depressive Affect/Somatic Retardation Depression Factor; PA = Positive Affect Depression Factor; T1 = Time 1; T2 = Time 2; MM = Multimorbidity; ~ indicates variable regressed.

Table 13

Chronic Conditions Model Effects

Path	*B*	*β*	*SE*	*CI* (95%)	
		Direct Effects			
Diabetes → DEPR (T2)	-0.066	-0.028	0.035	-0.096	0.040
Heart Trouble → DEPR (T2)	0.090	0.042	0.035	-0.027	0.110
Sleep Disorder → DEPR (T2)	0.644	0.278	0.040	0.201	0.356
Cancer → DEPR (T2)	0.119	0.061	0.036	-0.009	0.130
		Indirect Effects			
Diabetes → ELONE → DEPR (T2)	-0.002	-0.001	0.003	-0.007	0.005
Diabetes → SLONE → DEPR (T2)	-0.003	-0.001	0.002	-0.005	0.002
Heart Trouble → ELONE → DEPR (T2)	-0.006	-0.003	0.004	-0.011	0.006
Heart Trouble → SLONE → DEPR (T2)	0.001	0.001	0.002	-0.003	0.004
Sleep Disorder → ELONE → DEPR (T2)	0.039	0.017	0.019	-0.021	0.054
Sleep Disorder → SLONE → DEPR (T2)	0.009	0.004	0.004	-0.003	0.011
Cancer → ELONE → DEPR (T2)	-0.002	-0.001	0.004	-0.008	0.006
Cancer → SLONE → DEPR (T2)	-0.006	-0.003	0.003	-0.008	0.003
		Total Effects			
Total Direct Effect	0.787	0.352	0.069	0.217	0.488
Total Indirect Effect (ELONE)	0.028	0.012	0.015	-0.017	0.041
Total Indirect Effect (SLONE)	0.001	0.000	0.003	-0.005	0.006
Total Indirect Effect	0.030	0.012	0.015	-0.018	0.042
Total Effect	0.816	0.365	0.069	0.229	0.500
		Effect Sizes			
Mediation Ratio ($\hat{P}_M$)		0.033			
Relative Magnitude ($\hat{R}_M$)		0.034			
R^2 DA/SR (T2)		0.579			
R^2 PA (T2)		0.520			
R^2 ELONE		0.637			
R^2 SLONE		0.295			

Note. B = Estimated Coefficient; *β* = Standardised Coefficient; *SE* = Standard Error; ELONE = Emotional Loneliness; SLONE = Social Loneliness; DEPR = Depression; T2 = Time 2; DA/SR = Depressive Affect/Somatic Retardation Depression Factor; PA = Positive Affect Depression Factor.

Table 14

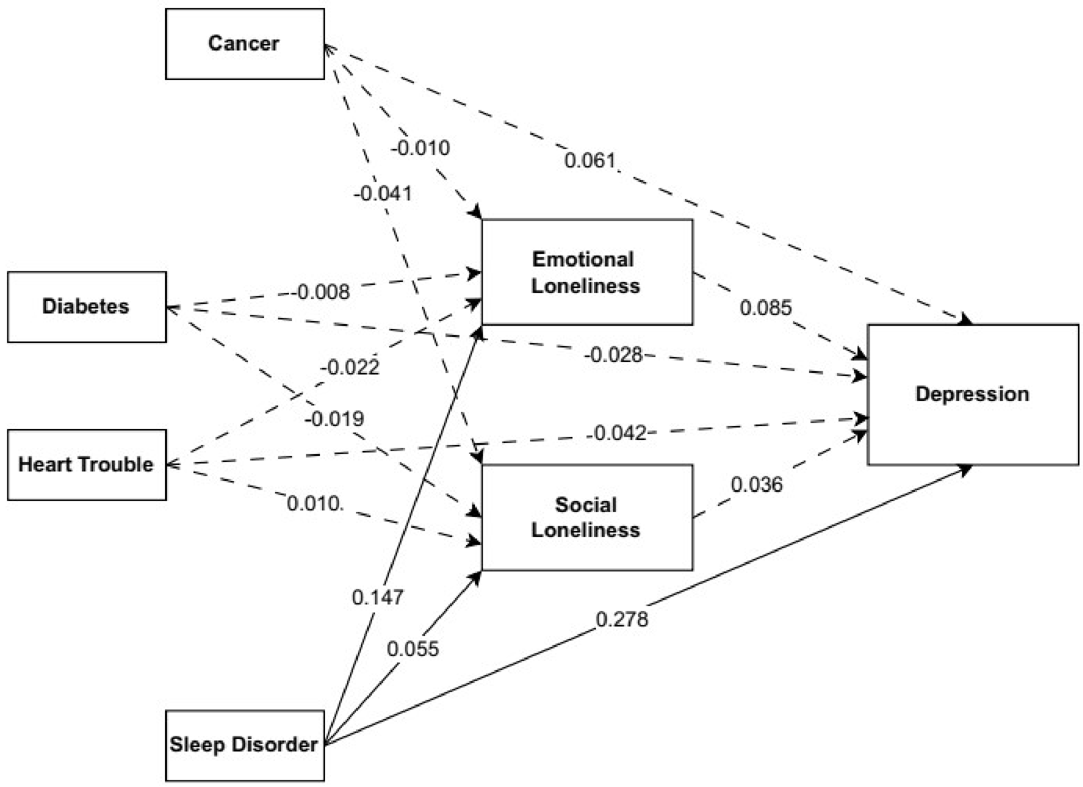
Multimorbidity Model Effects

Path	*B*	*β*	*SE*	*CI* (95%)	
		Direct Effects			
MM → DEPR (T2)	0.198	0.190	0.037	0.117	0.263
		Indirect Effects			
MM → ELONE → DEPR (T2)	0.008	0.007	0.009	-0.010	0.025
MM → SLONE → DEPR (T2)	0.000	0.000	0.002	-0.003	0.003
		Total Effects			
Total Indirect Effect	0.008	0.007	0.009	-0.011	0.025
Total Effect	0.206	0.197	0.037	0.125	0.270
		Effect Sizes			
Mediation Ratio ($\hat{P}_M$)		0.036			
Relative Magnitude ($\hat{R}_M$)		0.037			
R^2 DA/SR (T2)		0.579			
R^2 PA (T2)		0.520			
R^2 ELONE		0.640			
R^2 SLONE		0.295			

Note. B = Estimated Coefficient; *β* = Standardised Coefficient; *SE* = Standard Error; MM = Multimorbidity; ELONE = Emotional Loneliness; SLONE = Social Loneliness; DEPR = Depression; T2 = Time 2; DA/SR = Depressive Affect/Somatic Retardation Depression Factor; PA = Positive Affect Depression Factor.

Figure 4

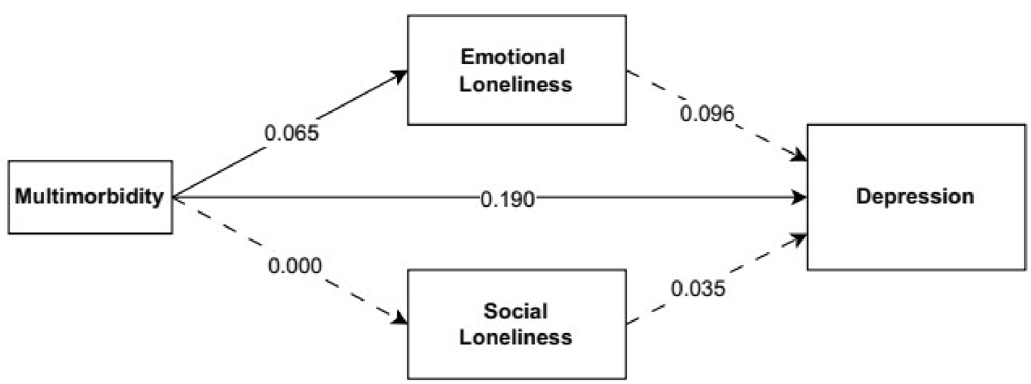
Chronic Conditions Model Path Diagram of Standardised Estimated Parameters



Note. Significant effects are represented with solid lines ($p < .05$), non-significant with dashed lines.

Figure 5

Multimorbidity Model Path Diagram of Standardised Estimated Parameters



Note. Significant effects are represented with solid lines ($p < .05$), non-significant with dashed lines.

4.3. Summary

Results provided little support for the hypotheses in this study. The hypotheses and their level of support are summarised here.

H1

Chronic conditions (cancer, diabetes, heart trouble, sleep disorder, and stroke) and multimorbidity at T1 will be positively associated with emotional and social loneliness at T1. H1 was partially supported. Regression coefficients in the full model (controlling for depression, age, ethnicity, gender, partner status, and SES at T1) showed that sleep disorder was positively related to emotional and social loneliness and that multimorbidity was positively related to emotional loneliness. All other associations were non-significant or negligible in size.

H2

Chronic conditions (cancer, diabetes, heart trouble, sleep disorder, and stroke) and multimorbidity at T1 will be positively associated with depression at T2 (controlling for depression, age, ethnicity, gender, partner status, and SES at T1). H2 was partially supported. Regression coefficients in the full model showed that sleep disorder and multimorbidity at T1 were positively related to depression at T2. All other associations were non-significant or negligible in size.

H3

Emotional and social loneliness at T1 will be associated with depression at T2. H3 was not supported. Emotional and social loneliness at T1 were not associated with depression at T2 in either model.

H4

Emotional and social loneliness at T1 will mediate the relationship between chronic conditions (cancer, diabetes, heart trouble, sleep disorder, and stroke) at T1 and depression at T2 (controlling for depression, age, ethnicity, gender, partner status, and SES at T1). H4 was not supported as all indirect effects were non-significant.

H5

Emotional and social loneliness at T1 will mediate the relationship between multimorbidity at T1 and depression at T2 (controlling for depression, age, ethnicity, gender, partner status, and SES at T1). H5 was not supported as all indirect effects were non-significant.

5. Discussion

The current study primarily aimed to investigate whether loneliness mediated the relationship between chronic conditions and depression. The predicted relationship anticipated that chronic conditions would be associated with depression and loneliness and that loneliness would be related to depression.

The predictors of depression in this study included sleep disorder, multimorbidity, and living standards. The remaining chronic conditions, including cancer, diabetes, heart trouble, and stroke, did not predict increases in depression after two years. Further, neither emotional nor social loneliness predicted later depression. Predictors of loneliness also included sleep disorder, multimorbidity, and living standards, while the remaining chronic conditions were not related to loneliness. As such, neither type of loneliness mediated the relationship found between chronic conditions and multimorbidity with depression.

This section includes a discussion of this study's findings and how they relate to the existing literature. It further includes implications for future research, the study's limitations, and conclusions about the findings and their importance.

5.1. Predictors of Depression

5.1.1. Sleep Disorder

The first main finding was that sleep disorder predicted depression. This relationship was over and above baseline depression, age, gender, ethnicity, partner status, and socioeconomic status. These results show that people who report sleep disorders are more likely to report higher depressive symptoms two years later.

It was surprising that only sleep disorder predicted depression, given the research support for a relationship between depression and cancer, diabetes, heart trouble, and stroke. One potential explanation for this is that sleep disorders may be unique among chronic conditions in their relationship with depression due to psychological factors. Sleep disorders often have significant psychological components in their development and maintenance, particularly depression and anxiety (Buela-Casal et al., 2024), that set them apart from more physical chronic conditions. Relatedly, many sleep disorders share symptoms with anxiety and depressive disorders, while sleep disturbance is both a symptom of and a diagnostic criterion for depression that is present in a high percentage of cases (American Psychiatric Association, 2022). This symptom overlap could inherently lead to a stronger relationship between sleep disorders and depressive symptoms. The current study found that sleep disorder showed a small association with depression and that this relationship was stable over time. Analyses further showed a modest effect of sleep disorder on future depression while accounting for baseline depression, effectively controlling for shared symptoms. These results suggest that sleep disorder is an independent predictor of depression, unique among the chronic conditions examined, that contributes additional variance not explained by baseline depressive symptoms and likely includes but is not due solely to symptom overlap.

Research supports sleep disorder as a unique type of predictor for depression. Similar to the results found in this study, Maier et al. (2021) discussed research in their systematic review that examined the relationship between chronic conditions and depression, noting that history of many of the more physical chronic conditions failed to predict depression in several studies, while history of sleep disturbance increased depressive symptoms. The authors further noted research that found the combination of difficulty falling asleep and presence of chronic disease increased the risk of depression. Much of the research on sleep's relationship with depression found in the literature examined sleep disturbance or poor sleep quality rather than sleep disorder explicitly (Wicke et al., 2022; Wu et al., 2022), and these symptoms are often associated with psychological elements (Buela-Casal et al., 2024). Research further supports the possibility that the association between sleep disorder and depression may be partly but not fully due to overlapping symptoms between the somatic symptoms of depression and those of common chronic physical conditions like sleep disturbance, fatigue, and the like (Spangenberg et al., 2011; Wicke et al., 2022).

5.1.2. Multimorbidity

The second main finding was that multimorbidity predicted depression. This relationship, though modest, was over and above baseline depression, age, gender, ethnicity, partner status, and socioeconomic status. These results show that the more chronic conditions people report, the more likely they are to report higher depressive symptoms two years later.

The literature supports the results found here. Research has found that people with chronic condition multimorbidities are more likely to be depressed (Birk et al., 2019) and that multimorbidity predicts a worsening in depressive symptoms in older people (Wicke et al., 2022). The results of this study align with the abundant evidence connecting multimorbidity to depression.

5.1.3. Cancer, Diabetes, Heart Trouble, and Stroke

This study found that cancer, diabetes, heart trouble, and stroke did not predict depression. While this finding was initially surprising, given the support found in the literature, it is important to acknowledge that the evidence for the relationship between these more physical conditions and depression is mixed. This contrasts with the stronger evidence supporting sleep disturbance as predictor of depression, as discussed above.

There is research support for these results in the literature. Maier et al. (2021) discussed research in their systematic review of risk factors for depression in older people that found history of stroke, cancer, diabetes, and heart disease failed to reach significance in several studies, while history of sleep disturbance was significantly related to increased depression. Additionally, in their umbrella review of risk factors for depression in older persons, Wu et al. (2022) critically evaluated the research. They judged the evidence supporting cancer, diabetes, heart trouble, and stroke as predictors of depression to be questionable as opposed to the highly suggestive evidence supporting sleep disturbance as predictor. The authors noted that much of the evidence for these more physical conditions was heterogeneous and that the quality of the evidence was relatively weak or merely suggestive in many cases. The findings of this study align with Wu and colleagues' assessment, suggesting that the evidence for cancer, diabetes, heart trouble, and stroke predicting depression remains unconvincing.

5.1.4. Loneliness

Emotional and social loneliness were found not to predict depression in this study, though the results indicated strong bivariate correlations of both types of loneliness with depression. This research instead found that SES, measured as living standards, explained a larger part of depression and predicted both types of loneliness as well.

Of the research discussed above that found that loneliness predicted depression, none assessed SES by measuring living standards. This difference offers a potential explanation for why loneliness was found not to predict depression in this study, while so much past research found that it does. It is possible that living standards is a better proxy for SES than some of the other measures when examining predictors of depression and that living standards explains the relationship between loneliness and depression. Rather than living standards, researchers often employed alternative proxies of SES including measures of income, financial resources or wealth, occupational status, education level, or a combination of these proxies (Brouwers et al., 2014; Cacioppo et al., 2006, 2010; Cohen-Mansfield & Parpura-Gill, 2007; Jongenelis et al., 2004; S. L. Lee et al., 2021; N. S. Park et al., 2017). Additionally, several studies that found a relationship between loneliness and depression did not control for SES (Holvast et al., 2015; Lim et al., 2016; Solmi et al., 2020; Wei et al., 2005).

This study provides a valuable contribution to the literature examining the relationship between SES and depression in older people, and it aligns with the considerable research on the importance of inequalities and their negative impact on health outcomes. SES is a well-known social determinant of health that impacts depression (Murata & Kondo, 2020). In their meta-analysis of research examining the effect of SES on depression, Lorant et al. (2003) discussed research that found people indicating the lowest SES were 1.25 times more likely to develop incident depression and that depression was 1.81 times more prevalent in people from this group than those indicating higher SES. Moreover, Vikram et al. (2018) investigated the literature to determine how SES impacted depression in the form of income and wealth inequalities. The authors noted that the unequal distribution of wealth and income has grown steadily over the last three decades, with an increasing number of people indicating lower SES. They found robust evidence that populations with higher inequality relative to populations with less inequality demonstrated a significantly greater risk of depression across most countries examined.

5.2. Predictors of Loneliness

5.2.1. Sleep Disorder

This study found that sleep disorder predicted emotional and social loneliness over and above known covariates in the literature. These results show that people who report sleep disorders are more likely to report higher symptoms of both emotional and social loneliness.

One potential explanation for this is that sleep disorders may be related to loneliness through psychological factors, similar to sleep's relationship with depression. Sleep disorders have a well-documented impact on individual wellbeing and daily functioning, causing fatigue, stress, irritability, and impairments in cognitive functioning (American Psychiatric Association, 2022; Cho et al., 2019; Deng et al., 2023; Zhou et al., 2023). Such effects make sleep disorders likely contributors to both types of loneliness by disrupting the ability to create and maintain intimate and social relationships.

Research supports the role of psychological factors in the relationship between sleep disorders and loneliness. Meta-analyses by Deng et al. (2023) and Hom et al. (2020) presented research associating poor sleep with diminished mental health and wellbeing in older adults, including increased risk for anxiety, dementia, and emotion dysregulation. Lower psychological wellbeing, in turn, was associated with difficulties engaging in intimate and social interactions and to the perception of non-belonging, leading to feelings of loneliness (Cohen-Mansfield et al., 2016; Deng et al., 2023; Hom et al., 2020). Additional research by Grey et al. (2023) found that generalised anxiety mediated the relationship between sleep disorder and loneliness, reinforcing the effect of psychological factors in the relationship.

5.2.2. Multimorbidity

This study further found that multimorbidity predicted emotional loneliness but not social loneliness. These results show that the more chronic conditions people report, the more likely they are to report higher levels of emotional loneliness.

One possible explanation for the relationship between multimorbidity and emotional loneliness is through their relationship with sleep quality. Managing multiple chronic conditions can be stressful and may lead to feelings of anxiety and distress, which can negatively affect sleep. Sleeping alone can be perceived as stressful, further affecting sleep quality, and the perceived lack of necessary emotional support due to being or feeling alone can lead to feelings of emotional loneliness. Research has found that multimorbidity of medical and chronic conditions is associated with poor sleep quality in older persons (Foley et al., 2004; McHugh et al., 2011). Research by McHugh et al. (2011) found that emotional loneliness was also associated with poor sleep quality in older adults. The authors emphasised past research showing that sleeping alone is often perceived as a stressful event, further interfering with sleep, and that living and sleeping alone has been associated with emotional loneliness (Schnittger et al., 2012). The results of this study align with this explanation, given that sleep disorder was associated with emotional loneliness and two of the four remaining chronic conditions, diabetes and heart trouble, as well as with multimorbidity even when sleep disorder was removed from its calculation. Furthermore, being single was related to multimorbidity, sleep disorder, and emotional loneliness, aligning with the research that suggests sleeping alone is associated with emotional loneliness, adding additional stress on top of the effects of multimorbidity.

5.2.3. Cancer, Diabetes, Heart Trouble, and Stroke

This study found that cancer, diabetes, heart trouble, and stroke did not predict social or emotional loneliness. One potential explanation for this may be due to the link between chronic conditions with psychological components rather than physical symptoms, as previously discussed. The more physical chronic conditions are often managed medically; consequently, the conditions may not directly interfere with an individual's social or emotional interactions with others. However, these conditions often impose additional costs on the individual, disproportionately impacting those of lower SES and potentially interfering with their ability to have these needed interactions.

This study found that SES predicted loneliness while the more physical chronic conditions did not. Some research in the literature supports the lack of a relationship between the more physical chronic conditions and loneliness, while SES is a strong predictor of loneliness. Kandola et al. (2023) examined the relationship between physical chronic conditions, including those investigated in this study, while controlling for a large number of confounds that included multiple proxies for SES. They found that no physical chronic condition predicted loneliness. Additional qualitative research by López-Entrambasaguas et al. (2020) found that older people with physical chronic conditions reported that the physiological needs related to their conditions were largely met and did not prevent them from interacting with others, stating instead that their condition created additional costs that worsened their socioeconomic situation. Lower SES, in turn, is a known predictor of loneliness in older adults, possibly due to the less diverse social networks, fewer friendship ties, and less friendship support found in those reporting lower SES (Pikhartova et al., 2016; Pinquart & Sorensen, 2001). Additional research by Meisters et al. (2021) examined the relationship between SES and loneliness and concluded that loneliness was independently associated with SES inequalities over and above demographic and lifestyle factors.

5.3. Mediation

The current study found that neither type of loneliness mediated the relationship between chronic conditions and depression or between multimorbidity and depression. Although direct relationships with depression were found with both sleep disorder and multimorbidity, loneliness did not predict depression; consequently, no mediation would be expected. These results align with the research discussed above and suggest that reducing loneliness in older adults with chronic conditions may not prevent future depression or reduce its symptoms.

In addition to SES, as previously discussed, there may be other relationships for loneliness. There is some evidence that psychosocial resources, including feeling less lonely, modify the effect between some chronic conditions and depression by acting as a buffer (Bisschop et al., 2004). However, a post-hoc test of moderating analyses with these data found no moderation effects.

5.4. Strengths

This study included several strengths. A big strength of this research included a large and diverse sample of older persons residing in Aotearoa. The sample was fairly representative of the aged population with respect to current age and gender demographics as compared to NZ census data, strengthening the generalisability of study results to the population, and it over-represented the Māori population as required by the HWR study. The sample was taken from two waves of the longitudinal HWR study that exhibited good response rates for existing participants, allowing for comparisons of depression scores at two time points.

The current study further employed SEM, which allows measured data to be treated as approximating hypothetical constructs that can be analysed within validated theories found in the literature and directly accounts for measurement error through latent variables (Kline, 2023).

Further, this study controlled for several confounders of depression and loneliness frequently found in the literature, increasing confidence in study results and conclusions. Validated measures were used for all constructs, with strong reliability for the SES and social loneliness measures when assessed against the current data set.

5.5. Limitations

5.5.1. Measurement Reliability

One significant limitation of this study concerned the questionable reliability of the depression and emotional loneliness measures. While the instruments used in the study were constrained to those used in the larger HWR study, the measures were well-studied and validated in the literature. Nevertheless, the depression instrument unexpectedly fit a two-factor measure at T2 with one of the factors consisting of only two items and low reliability. This was in contrast to the depression data at T1, which fit a single-factor measure. The finding that the instrument fit the data for depression at T2 as a two-factor measure conflicts with psychometric research provided by the measure's authors (Andresen et al., 1994) and with considerable subsequent research on the CES-D-10 (Mohebbi et al., 2018). Though there is research support for a two-factor CES-D-10 measure, as previously discussed, the authors of these studies did not remove the loneliness item as this study did, and the effect of doing so with two factors is unknown. While the reliability of the single-factor CES-D-10 was good in this study, reliability for the two-factor measure was split with higher alpha coefficients for the seven-item DA/SR factor ranging from 0.78 – 0.81 and from 0.60 to 0.62 for the two-item PA factor. There is, however, wide disagreement concerning the best way to measure the reliability of two-item constructs, and most researchers advocate for more than two items (Eisinga et al., 2013). It was further intriguing that the PA factor consisted of the reverse-coded items from the measure. Given that others have found this extra factor in their research, it is possible that the items are not being well-responded to by participants, perhaps due to the change in direction of the questions. The varying levels of reliability found cast doubt on the use of the CES-D-10 to consistently and accurately measure participant depression levels at two time points in this study.

Furthermore, while reliability in this study for the social loneliness subscale was good, the reliability of the overall loneliness scale and emotional loneliness subscale were questionable. Analysis of local model fit residuals indicated one problematic emotional loneliness item in particular, "I often feel rejected." Psychometric research by Cheung et al. (2022) likewise identified this item as an issue for their Chinese sample but not for their Dutch sample. The authors questioned the cultural appropriateness of the item but stopped short of recommending its exclusion. In addition, another emotional loneliness item, "I miss having people around," exhibited a low factor loading in this study. The low reliability of the emotional and overall loneliness scales suggests dubious internal reliability for measuring loneliness in this sample, and it could be worth investigating whether the problematic emotional loneliness item is acceptable for use when assessing emotional loneliness in Aotearoa.

Finally, as the HWR study did not include a specific measure of multimorbidity, the variable was constructed as a simple count of a participant's chronic conditions. Consequently, the multimorbidity construct contained uncertain reliability and validity. While a simple count is frequently used in the literature to represent multimorbidity, there is evidence that this method is less suitable for predicting outcomes than a weighted score of conditions used by some measures (Peters et al., 2018). However, others provide evidence that the simple count method is reasonable and performs almost as well as complex measures (Huntley et al., 2012). Ideally, future research on multimorbidity would employ a validated measure to confirm reliability and validity.

5.5.2. Model Limitations

Another limitation to consider here is the cross-sectional design of this study. Cross-sectional research is unable to address causation when examining effects. Instead, this study was based on a theoretical model that assumed a given direction of effects. The hypotheses, as derived by MODEL, postulated that chronic conditions and multimorbidity would predict depression and that loneliness would mediate this effect. Mediation, therefore, assumed that chronic conditions and multimorbidity would predict loneliness and that loneliness, in turn, would predict depression. However, it is conceivable that the direction of any of these effects could differ from what was hypothesised in this study. There is evidence that loneliness predicts chronic conditions (Böger & Huxhold, 2018; McMullan et al., 2021; Perissinotto et al., 2012; Solmi et al., 2020) and that depression predicts loneliness (Dahlberg et al., 2022; Lundmark et al., 2023) and chronic conditions (Birk et al., 2019; Li et al., 2019). Furthermore, evidence exists in support of a bidirectional relationship between depression and chronic conditions (Li et al., 2019), loneliness and chronic conditions (Paul et al., 2021), and depression and loneliness (Kraav et al., 2021).

Accordingly, it is possible that the model employed by this study does not adequately address the direction and complexity of these relationships. Indeed, both SEM models indicated questionable global and local fit, likely due at least in part to the questionable reliability of the depression and emotional loneliness measures. Both models failed the chi-square exact fit test with variable support from approximate fit indices. Local fit analyses indicated concerns with two of the emotional loneliness items, the latter likely related to the low reliability found for the measure as described above. If the goal of evaluating model fit in SEM is to evaluate how well a given model estimates the true model (Hox & Bechger, 1998), then it is likely that neither of the models examined in this study represented the true model given the data. Overall, questionable model fit limits the ability to draw conclusions about the precision, magnitude, and direction of effects from this study based on the conceptual model from the literature (Kline, 2023).

5.5.3. Sample Representativeness

Another limitation of this study concerned the representativeness of the sample. While most demographic variables were fairly representative, it is possible that the sample underrepresented the number of chronic conditions found in the older population. The number of study participants indicating chronic conditions of any type was on the low end according to research. As previously reported, 60.7% of study participants indicated no chronic conditions. This appears at odds with the findings by Aspin et al. (2010) that 51% of the population in Aotearoa reported at least one chronic condition, with the number of chronic conditions reported by individuals increasing with age.

The stroke variable was of particular concern in this study due to its low variability. While the incidence of stroke in Aotearoa and other high-income countries has declined in recent decades (Feigin et al., 2015), the Stroke Foundation NZ (2024) currently reports more than 10,000 new strokes per year, with 70-75% of those experienced by adults aged 65+ years, approximately 0.9% of the population aged 65+ (Statistics New Zealand Tatauranga Aotearoa, 2024). The number of participants indicating stroke within the previous 12 months aged 65+ was 0.4% in this study, less than half of what may be expected from the population. Furthermore, the effects of stroke can be severe. The condition can affect how a person functions (Stroke Foundation NZ, 2024), is associated with cognitive impairment and dementia (Rost et al., 2022), and is a leading cause of disability in Aotearoa with increased risk due to age (Barker-Collo et al., 2019). It is feasible that such effects could impair a participant’s ability to answer the survey questions, offering one potential explanation for the low number found in this study. As the stroke variable was later removed from the chronic conditions SEM model, it is unknown if stroke predicted a change in depression or loneliness, though correlational analysis indicated no significant relationship between stroke and depression or with either type of loneliness.

Moreover, the data set included some moderately skewed data. SES and emotional loneliness scores were negatively and positively skewed, respectively. Participants indicated higher SES levels than what was found in the population for the age group examined according to census data. Emotional loneliness scores indicated low levels of emotional loneliness, though the measure's low reliability as previously discussed should be considered here. Additionally, refresh cohort response rates were consistently low, particularly for Māori. While the refresh cohort for T2 was excluded from the analysis, T1 data included refresh participants as their depression responses could be compared at both time points. The skewed data and refresh cohort response rates raise the possibility of response bias as it is possible that participants who were less lonely, of higher SES, or who experienced fewer chronic conditions may have been more likely to respond to the surveys. Furthermore, loneliness in older adults is associated with impaired cognitive functioning and cognitive decline (Hodgson et al., 2020; Solmi et al., 2020) and increased risk for dementia (Griffin et al., 2024), offering a potential reason that participants might not return the survey or perhaps drop out of the study, which could bias the rates of loneliness found in this study. These concerns around the sample's representativeness reduce the confidence in generalising the results to the general population.

5.6. Implications and Future Research

This study contributes to the research on precursors of depression among older people. The results of this study highlight the distinctive role that sleep disorders have on depressive symptoms, possibly due to their psychological components or other qualities related to sleep disturbance. Though modest in size, the relationship found between depression and sleep disorders provides an additional potential target for intervention and prevention of depression in older adults. The modest effects among several significant covariates suggest that other factors should be considered along with sleep disorder when addressing depression in older adults. In particular, living standards consistently predicted depression in both models. These results further add to the literature showing that SES predicts depression. Future research could explore the mechanisms associating sleep disorder and depression, including the role of psychological factors, while controlling for overlapping symptoms between the two conditions.

This study additionally adds to the literature supporting the role that multimorbidity has in predicting depression. While the more physical chronic conditions did not individually predict depression, a greater number of the chronic conditions examined did predict depression. This aligns with considerable research. Here again, effects were small, suggesting that multimorbidity is worth considering when addressing depression in older people but should not be the sole focus. Future research on the relationship between depression and multimorbidity could separate the more physical conditions from those with strong psychological components to determine if the effect on depression persists.

Just as it is important to understand where to focus one's efforts to intervene or prevent conditions like depression, it is equally important to determine where there may be no need to focus. This study found that loneliness did not predict depression in older adults experiencing chronic conditions, nor did it mediate the relationship between chronic conditions and depression. This is a valuable contribution to the literature with implications for preventing and treating depression. While addressing loneliness in older adults is a worthy goal in its own right, to tackle depression, it may be more useful to focus on individual sleep concerns, multimorbidity, and the inequalities in society.

5.7. Conclusion

In Aotearoa and around the world, the growth in the ageing population is accelerating. Older adults are experiencing an increasing number of chronic conditions and are vulnerable to depression. Health outcomes of the ageing population are fundamentally connected to the ability to age well. As such, it is vital that research addresses the predictors of depression.

This study endeavored to examine the relationship between several chronic conditions and depression as well as the potential mediating effect of social and emotional loneliness. Despite the study's limitations, the results offer several contributions to the current literature. While sleep disorder predicted depression, the more physical chronic conditions did not, suggesting that chronic conditions with more psychological components have a stronger relationship with depression. Nevertheless, multimorbidity, including having multiple physical chronic conditions, also predicted depression, aligning with considerable research. Similar results were found for loneliness, with sleep disorder alone of the chronic conditions predicting both types of loneliness, likely for similar reasons as the relationship found with depression. Interestingly, multimorbidity predicted emotional loneliness but not social loneliness, suggesting that this relationship may operate through poor sleep quality, given that poor sleep quality has been associated with both physical chronic conditions and emotional loneliness in the literature. This study adds to the literature supporting the possible relationship between multimorbidity and emotional loneliness through sleep quality. Finally, in contrast to considerable past research, the current research found that loneliness did not mediate the relationship between chronic conditions and depression, nor between multimorbidity and depression. Instead, these relationships may be through SES measured as living standards. This is an important contribution to the literature as none of the research reviewed that previously indicated loneliness predicted depression employed living standards as proxy for SES. This study aligns well with the literature supporting SES as a psychosocial determinant of health.

What is clear from the existing research and the results of this study is that the relationships between chronic conditions, loneliness, and depression are complex. Tackling depression is a daunting task, particularly in light of the rising inequalities felt around the world. This research provides additional understanding of reducing depression in older adults and adds to the literature for Aotearoa.

6. References

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Appendix A

R Code

```
"
****************************************************************
*************
  R Syntax for all analyses
****************************************************************
*************
"
# Libraries
  library(psych)       # Main psychology statistical package
  library(Amelia)      # Missing data and imputation package
  library(matrixcalc) # Test for positive definite matrix
  library(lavaan)      # Main SEM package
  library(moments)     # To test skewness/kurtosis
  library(naniar)      # To test missing data
  library(MVN)         # Multivariate normality testing
  library(MASS)        # Multivariate outlier detection
  library(semPlot)     # Creating diagrams

# Read in data files and merge
  data1 <- read.csv("HWRShare1.csv") # Initial file provided
  # File provided at a later date containing SES items
  data2 <- read.csv("HWRShare2.csv")
  data <- merge(data1, data2[, c("ID_Thomas", grep("^DEL",
    names(data2), value = TRUE))], by = "ID_Thomas", all.x =
    TRUE)

"
****************************************************************
*************
  Data preparation and initial analysis
****************************************************************
*************
"
  options(max.print=999999)
  str(data)
  psych::describe(data)
  summary(data)

# Remove refresh cohort, ie participants who were added in 2022
# and therefore contain # no data from 2020
```

```
sum( is.na(data$age20) & is.na(data$DETMAO20) &
is.na(data$DETNIU20) & is.na(data$DETEUR20) &
is.na(data$DETCHI20) & is.na(data$DETSAM20) &
is.na(data$DETIND20) & is.na(data$DETCIM20) &
is.na(data$DETTON20) &
is.na(data$DETOTH20) & is.na(data$DMRSTSc20) &
is.na(data$HCESDa20) & is.na(data$HCESDb20) &
is.na(data$HCESDc20) & is.na(data$HCESDd20) &
is.na(data$HCESDe20) & is.na(data$HCESDf20) &
is.na(data$HCESDg20) &
is.na(data$HCESDh20) & is.na(data$HCESDi20) &
is.na(data$HCESDj20) & is.na(data$HDGDBT20) &
is.na(data$HDGHRT20) &
is.na(data$HDGSLP20) & is.na(data$HDGSTK20) &
is.na(data$HDGCAN20) & is.na(data$FLONEc20) &
is.na(data$FLONEd20) & is.na(data$FLONEg20) &
is.na(data$FLONEh20) & is.na(data$FLONEi20) &
is.na(data$FLONEj20) &
is.na(data$ELSI_est20) ) # 1,975

no_2020 <- is.na(data$age20) & is.na(data$DETMAO20) &
is.na(data$DETNIU20) & is.na(data$DETEUR20) &
is.na(data$DETCHI20) & is.na(data$DETSAM20) &
is.na(data$DETIND20) & is.na(data$DETCIM20) &
is.na(data$DETTON20) &
is.na(data$DETOTH20) & is.na(data$DMRSTSc20) &
is.na(data$HCESDa20) & is.na(data$HCESDb20) &
is.na(data$HCESDc20) & is.na(data$HCESDd20) &
is.na(data$HCESDe20) & is.na(data$HCESDf20) &
is.na(data$HCESDg20) &
is.na(data$HCESDh20) & is.na(data$HCESDi20) &
is.na(data$HCESDj20) & is.na(data$HDGDBT20) &
is.na(data$HDGHRT20) &
is.na(data$HDGSLP20) & is.na(data$HDGSTK20) &
is.na(data$HDGCAN20) & is.na(data$FLONEc20) &
is.na(data$FLONEd20) & is.na(data$FLONEg20) &
is.na(data$FLONEh20) & is.na(data$FLONEi20) &
is.na(data$FLONEj20) &
is.na(data$ELSI_est20)

# Remove refresh participants by keeping the rest
data <- data[!no_2020, ]

# Remove participants who:
  # left any loneliness item  blank (per Gierveld cannot score
  # if any items are missing)
  # OR left all depression items blank in 2020
```

```
  # OR left all depression items blank in 2022
  # OR left any covariate blank (no blanks for age or Gender in
  # current data set)
  # Total rows removed is not the sum of the above due to
  # overlap
  sum(
    (is.na(data$FLONEc20) | is.na(data$FLONEd20) |
is.na(data$FLONEg20) | is.na(data$FLONEh20) |
is.na(data$FLONEi20) | is.na(data$FLONEj20)) | # Loneliness
   # 164 rows, 3.8%
 (
is.na(data$HCESDa20) & is.na(data$HCESDb20) &
is.na(data$HCESDc20) & is.na(data$HCESDd20) &
is.na(data$HCESDe20) &
is.na(data$HCESDf20) & is.na(data$HCESDg20) &
is.na(data$HCESDh20) & is.na(data$HCESDi20) &
is.na(data$HCESDj20)                    # CESD 2020, 33 rows
         ) |
      (
is.na(data$HCESDa22) & is.na(data$HCESDb22) &
is.na(data$HCESDc22) & is.na(data$HCESDd22) &
is.na(data$HCESDe22) &
is.na(data$HCESDf22) & is.na(data$HCESDg22) &
is.na(data$HCESDh22) & is.na(data$HCESDi22) &
is.na(data$HCESDj22)                     # CESD 2022, 824 rows
      ) |
      (
is.na(data$DETMAO20) & is.na(data$DETNIU20) &
is.na(data$DETEUR20) & is.na(data$DETCHI20) &
is.na(data$DETSAM20) &
is.na(data$DETIND20) & is.na(data$DETCIM20) &
is.na(data$DETTON20) & is.na(data$DETOTH20)
# Ethnicity, 37 rows, 0.9%
# 37
      ) |
      (
        is.na(data$ELSI_est20)
# SES, 214 rows, 4.9%
      ) |
      (
        is.na(data$DMRSTSc20)
# Partnership, 54 rows, 1.2%
      ) |
      (
        is.na(data$Gender)
# Gender, 0 rows, 0%
      ) |
```

```
      (
        is.na(data$age20)
# Age, 0 rows, 0%
      )
    )
# 1094 total rows, 25.2%

no_items <- (is.na(data$FLONEc20) | is.na(data$FLONEd20) |
is.na(data$FLONEg20) | is.na(data$FLONEh20) |
is.na(data$FLONEi20) | is.na(data$FLONEj20)) |
    (
is.na(data$HCESDa20) & is.na(data$HCESDb20) &
is.na(data$HCESDc20) & is.na(data$HCESDd20) &
is.na(data$HCESDe20) &
is.na(data$HCESDf20) & is.na(data$HCESDg20) &
is.na(data$HCESDh20) & is.na(data$HCESDi20) &
is.na(data$HCESDj20)
    ) |
    (
is.na(data$HCESDa22) & is.na(data$HCESDb22) &
is.na(data$HCESDc22) & is.na(data$HCESDd22) &
is.na(data$HCESDe22) &
is.na(data$HCESDf22) & is.na(data$HCESDg22) &
is.na(data$HCESDh22) & is.na(data$HCESDi22) &
is.na(data$HCESDj22)
    ) |
    (
is.na(data$DETMAO20) & is.na(data$DETNIU20) &
is.na(data$DETEUR20) & is.na(data$DETCHI20) &
is.na(data$DETSAM20) &
is.na(data$DETIND20) & is.na(data$DETCIM20) &
is.na(data$DETTON20) & is.na(data$DETOTH20)
    ) |
    (
      is.na(data$ELSI_est20)
    ) |
    (
      is.na(data$DMRSTSc20)
    ) |
    (
      is.na(data$Gender)
    ) |
    (
      is.na(data$age20)
    )

  data <- data[!no_items, ]
```

```
# Exclude 1 row with gender=3 (gender diverse), insufficient
# number for analysis
  table(data$Gender)
  data <- data[-which(data$Gender==3),]
  table(data$Gender)

# Categorise ethnicity, Maori = 1, non-Māori = 0.
  table(data$DETMAO20)
  data$Ethnicity <- ifelse(!is.na(data$DETMAO20), 1,  0)
  table(data$Ethnicity)

# Categorise partnership status as partnered (0) or single (1).
# Current data: 1 = married, 2 = widowed, 3 = civil union, 4 =
# single, and 5 = divorced
  table(data$DMRSTSc20)
  data$PartnerStatus <- ifelse(data$DMRSTSc20 == 1 |
    data$DMRSTSc20 == 3, 0, 1)
  table(data$PartnerStatus)

# Categorise chronic conditions
# NA values are assumed to be No. If cancer type was entered,
# participant assumed to # have cancer.
  summary(data[, c("HDGHRT20", "HDGDBT20", "HDGSLP20",
    "HDGSTK20", "HDGCAN20")])
sum(is.na(data$HDGDBT20) | is.na(data$HDGHRT20) |
is.na(data$HDGSLP20) | is.na(data$HDGSTK20) |
(is.na(data$HDGCAN20) & trimws(data$HDGCANtype20) == ''))
sum((is.na(data$HDGCAN20) | data$HDGCAN20 == 1) &
trimws(data$HDGCANtype20) != '') # Number saying no to cancer or
not answering but # entered type
data$HDiabetes <- ifelse(is.na(data$HDGDBT20), 0,
ifelse(data$HDGDBT20 > 1, 1, 0)) # 1 = Has Diabetes, 0 = doesn't
data$HHeart <- ifelse(is.na(data$HDGHRT20), 0,
ifelse(data$HDGHRT20 > 1, 1, 0))    # 1 = Has Heart Trouble, 0 =
     # does not
data$HSleep <- ifelse(is.na(data$HDGSLP20), 0,
ifelse(data$HDGSLP20 > 1, 1, 0))    # 1 = Has Sleep Disorder, 0
    # = does not
data$HStroke <- ifelse(is.na(data$HDGSTK20), 0,
ifelse(data$HDGSTK20 > 1, 1, 0))   # 1 = Had Stroke, 0 = did not
data$HCancer <- ifelse(is.na(data$HDGCAN20), 0,
ifelse(data$HDGCAN20 > 1, 1, 0))   # 1 = Has Cancer, 0 = doesn't
  table (data$HDGDBT20, useNA = "always")
  table (data$HDiabetes, useNA = "always")
  table (data$HDGHRT20, useNA = "always")
  table (data$HHeart, useNA = "always")
```

```
  table (data$HDGSLP20, useNA = "always")
  table (data$HSleep, useNA = "always")
  table (data$HDGSTK20, useNA = "always")
  table (data$HStroke, useNA = "always")
  table (data$HDGCAN20, useNA = "always")
  table (data$HCancer, useNA = "always")
  # If cancer type exists, then HCancer = 1 regardless of the
  # value of HDGCAN20
data$HCancer <- ifelse(trimws(data$HDGCANtype20) != '', 1,
data$HCancer)

# Verify data preparation tasks
data_verify <- c("Gender", "age20", "Ethnicity", "DETMAO20",
"DETNIU20", "DETEUR20", "DETCHI20", "DETSAM20", "DETIND20",
"DETCIM20", "DETTON20", "DETOTH20",
                   "PartnerStatus", "DMRSTSc20", "ELSI_est20",
                   "HCESDa20", "HCESDb20", "HCESDc20",
"HCESDd20", "HCESDe20", "HCESDf20", "HCESDg20", "HCESDh20",
"HCESDi20", "HCESDj20",
                   "HCESDa22", "HCESDb22", "HCESDc22",
"HCESDd22", "HCESDe22", "HCESDf22", "HCESDg22", "HCESDh22",
"HCESDi22", "HCESDj22",
                   "HDGDBT20", "HDiabetes", "HDGHRT20",
"HHeart", "HDGSLP20", "HSleep", "HDGSTK20", "HStroke",
"HDGCAN20", "HCancer", "HDGCANtype20",
                   "FLONEc20", "FLONEd20", "FLONEg20",
"FLONEh20", "FLONEi20", "FLONEj20")
summary(data[, data_verify])

# Missing data
# Missing depression (any field) 2020
depr_vars_2020 <- c("HCESDa20", "HCESDb20", "HCESDc20",
"HCESDd20", "HCESDe20", "HCESDf20", "HCESDg20", "HCESDh20",
"HCESDj20")
depr_vars_2022 <- c("HCESDa22", "HCESDb22", "HCESDc22",
"HCESDd22", "HCESDe22", "HCESDf22", "HCESDg22", "HCESDh22",
"HCESDj22")

sum(is.na(data$HCESDa20) | is.na(data$HCESDb20) |
is.na(data$HCESDc20) | is.na(data$HCESDd20) |
is.na(data$HCESDe20) |
is.na(data$HCESDf20) | is.na(data$HCESDg20) |
is.na(data$HCESDh20) | is.na(data$HCESDj20) )

sum(is.na(data$HCESDa20) | is.na(data$HCESDb20) |
is.na(data$HCESDc20) | is.na(data$HCESDd20) |
is.na(data$HCESDe20) |
```

```
is.na(data$HCESDf20) | is.na(data$HCESDg20) |
is.na(data$HCESDh20) | is.na(data$HCESDj20) ) / (nrow(data) *
ncol(data[, depr_vars_2020])) * 100

# Missing depression (any field) 2022
sum(is.na(data$HCESDa22) | is.na(data$HCESDb22) |
is.na(data$HCESDc22) | is.na(data$HCESDd22) |
is.na(data$HCESDe22) |
is.na(data$HCESDf22) | is.na(data$HCESDg22) |
is.na(data$HCESDh22) | is.na(data$HCESDj22) )

sum(is.na(data$HCESDa22) | is.na(data$HCESDb22) |
is.na(data$HCESDc22) | is.na(data$HCESDd22) |
is.na(data$HCESDe22) |
is.na(data$HCESDf22) | is.na(data$HCESDg22) |
is.na(data$HCESDh22) | is.na(data$HCESDj22) ) / (nrow(data) *
ncol(data[, depr_vars_2022])) * 100

# Missing any study variable
sum(is.na(data$HCESDa20) | is.na(data$HCESDa22) |
is.na(data$HCESDb20) | is.na(data$HCESDb22) |
        is.na(data$HCESDc20) | is.na(data$HCESDc22) |
is.na(data$HCESDd20) | is.na(data$HCESDd22) |
        is.na(data$HCESDe20) | is.na(data$HCESDe22) |
is.na(data$HCESDf20) | is.na(data$HCESDf22) |
        is.na(data$HCESDg20) | is.na(data$HCESDg22) |
is.na(data$HCESDh20) | is.na(data$HCESDh22) |
        is.na(data$HCESDi20) | is.na(data$HCESDi22) |
is.na(data$HCESDj20) | is.na(data$HCESDj22) |
        is.na(data$Gender) | is.na(data$age20) |
is.na(data$Ethnicity) | is.na(data$PartnerStatus) |
is.na(data$ELSI_est20) |
        is.na(data$HDiabetes) | is.na(data$HHeart) |
is.na(data$HSleep) | is.na(data$HStroke) | is.na(data$HCancer) |
        is.na(data$FLONEc20) | is.na(data$FLONEd20) |
is.na(data$FLONEg20) | is.na(data$FLONEh20) |
is.na(data$FLONEi20) | is.na(data$FLONEj20))

# Total missing data on study variables
study_vars <- c("Gender", "age20", "Ethnicity", "PartnerStatus",
"ELSI_est20",
"HCESDa20", "HCESDb20", "HCESDc20", "HCESDd20", "HCESDe20",
"HCESDf20", "HCESDg20", "HCESDh20", "HCESDj20",
"HCESDa22", "HCESDb22", "HCESDc22", "HCESDd22", "HCESDe22",
"HCESDf22", "HCESDg22", "HCESDh22", "HCESDj22",
"HDiabetes", "HHeart", "HSleep", "HStroke", "HCancer",
```

```
"FLONEc20", "FLONEd20", "FLONEg20", "FLONEh20", "FLONEi20",
"FLONEj20")

sum(is.na(data[, study_vars]))
sum(is.na(data[, study_vars])) / (nrow(data) * ncol(data[,
study_vars])) * 100
# sum(is.na(data[, study_vars]))/prod(dim(data[, study_vars])) *
100

# Univariate outlier detection
summary(data) # No obvious outliers based on summary data
boxplot(data[, study_vars], main="Boxplot", ylab="Values")
hist(data[, study_vars], main="Histogram", xlab="Values",
breaks=10)

# Test for multivariate normality and data missing completely at
# random (MCAR).
# Little's Test assumes multivariate normality, unless sample
# size is large, and is not
# appropriate for categorical variables.
# Sample size is large but perform the test first.
study_vars_missing <- c("HCESDa20", "HCESDb20", "HCESDc20",
"HCESDd20", "HCESDe20", "HCESDf20", "HCESDg20", "HCESDh20",
"HCESDj20",
                          "HCESDa22", "HCESDb22", "HCESDc22",
"HCESDd22", "HCESDe22", "HCESDf22", "HCESDg22", "HCESDh22",
"HCESDj22")
# Test for multivariate normality for only variables with
# missing data. Test = not normally # distributed.
MVN::mvn(data = data[, study_vars_missing], mvnTest = "mardia")
# Test for multivariate normality on data set. Test = not
# normally distributed.
MVN::mvn(data = data[, study_vars], mvnTest = "mardia")
naniar::mcar_test(data[, study_vars_missing])
# Although non-normal, Little's MCAR test can still be used with
large samples. Significant so not MCAR.

# Excessive missing values. Look for person-level response rate
# < 30% per Newman (2014) Guideline 5. 34 columns * .3 = 10.2.
count_missing <- function(x){sum(is.na(x))}
data$nmiss = apply(X = data[, study_vars], MARGIN = 1, FUN =
count_missing)
table(data$nmiss) # Max is 8
sum(data$nmiss > length(study_vars) * 0.3) # 0 missing greater
   # than 30%, no sensitivity-analysis needed

# Overly consistent responding, look for low participant
```

```
# standard deviation.
# Code from Quantitative Data Analysis course.
data$sd_cesd20 <- apply(X = data[,c("HCESDa20", "HCESDb20",
"HCESDc20", "HCESDd20", "HCESDe20", "HCESDf20", "HCESDg20",
"HCESDh20", "HCESDi20", "HCESDj20")], MARGIN = 1, FUN = sd,
na.rm = TRUE)
data$sd_cesd22 <- apply(X = data[,c("HCESDa22", "HCESDb22",
"HCESDc22", "HCESDd22", "HCESDe22", "HCESDf22", "HCESDg22",
"HCESDh22", "HCESDi22", "HCESDj22")], MARGIN = 1, FUN = sd,
na.rm = TRUE)
data$sd_cesd <- apply(X = data[,c("HCESDa20", "HCESDb20",
"HCESDc20", "HCESDd20", "HCESDe20", "HCESDf20", "HCESDg20",
"HCESDh20", "HCESDi20", "HCESDj20", "HCESDa22", "HCESDb22",
"HCESDc22", "HCESDd22", "HCESDe22", "HCESDf22", "HCESDg22",
"HCESDh22", "HCESDi22", "HCESDj22")], MARGIN = 1, FUN = sd,
na.rm = TRUE)
data$sd_lone <- apply(X = data[,c("FLONEc20", "FLONEd20",
"FLONEg20", "FLONEh20", "FLONEi20", "FLONEj20")], MARGIN = 1,
FUN = sd, na.rm = TRUE)
study_items <- c("HCESDa20", "HCESDb20", "HCESDc20", "HCESDd20",
"HCESDe20", "HCESDf20", "HCESDg20", "HCESDh20", "HCESDj20",
                  "HCESDa22", "HCESDb22", "HCESDc22",
"HCESDd22", "HCESDe22", "HCESDf22", "HCESDg22", "HCESDh22",
"HCESDj22",
                  "FLONEc20", "FLONEd20", "FLONEg20",
"FLONEh20", "FLONEi20", "FLONEj20")
data$sd_items <- apply(X = data[,study_items], MARGIN = 1, FUN =
sd, na.rm = TRUE)
summary(data)

  # Test for multicollinearity
  corr.test(data[, study_vars])
  # Print correlation matrix to csv file
  corr_result <- corr.test(data[, study_vars])
  corr_matrix <- round(corr_result$r, 2)
  # Remove repeated values from the diagonal
  corr_matrix[upper.tri(corr_matrix, diag = TRUE)] <- ''


# Imputation using expectation-maximization algorithm
set.seed(123)
am_imp = amelia(x = data[,study_vars], m = 1, boot.type =
"none",
                  ord = c("HCESDa20", "HCESDb20", "HCESDc20",
"HCESDd20", "HCESDe20", "HCESDf20", "HCESDg20", "HCESDh20",
"HCESDj20",
```

```
                           "HCESDa22", "HCESDb22", "HCESDc22",
"HCESDd22", "HCESDe22", "HCESDf22", "HCESDg22", "HCESDh22",
"HCESDj22"))
summary(am_imp)
str(am_imp)
#View(am_imp$imputations$imp1)
# Combine imputed data set with the other columns not imputed
old_data <- subset(data, select = !names(data) %in% study_vars)
data_imp = cbind(old_data, am_imp$imputations$imp1)
summary(data_imp[, study_vars])
sum(is.na(data_imp[, study_vars])) / (nrow(data_imp) *
ncol(data_imp[, study_vars])) * 100

# Multivariate outlier detection using Mahalanobis Distance
# which requires full data set
# (no missing values)
data_imp$mahalanobis <- mahalanobis(data_imp[,study_vars],
colMeans(data_imp[,study_vars]), cov(data_imp[,study_vars]))
data_imp$pmaha <- pchisq(data_imp$mahalanobis,
df=ncol(data_imp[,study_vars]), lower.tail=FALSE)
summary(data_imp$pmaha)

data_delete <- subset(data_imp[, c("pmaha", "mahalanobis",
"nmiss", study_vars)], pmaha < 0.001)  # 241, 7.4%
data_final <- subset(data_imp[, c("pmaha", "mahalanobis",
"nmiss", "HCESDi20", "HCESDi22", study_vars)], pmaha >= 0.001)
# Remove outliers from data set
summary(data_final)

# Check for positive definite matrix per Kline
is.positive.definite(cor(as.matrix(data_final[,
c(study_vars)])), tol=1e-8)

"
*****************************************************************
*************
  Measures
*****************************************************************
*************
"
# Reverse-coding: Reverse-coded response = maximum possible
# response + minimum # possible response - original response = 4
# + 1 - original response
# CES-D-10 reverse code two positive mood items
  data_final$HCESDe20r <- 5 - data_final$HCESDe20
  data_final$HCESDe22r <- 5 - data_final$HCESDe22
  data_final$HCESDh20r <- 5 - data_final$HCESDh20
```

```
  data_final$HCESDh22r <- 5 - data_final$HCESDh22

# Transform depression items. Documentation indicates scoring 0-
# 3 while data is 1-4.
  data_final$HCESDa20 <- data_final$HCESDa20 - 1
  data_final$HCESDb20 <- data_final$HCESDb20 - 1
  data_final$HCESDc20 <- data_final$HCESDc20 - 1
  data_final$HCESDd20 <- data_final$HCESDd20 - 1
  data_final$HCESDe20r <- data_final$HCESDe20r - 1
  data_final$HCESDe20 <- data_final$HCESDe20 - 1
  data_final$HCESDf20 <- data_final$HCESDf20 - 1
  data_final$HCESDg20 <- data_final$HCESDg20 - 1
  data_final$HCESDh20r <- data_final$HCESDh20r - 1
  data_final$HCESDh20 <- data_final$HCESDh20 - 1
  data_final$HCESDj20 <- data_final$HCESDj20 - 1
  data_final$HCESDa22 <- data_final$HCESDa22 - 1
  data_final$HCESDb22 <- data_final$HCESDb22 - 1
  data_final$HCESDc22 <- data_final$HCESDc22 - 1
  data_final$HCESDd22 <- data_final$HCESDd22 - 1
  data_final$HCESDe22r <- data_final$HCESDe22r - 1
  data_final$HCESDe22 <- data_final$HCESDe22 - 1
  data_final$HCESDf22 <- data_final$HCESDf22 - 1
  data_final$HCESDg22 <- data_final$HCESDg22 - 1
  data_final$HCESDh22r <- data_final$HCESDh22r - 1
  data_final$HCESDh22 <- data_final$HCESDh22 - 1
  data_final$HCESDj22 <- data_final$HCESDj22 - 1
  summary(data_final)

# Reliability. Warning message w/o discrete set - output is
# the same regardless.
psych::alpha(data_final[, c("HCESDa20", "HCESDb20", "HCESDc20",
"HCESDd20",
   "HCESDe20r", "HCESDf20", "HCESDg20", "HCESDh20r",
"HCESDj20")],
   discrete=FALSE)
  psych::alpha(data_final[, c("HCESDa22", "HCESDb22",
"HCESDc22", "HCESDd22",
   "HCESDe22r", "HCESDf22", "HCESDg22", "HCESDh22r",
"HCESDj22")],
   discrete=FALSE)
  # Test reliability with the loneliness variable for comparison
  psych::alpha(data_final[, c("HCESDa20", "HCESDb20",
"HCESDc20", "HCESDd20",
   "HCESDe20r", "HCESDf20", "HCESDg20", "HCESDh20r", "HCESDi20",
   "HCESDj20")], discrete=FALSE)
  psych::alpha(data_final[, c("HCESDa22", "HCESDb22",
"HCESDc22", "HCESDd22",
```

```
   "HCESDe22r", "HCESDf22", "HCESDg22", "HCESDh22r", "HCESDi22",
   "HCESDj22")], discrete=FALSE)

# Reliability for 2-factor measure
# DA/SR
psych::alpha(data_final[, c("HCESDa20", "HCESDb20", "HCESDc20",
"HCESDd20",
   "HCESDf20", "HCESDg20", "HCESDj20")], discrete=FALSE)
  psych::alpha(data_final[, c("HCESDa22", "HCESDb22",
"HCESDc22", "HCESDd22",
   "HCESDf22", "HCESDg22", "HCESDj22")], discrete=FALSE)
# PA
psych::alpha(data_final[, c("HCESDe20r", "HCESDh20r")],
discrete=FALSE)
psych::alpha(data_final[, c("HCESDe22r", "HCESDh22r")],
discrete=FALSE)

# Compute depression scores
data_final$cesd10_score20 <- data_final$HCESDa20 +
data_final$HCESDb20 + data_final$HCESDc20 + data_final$HCESDd20
+ data_final$HCESDe20r +
data_final$HCESDf20 + data_final$HCESDg20 + data_final$HCESDh20r
+ data_final$HCESDj20
data_final$cesd10_score22 <- data_final$HCESDa22 +
data_final$HCESDb22 + data_final$HCESDc22 + data_final$HCESDd22
+ data_final$HCESDe22r +
data_final$HCESDf22 + data_final$HCESDg22 + data_final$HCESDh22r
+ data_final$HCESDj22

# Loneliness scale
# Transform loneliness scores per Gierveld
# (1=0) (2=1) (3=1) Positively worded item
data_final$tFLONEd20 <- ifelse(data_final$FLONEd20 == 1, 0, 1)
data_final$tFLONEg20 <- ifelse(data_final$FLONEg20 == 1, 0, 1) #
(1=0) (2=1) (3=1)
# Positively worded item
  data_final$tFLONEh20 <- ifelse(data_final$FLONEh20 == 1, 0, 1)
# (1=0) (2=1) (3=1)
# Positively worded item
  data_final$tFLONEc20 <- ifelse(data_final$FLONEc20 == 3, 0, 1)
# (1=1) (2=1) (3=0)
# Negatively worded item
  data_final$tFLONEi20 <- ifelse(data_final$FLONEi20 == 3, 0, 1)
# (1=1) (2=1) (3=0)
# Negatively worded item
  data_final$tFLONEj20 <- ifelse(data_final$FLONEj20 == 3, 0, 1)
# (1=1) (2=1) (3=0)
```

```
# Negatively worded item

# Compute loneliness scores, reliability
data_final$EmotionalLoneliness <- data_final$tFLONEc20 +
data_final$tFLONEi20 + data_final$tFLONEj20
  # Emotional Loneliness score
data_final$SocialLoneliness <- data_final$tFLONEd20 +
data_final$tFLONEg20 + data_final$tFLONEh20
  # Social Loneliness score
data_final$OverallLoneliness <- data_final$EmotionalLoneliness +
data_final$SocialLoneliness         # Overall loneliness score
psych::alpha(data_final[, c("tFLONEc20", "tFLONEd20",
"tFLONEg20", "tFLONEh20", "tFLONEi20", "tFLONEj20")])
   # Full loneliness scale
psych::alpha(data_final[, c("tFLONEc20", "tFLONEi20",
"tFLONEj20")])                     # Emotional loneliness scale
psych::alpha(data_final[, c("tFLONEd20", "tFLONEg20",
"tFLONEh20")])                     # Social loneliness scale

# SES
# Reverse-code one positive item: Reverse-coded response =
# maximum possible response + minimum possible response –
# original response = 4 + 1 - original response
data$DELMSc20r <- 5 - data$DELMSc20
psych::alpha(data[, c("DELOWa20", "DELOWb20", "DELOWd20",
"DELOWe20", "DELOWf20", "DELOWg20", "DELSPd20", "DELOWc20",
"DELSPa20",
                        "DELSPb20", "DELSPc20", "DELSPe20",
"DELSPf20", "DELSPg20", "DELECa20", "DELECb20", "DELECc20",
"DELECd20",
                        "DELECe20", "DELECf20", "DELECg20",
"DELECh20", "DELMSa20", "DELMSb20", "DELMSc20r")],
discrete=FALSE)

# Number of chronic donditions
data_final$NumCC <- data_final$HDiabetes + data_final$HHeart +
data_final$HSleep + data_final$HStroke + data_final$HCancer

# Update study_vars for reverse-coded variables
study_vars <- c("Gender", "age20", "Ethnicity", "PartnerStatus",
"ELSI_est20",
                  "HCESDa20", "HCESDb20", "HCESDc20",
"HCESDd20", "HCESDe20r", "HCESDf20", "HCESDg20", "HCESDh20r",
"HCESDj20",
                  "HCESDa22", "HCESDb22", "HCESDc22",
"HCESDd22", "HCESDe22r", "HCESDf22", "HCESDg22", "HCESDh22r",
"HCESDj22",
```

```
                  "HDiabetes", "HHeart", "HSleep", "HStroke",
"HCancer",
                  "tFLONEc20", "tFLONEd20", "tFLONEg20",
"tFLONEh20", "tFLONEi20", "tFLONEj20")
"

****************************************************************
*************
    Final Summary

****************************************************************
*************
"
# Compute skewness and kurtosis
moments::skewness(data_final)
moments::kurtosis(data_final)
# Re-check for normality
MVN::mvn(data = data_final[, study_vars_missing], mvnTest =
"mardia")
MVN::mvn(data = data_final[, study_vars], mvnTest = "mardia")
summary(data_final)

"
****************************************************************
*************
  Correlations using Pearson r
****************************************************************
*************
"
# Correlation matrix
# Correlation matrix for study variables of different types,
# check for multicollinearity after imputation
corr.test(data_final[, study_vars])
corr.test(data_final[, c("Gender", "age20", "Ethnicity",
"PartnerStatus", "ELSI_est20",
                     "HDiabetes", "HHeart", "HSleep", "HStroke",
"HCancer", "NumCC",
                     "cesd10_score20", "cesd10_score22",
"EmotionalLoneliness", "SocialLoneliness")])        #
Correlation matrix for hypotheses
cor.test(data_final$EmotionalLoneliness,
data_final$SocialLoneliness, method="pearson", conf.level =
0.95) # Loneliness scales correlation

# Print correlation matrix for final study variables to csv
corr_result <- corr.test(data_final[, study_vars])
corr_matrix <- round(corr_result$r, 2)
```

```
# Remove repeated values from the diagonal
corr_matrix[upper.tri(corr_matrix, diag = TRUE)] <- ''

# Print correlation matrix for hypotheses to csv
corr_result <- corr.test(data_final[, c("Gender", "age20",
"Ethnicity", "PartnerStatus", "ELSI_est20",
                                     "HDiabetes", "HHeart",
"HSleep", "HStroke", "HCancer", "NumCC",
                                     "cesd10_score20",
"cesd10_score22", "EmotionalLoneliness", "SocialLoneliness")])
corr_matrix <- round(corr_result$r, 2)
# Remove repeated values from the diagonal
corr_matrix[upper.tri(corr_matrix, diag = TRUE)] <- ''

"
****************************************************************
*************
  Descriptive/Demographic
****************************************************************
*************
"
  sum(data_final$age20 < 65)
  sum(data_final$age20 >= 65 & data_final$age20 < 75)
  sum(data_final$age20 >= 75 & data_final$age20 < 85)
  sum(data_final$age20 >= 85 )
  sum(data_final$ELSI_est20 <= 8)
# Severe hardship
  sum(data_final$ELSI_est20 >= 9 & data_final$ELSI_est20 <= 12)
# Significant hardship
  sum(data_final$ELSI_est20 >= 13 & data_final$ELSI_est20 <= 16)
# Some hardship
  sum(data_final$ELSI_est20 >= 17 & data_final$ELSI_est20 <= 20)
# Fairly comfortable
  sum(data_final$ELSI_est20 >= 21 & data_final$ELSI_est20 <= 24)
# Comfortable
  sum(data_final$ELSI_est20 >= 25 & data_final$ELSI_est20 <= 28)
# Good
  sum(data_final$ELSI_est20 > 28)
# Very good
  table(data_final$Gender)
  table(data_final$Ethnicity)
  table(data_final$PartnerStatus)
  table (data_final$HDiabetes, useNA = "always")
  table (data_final$HHeart, useNA = "always")
  table (data_final$HSleep, useNA = "always")
  table (data_final$HStroke, useNA = "always")
  table (data_final$HCancer, useNA = "always")
```

```
  table(data_final$NumCC)

  sd(data_final$age20)
  sd(data_final$ELSI_est20)
  sd(data_final$cesd10_score20)
  sd(data_final$cesd10_score22)
  sd(data_final$EmotionalLoneliness)
  sd(data_final$SocialLoneliness)
  sd(data_final$OverallLoneliness)
  sd(data_final$NumCC)

  summary(data_final)

"
*****************************************************************
*************
  SEM analyses
*****************************************************************
*************
"

# CFA SR model restructured
model.all <- '
CESD20 =~ HCESDa20 + HCESDb20 + HCESDc20 + HCESDd20 + HCESDf20 +
HCESDg20 + HCESDj20
CESD22 =~ HCESDa22 + HCESDb22 + HCESDc22 + HCESDd22 + HCESDf22 +
HCESDg22 + HCESDj22
CESD20r =~ HCESDe20r + HCESDh20r
CESD22r =~ HCESDe22r + HCESDh22r
ELONE =~ tFLONEc20 + tFLONEi20 + tFLONEj20
SLONE =~ tFLONEd20 + tFLONEg20 + tFLONEh20

# Covariances
ELONE ~~ SLONE
CESD20 ~~ CESD20r
CESD22 ~~ CESD22r

# Error covariances for items measured at different time points
# (repeated measures)
     HCESDa20 ~~ HCESDa22
     HCESDb20 ~~ HCESDb22
     HCESDc20 ~~ HCESDc22
     HCESDd20 ~~ HCESDd22
     HCESDe20r ~~ HCESDe22r
     HCESDf20 ~~ HCESDf22
     HCESDg20 ~~ HCESDg22
     HCESDh20r ~~ HCESDh22r
```

```
     HCESDj20 ~~  HCESDj22

  '

fit <- lavaan::cfa(model.all, data = data_final,
estimator="WLSMV", ordered=TRUE, parameterization = "delta")
lavaan::summary(fit, fit = TRUE, standardized = TRUE, rsquare =
TRUE)
lavaan::standardizedSolution(fit)
lavaan::lavResiduals(fit, type = "cor.bentler")
lavaan::residuals(fit, type = "cor.bentler")
lavaan::modindices(fit, sort=TRUE)


# SEM

# Number of chronic Conditions model
model.mm <- '
# Measurement
CESD20 =~ HCESDa20 + HCESDb20 + HCESDc20 + HCESDd20 + HCESDf20 +
HCESDg20 + HCESDj20
CESD22 =~ HCESDa22 + HCESDb22 + HCESDc22 + HCESDd22 + HCESDf22 +
HCESDg22 + HCESDj22
CESD20r =~ HCESDe20r + HCESDh20r
CESD22r =~ HCESDe22r + HCESDh22r
ELONE =~ tFLONEc20 + tFLONEi20 + tFLONEj20
SLONE =~ tFLONEd20 + tFLONEg20 + tFLONEh20

# Covariances
ELONE ~~ SLONE
CESD20 ~~ CESD20r
CESD22 ~~ CESD22r

# Error covariances for items measured at different time points
# (repeated measures)
     HCESDa20 ~~ HCESDa22
     HCESDb20 ~~ HCESDb22
     HCESDc20 ~~ HCESDc22
     HCESDd20 ~~ HCESDd22
     HCESDe20r ~~ HCESDe22r
     HCESDf20 ~~ HCESDf22
     HCESDg20 ~~ HCESDg22
     HCESDh20r ~~ HCESDh22r
     HCESDj20 ~~  HCESDj22

# Structural
```

```
ELONE ~ age20 + Gender + Ethnicity + PartnerStatus + ELSI_est20
+ el_num*NumCC + CESD20 + CESD20r
SLONE ~ age20 + Gender + Ethnicity + PartnerStatus + ELSI_est20
+ sl_num*NumCC + CESD20 + CESD20r
CESD22 ~ age20 + Gender + Ethnicity + PartnerStatus + ELSI_est20
+ d22_num*NumCC + d22_sl*SLONE + d22_el*ELONE + CESD20 + CESD20r
CESD22r ~ age20 + Gender + Ethnicity + PartnerStatus +
ELSI_est20 + d22r_num*NumCC + d22r_sl*SLONE + d22r_el*ELONE +
CESD20 + CESD20r

# Direct effect
dir_mm := d22_num + d22r_num

# Indirect effects
ind_el := el_num*d22_el + el_num*d22r_el
ind_sl := sl_num*d22_sl + sl_num*d22r_sl
tot_ind := ind_sl + ind_el

# Total effect
tot := dir_mm + tot_ind

'

# Fit the model
# https://lavaan.ugent.be/tutorial/cat.html - use ordered=TRUE
# if all endogenous vars are ordinal/categorical
fit <- sem(model.mm, data = data_final, estimator="WLSMV",
ordered=TRUE, parallel = "multicore")
# Inspect, summarise, and estimate parameters code from Kline:
# check for negative error variances, output of "TRUE" means no
# negative variances
lavaan::lavInspect(fit, add.labels = TRUE, "post.check")
# request output including 2 standardized solutions (all, lv)
lavaan::summary(fit, fit.measures = TRUE, standardized = TRUE,
rsquare = TRUE)
# request partially standardized solution nox, which replaces
# Std.all in the output
lavaan::summary(fit, header = FALSE, std.nox = TRUE)
# generate predicted covariance matrix
lavaan::fitted(fit)
# generate predicted correlation matrix
lavaan::lavInspect(fit, add.labels = TRUE, "cor.ov")
# Residuals
lavaan::lavResiduals(fit, type = "cor.bentler")
lavaan::residuals(fit, type = "cor.bentler")
# print modification indices
lavaan::modindices(fit, sort=TRUE)
```

```
# Parameter estimates
lavaan::parameterEstimates(fit)
lavaan::standardizedSolution(fit)

# Chronic conditions
# initial lavaan WARNING: trouble constructing W matrix, due to
# low variability of HStroke
sapply(data_final, var)
# HStroke does not have enough variability: 0.01278899
table(data_final$HStroke) # 39 Yes of 3011, 1.3%

# Chronic Conditions model w/o stroke due to low variability
# using diagonally weighted least squares estimation
model.cc <- '
# Measurement
CESD20 =~ HCESDa20 + HCESDb20 + HCESDc20 + HCESDd20 + HCESDf20 +
HCESDg20 + HCESDj20
CESD22 =~ HCESDa22 + HCESDb22 + HCESDc22 + HCESDd22 + HCESDf22 +
HCESDg22 + HCESDj22
CESD20r =~ HCESDe20r + HCESDh20r
CESD22r =~ HCESDe22r + HCESDh22r
ELONE =~ tFLONEc20 + tFLONEi20 + tFLONEj20
SLONE =~ tFLONEd20 + tFLONEg20 + tFLONEh20

# Covariances
ELONE ~~ SLONE
CESD20 ~~ CESD20r
CESD22 ~~ CESD22r

# Error covariances for items measured at different time points
# (repeated measures)
     HCESDa20 ~~ HCESDa22
     HCESDb20 ~~ HCESDb22
     HCESDc20 ~~ HCESDc22
     HCESDd20 ~~ HCESDd22
     HCESDe20r ~~ HCESDe22r
     HCESDf20 ~~ HCESDf22
     HCESDg20 ~~ HCESDg22
     HCESDh20r ~~ HCESDh22r
     HCESDj20 ~~  HCESDj22

# Structural
ELONE ~ age20 + Gender + Ethnicity + PartnerStatus + ELSI_est20
+ el_dia*HDiabetes + el_hrt*HHeart + el_slp*HSleep +
el_can*HCancer + CESD20 + CESD20r
SLONE ~ age20 + Gender + Ethnicity + PartnerStatus + ELSI_est20
+ sl_dia*HDiabetes + sl_hrt*HHeart + sl_slp*HSleep +
```

```
    sl_can*HCancer + CESD20  + CESD20r
CESD22 ~ age20 + Gender + Ethnicity + PartnerStatus + ELSI_est20
+ d22_dia*HDiabetes + d22_hrt*HHeart + d22_slp*HSleep +
    d22_can*HCancer + d22_sl*SLONE + d22_el*ELONE + CESD20 +
CESD20r
CESD22r ~ age20 + Gender + Ethnicity + PartnerStatus +
ELSI_est20 + d22r_dia*HDiabetes + d22r_hrt*HHeart +
d22r_slp*HSleep +
d22r_can*HCancer + d22r_sl*SLONE + d22r_el*ELONE + CESD20 +
CESD20r

# Direct effects
dir_dia := d22_dia + d22r_dia
dir_hrt := d22_hrt + d22r_hrt
dir_slp := d22_slp + d22r_slp
dir_can := d22_can + d22r_can
tot_dir := dir_dia + dir_hrt + dir_slp + dir_can

# Indirect effects
ind_dia_el := el_dia*d22_el + el_dia*d22r_el
ind_dia_sl := sl_dia*d22_sl + sl_dia*d22r_sl
ind_hrt_el := el_hrt*d22_el + el_hrt*d22r_el
ind_hrt_sl := sl_hrt*d22_sl + sl_hrt*d22r_sl
ind_slp_el := el_slp*d22_el + el_slp*d22r_el
ind_slp_sl := sl_slp*d22_sl + sl_slp*d22r_sl
ind_can_el := el_can*d22_el + el_can*d22r_el
ind_can_sl := sl_can*d22_sl + sl_can*d22r_sl
tot_ind_el := ind_dia_el + ind_hrt_el + ind_slp_el + ind_can_el
tot_ind_sl := ind_dia_sl + ind_hrt_sl + ind_slp_sl + ind_can_sl
tot_ind := tot_ind_el + tot_ind_sl

# Total effect
tot := tot_dir + tot_ind

'

# Fit the model
fit <- sem(model.cc, data = data_final, estimator="WLSMV",
ordered=TRUE, parallel = "multicore")
# Inspect, summarise, and estimate parameters code from Kline:
# check for negative error variances, output of "TRUE" means
# no negative variances
lavaan::lavInspect(fit, add.labels = TRUE, "post.check")
# request output including 2 standardized solutions (all, lv)
lavaan::summary(fit, fit.measures = TRUE, standardized = TRUE,
rsquare = TRUE)
```

```
# request partially standardized solution nox, which replaces
Std.all in the output
lavaan::summary(fit, header = FALSE, std.nox = TRUE)
# generate predicted covariance matrix
lavaan::fitted(fit)
# generate predicted correlation matrix
lavaan::lavInspect(fit, add.labels = TRUE, "cor.ov")
# Residuals
lavaan::lavResiduals(fit, type = "cor.bentler")
lavaan::residuals(fit, type = "cor.bentler")
lavaan::modindices(fit, sort=TRUE)
# Parameter estimates
lavaan::parameterEstimates(fit)
lavaan::standardizedSolution(fit)

"
****************************************************************
*************
```

References

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```
****************************************************************
*************
"
```

Appendix B

Model Fit

Table B1

Initial Measurement Model Global Fit Statistics

Fit index	Standard	Scaled [a]
Model chi-square		
chi_M	1,421.881	1,909.145
p	0.000	0.000
df_M	237	237
Scaling correction factor		0.767
Approximate fit		
RMSEA [90% CI]	.041 [.039, .043]	.048 [.046, .050]
CFI	.988	.956
SRMR	.045	.045
Baseline model		
chi_B	101,329.892	38,135.148
p	0.000	0.000
df_B	276	276
Scaling correction factor		2.669

[a] Scaled indexes are adjusted to account for non-normality.

Table B2

Initial Measurement Model Correlation Residuals

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1. HCESDa20	-----																						
2. HCESDb20	0.09	-----																					
3. HCESDc20	0.01	-0.04	-----																				
4. HCESDd20	0.06	0.04	-0.05	-----																			
5. HCESDe20r	-0.06	-0.10	-0.01	-0.09	-----																		
6. HCESDf20	0.04	0.01	0.04	-0.03	0.01	-----																	
7. HCESDg20	-0.03	0.03	-0.05	-0.01	-0.08	0.01	-----																
8. HCESDh20r	-0.02	-0.04	0.01	-0.07	**0.14**	0.03	-0.05	-----															
9. HCESDj20	-0.03	0.04	-0.05	**0.11**	-0.10	-0.06	0.04	-0.11	-----														
10. HCESDa22	0.00	0.06	-0.03	0.01	-0.05	0.01	0.03	-0.07	-0.01	-----													
11. HCESDb22	0.06	0.00	-0.01	0.01	-0.07	-0.02	0.04	-0.03	0.06	0.08	-----												
12. HCESDc22	0.01	-0.03	0.00	-0.03	0.01	0.02	0.02	0.01	0.00	0.04	-0.07	-----											
13. HCESDd22	0.00	0.00	-0.02	0.00	-0.05	-0.01	0.01	-0.04	0.07	0.01	0.03	-0.06	-----										
14. HCESDe22r	-0.02	-0.04	0.00	-0.04	0.00	0.01	-0.02	0.08	0.01	-0.06	-0.09	-0.02	-0.08	-----									
15. HCESDf22	0.04	0.00	0.02	-0.04	-0.02	0.00	0.02	-0.03	-0.04	0.05	-0.01	0.03	-0.02	-0.02	-----								
16. HCESDg22	-0.03	0.04	-0.04	-0.01	-0.03	-0.01	0.00	-0.01	0.03	0.03	0.02	0.01	0.02	-0.10	0.02	-----							
17. HCESDh22r	-0.03	-0.04	-0.01	-0.04	0.10	0.02	-0.01	0.00	-0.02	-0.03	-0.05	0.03	-0.07	**0.15**	-0.01	-0.04	-----						
18. HCESDj22	0.00	0.05	-0.01	**0.11**	-0.06	-0.04	0.05	-0.07	0.00	-0.03	0.03	-0.05	**0.10**	-0.08	-0.06	0.04	-0.10	-----					
19. FLONEc20	0.08	0.06	-0.09	0.01	-0.08	-0.03	0.00	-0.04	0.02	0.08	0.03	-0.05	0.02	-0.04	-0.01	-0.03	0.00	0.01	-----				
20. FLONEi20	-0.01	0.05	-0.03	0.07	0.00	-0.02	0.03	0.01	0.03	-0.01	0.02	-0.02	0.01	0.01	-0.05	0.01	0.02	0.00	0.06	-----			
21. FLONEj20	0.08	0.06	-0.06	0.08	-0.02	0.05	-0.02	0.00	0.05	0.01	0.01	-0.05	0.03	0.00	-0.03	0.02	0.00	0.04	-0.05	**0.14**	-----		
22. FLONEd20r	0.08	0.05	0.00	0.02	-0.07	0.09	-0.01	-0.06	0.02	0.06	0.03	0.00	0.02	-0.06	0.00	0.01	-0.01	0.02	-0.06	-0.04	0.03	-----	
23. FLONEg20r	0.06	0.03	-0.01	0.06	-0.03	0.07	-0.01	-0.04	0.04	0.04	0.01	0.00	0.01	-0.04	-0.01	-0.04	-0.05	0.02	-0.08	-0.07	0.05	0.03	-----
24. FLONEh20r	0.05	-0.02	-0.05	0.02	-0.10	0.05	-0.03	-0.11	-0.01	0.07	0.02	-0.01	0.01	-0.06	-0.03	0.00	-0.04	0.02	0.00	0.05	**0.11**	-0.03	-0.03

Note. Values bolded that exceed .10 in absolute value.

Table B3

Final Measurement Model Global Fit Statistics

Fit index	Standard	Scaled [a]
Model chi-square		
chi_M	802.860	1,158.882
p	0.000	0.000
df_M	228	228
Scaling correction factor		0.724
Approximate fit		
RMSEA [90% CI]	.029 [.027, .031]	.037 [.035, .039]
CFI	0.994	0.975
SRMR	0.037	0.037
Baseline model		
chi_B	101,329.892	38,135.148
p	0.000	0.000
df_B	276	276
Scaling correction factor		2.669

[a] Scaled indexes are adjusted to account for non-normality.

Table B4

Final Measurement Model Correlation Residuals

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1. HCESDa20	-----																						
2. HCESDb20	0.09	**-----**																					
3. HCESDc20	0.01	-0.04	**-----**																				
4. HCESDd20	0.06	0.04	-0.05	**-----**																			
5. HCESDf20	-0.06	-0.10	0.00	-0.09	**-----**																		
6. HCESDg20	0.04	0.01	0.04	-0.03	0.02	**-----**																	
7. HCESDj20	-0.03	0.03	-0.05	-0.01	-0.08	0.01	**-----**																
8. HCESDa22	-0.02	-0.04	0.01	-0.07	**0.14**	0.03	-0.05	**-----**															
9. HCESDb22	-0.04	0.04	-0.05	**0.11**	-0.10	-0.06	0.04	-0.10	**-----**														
10. HCESDc22	0.00	0.05	-0.03	0.00	-0.05	0.00	0.04	-0.07	-0.02	**-----**													
11. HCESDd22	0.06	0.00	-0.01	0.01	-0.07	-0.02	0.04	-0.03	0.05	0.08	**-----**												
12. HCESDf22	0.01	-0.03	0.00	-0.03	0.01	0.02	0.03	0.01	0.00	0.04	-0.07	-----											
13. HCESDg22	0.00	0.00	-0.02	0.00	-0.05	-0.01	0.01	-0.03	0.07	0.01	0.03	-0.06	**-----**										
14. HCESDj22	-0.02	-0.04	0.00	-0.04	0.00	0.01	-0.02	0.08	0.01	-0.06	-0.09	-0.02	-0.08	**-----**									
15. HCESDe20r	0.04	0.00	0.02	-0.04	-0.02	0.00	0.02	-0.03	-0.04	0.05	-0.01	0.03	-0.02	-0.02	**-----**								
16. HCESDh20r	-0.03	0.04	-0.04	-0.01	-0.03	-0.01	0.00	-0.01	0.03	0.03	0.02	0.01	0.02	-0.10	0.02	**-----**							
17. HCESDe22r	-0.03	-0.04	-0.01	-0.04	0.10	0.02	0.00	0.00	-0.02	-0.03	-0.05	0.03	-0.07	**0.15**	-0.01	-0.04	**-----**						
18. HCESDh22r	0.00	0.05	-0.01	**0.11**	-0.05	-0.04	0.05	-0.07	0.00	-0.03	0.03	-0.05	**0.10**	-0.08	-0.06	0.04	-0.10	**-----**					
19. tFLONEc20	-0.08	-0.06	**0.10**	-0.01	0.07	0.03	0.01	0.04	-0.02	-0.09	-0.03	0.05	-0.02	0.04	0.01	0.03	-0.01	-0.01	**-----**				
20. tFLONEi20	0.01	-0.05	0.02	-0.07	-0.01	0.01	-0.05	-0.01	-0.03	0.01	-0.01	0.01	-0.01	-0.01	0.04	-0.02	-0.01	0.01	0.04	**-----**			
21. tFLONEj20	-0.08	-0.07	0.07	-0.09	0.02	-0.05	0.00	0.00	-0.04	-0.01	0.00	0.07	-0.02	0.01	0.03	-0.03	0.00	-0.04	-0.05	**0.14**	**-----**		
22. tFLONEd20	-0.08	-0.04	0.01	-0.02	0.07	-0.07	0.00	0.07	-0.02	-0.06	-0.01	0.01	-0.02	0.06	0.01	-0.01	0.01	-0.01	-0.08	-0.01	0.05	**-----**	
23. tFLONEg20	-0.06	-0.03	0.00	-0.08	0.02	-0.06	-0.01	0.05	-0.04	-0.04	-0.01	0.00	-0.02	0.04	0.01	0.02	0.04	-0.03	-0.10	-0.06	0.06	0.04	**-----**
24. tFLONEh20	-0.05	0.02	0.05	-0.03	0.10	-0.05	0.03	**0.11**	0.01	-0.07	-0.02	0.00	0.00	0.06	0.02	0.01	0.03	-0.02	-0.01	0.04	0.10	-0.04	-0.01

Note. Values bolded that exceed .10 in absolute value.

Table B5

Chronic Conditions Model Correlation Residuals

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1. HCESDa20	-----																						
2. HCESDb20	0.08	-----																					
3. HCESDc20	-0.01	-0.07	-----																				
4. HCESDd20	0.05	0.03	-0.08	-----																			
5. HCESDf20	0.03	0.00	0.03	-0.04	-----																		
6. HCESDg20	-0.05	0.02	-0.08	-0.02	-0.01	-----																	
7. HCESDj20	-0.06	0.03	-0.08	0.09	-0.08	0.04	-----																
8. HCESDa22	0.00	0.05	-0.05	-0.01	-0.01	0.03	-0.03	-----															
9. HCESDb22	0.05	0.00	-0.02	0.00	-0.03	0.03	0.05	0.08	-----														
10. HCESDc22	0.00	-0.05	0.00	-0.05	0.00	0.01	-0.02	0.03	-0.10	-----													
11. HCESDd22	-0.01	-0.01	-0.04	0.00	-0.02	0.00	0.06	-0.01	0.01	-0.09	-----												
12. HCESDf22	0.03	-0.02	0.01	-0.05	0.00	0.00	-0.06	0.05	-0.03	0.02	-0.04	-----											
13. HCESDg22	-0.05	0.03	-0.06	-0.03	-0.04	0.00	0.03	0.01	0.01	-0.01	0.00	0.00	-----										
14. HCESDj22	-0.02	0.05	-0.01	0.10	-0.05	0.06	0.00	-0.06	0.01	-0.07	0.09	-0.08	0.04	-----									
15. HCESDe20r	-0.01	-0.06	0.06	-0.05	0.07	-0.04	-0.05	-0.02	-0.04	0.06	-0.02	0.02	-0.01	-0.02	-----								
16. HCESDh20r	0.02	-0.01	0.06	-0.02	0.08	-0.02	-0.07	-0.04	0.02	0.05	0.01	0.00	0.01	-0.03	0.00	-----							
17. HCESDe22r	0.01	-0.02	0.04	-0.03	0.04	0.00	0.02	-0.01	-0.05	0.05	-0.04	0.04	-0.06	-0.04	0.00	-0.01	-----						
18. HCESDh22r	-0.02	-0.02	0.01	-0.02	0.03	0.01	0.00	0.02	-0.01	0.09	-0.03	0.03	-0.02	-0.06	0.02	0.00	0.00	-----					
19. FLONEi20	-0.01	0.05	-0.03	0.08	-0.02	0.03	0.03	-0.01	0.03	-0.02	0.02	-0.05	0.01	0.01	0.01	0.03	0.03	0.03	-----				
20. FLONEj20	0.07	0.07	-0.08	0.09	0.06	-0.01	0.03	0.00	0.01	-0.06	0.02	-0.04	0.03	0.03	-0.02	0.04	-0.01	0.02	**0.16**	-----			
21. FLONEc20	0.08	0.06	**-0.12**	0.00	-0.04	0.01	0.00	0.10	0.03	-0.07	0.00	-0.01	-0.03	-0.02	-0.08	0.00	-0.05	0.03	0.06	-0.06	-----		
22. FLONEd20r	0.06	0.03	-0.03	0.00	0.07	-0.03	-0.02	0.06	0.02	-0.02	0.01	-0.03	0.00	-0.01	-0.02	0.02	-0.03	0.04	-0.04	0.03	-0.06	-----	
23. FLONEg20r	0.04	0.02	-0.03	0.05	0.05	-0.03	0.00	0.03	0.01	-0.01	0.00	-0.03	-0.05	-0.01	0.02	0.04	-0.01	0.01	-0.07	0.05	-0.10	0.03	-----
24. FLONEh20r	0.02	-0.05	-0.08	0.01	0.03	-0.05	-0.05	0.06	0.01	-0.02	-0.01	-0.05	-0.01	0.00	-0.06	-0.04	-0.02	0.01	0.05	**0.13**	0.01	-0.03	-0.03

Note. *Values bolded that exceed .10 in absolute value.*

Table B6

Multimorbidity Model Correlation Residuals

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1. HCESDa20	-----																						
2. HCESDb20	0.08	-----																					
3. HCESDc20	-0.01	-0.07	-----																				
4. HCESDd20	0.05	0.03	-0.08	-----																			
5. HCESDf20	0.03	0.00	0.03	-0.04	-----																		
6. HCESDg20	-0.05	0.02	-0.08	-0.03	-0.01	-----																	
7. HCESDj20	-0.06	0.03	-0.08	0.09	-0.08	0.03	-----																
8. HCESDa22	0.00	0.04	-0.05	-0.02	-0.02	0.03	-0.04	-----															
9. HCESDb22	0.05	0.00	-0.02	0.00	-0.03	0.04	0.04	0.07	-----														
10. HCESDc22	0.00	-0.05	0.00	-0.05	0.00	0.02	-0.02	0.03	-0.09	-----													
11. HCESDd22	-0.01	-0.01	-0.04	0.00	-0.02	0.01	0.06	-0.01	0.01	-0.08	-----												
12. HCESDf22	0.03	-0.02	0.01	-0.05	0.00	0.00	-0.06	0.04	-0.03	0.02	-0.04	-----											
13. HCESDg22	-0.05	0.03	-0.05	-0.02	-0.03	0.00	0.03	0.02	0.01	0.00	0.01	0.01	-----										
14. HCESDj22	-0.02	0.04	-0.01	0.10	-0.05	0.05	0.00	-0.06	0.01	-0.07	0.09	-0.08	0.04	-----									
15. HCESDe20r	-0.01	-0.06	0.06	-0.04	0.07	-0.04	-0.05	-0.02	-0.04	0.06	-0.02	0.02	-0.01	-0.02	-----								
16. HCESDh20r	0.02	-0.01	0.05	-0.02	0.08	-0.02	-0.07	-0.04	0.01	0.05	0.01	0.00	0.01	-0.03	0.00	-----							
17. HCESDe22r	0.01	-0.02	0.04	-0.03	0.04	0.00	0.03	-0.01	-0.05	0.05	-0.04	0.04	-0.06	-0.04	0.00	-0.01	-----						
18. HCESDh22r	-0.02	-0.02	0.01	-0.02	0.03	0.00	0.00	0.01	-0.01	0.09	-0.03	0.03	-0.02	-0.06	0.02	0.00	0.00	-----					
19. FLONEi20	-0.01	0.05	-0.03	0.08	-0.02	0.03	0.03	-0.01	0.03	-0.02	0.02	-0.05	0.01	0.01	0.01	0.03	0.03	0.03	-----				
20. FLONEj20	0.07	0.07	-0.07	0.09	0.06	-0.02	0.03	0.00	0.01	-0.07	0.02	-0.04	0.03	0.03	-0.02	0.03	-0.01	0.02	**0.16**	-----			
21. FLONEc20	0.08	0.06	**-0.11**	0.00	-0.04	0.01	0.00	0.10	0.03	-0.06	0.01	-0.01	-0.03	-0.01	-0.08	0.00	-0.05	0.03	0.06	-0.06	-----		
22. FLONEd20r	0.06	0.03	-0.03	0.00	0.07	-0.03	-0.02	0.06	0.01	-0.02	0.01	-0.03	-0.01	-0.01	-0.02	0.02	-0.03	0.04	-0.04	0.03	-0.06	-----	
23. FLONEg20r	0.04	0.02	-0.03	0.05	0.05	-0.03	0.00	0.03	0.01	-0.01	0.00	-0.03	-0.05	0.00	0.02	0.04	-0.01	0.01	-0.07	0.05	-0.10	0.03	-----
24. FLONEh20r	0.02	-0.04	-0.08	0.00	0.03	-0.05	-0.05	0.06	0.01	-0.02	-0.01	-0.05	-0.01	0.00	-0.06	-0.04	-0.03	0.01	0.05	**0.13**	0.01	-0.03	-0.03

Note. *Values bolded that exceed .10 in absolute value.*