Journal of Public Health
https://doi.org/10.1007/s10389-025-02490-5

ORIGINAL ARTICLE

Comorbidity and health-related quality of life among Australian adults with psychological distress: a detailed longitudinal study

Muhammad Iftikhar ul Husnain[1] · Mohammad Hajizadeh[2] · Hasnat Ahmad[3] · Rasheda Khanam[4]

Received: 8 January 2025 / Accepted: 30 April 2025

Abstract

Aim This observational study explores how clinically relevant comorbidities affect health-related quality of life (HRQoL) in individuals with psychological distress (PD), focusing on the number, types, and patterns of comorbidities to improve patient care and outcomes.

Subject and methods We utilized unit record data for individuals with PD from the Household, Income, and Labor Dynamics in Australia (HILDA) survey. HRQoL, expressed as the health state utility score (HSU), was assessed via the Short-Form Six-Dimension (SF-6D) health survey derived from the 36-Item Short Form Survey (SF-36) and calculated using an Australian scoring algorithm. Multimorbidity was defined as the presence of two or more chronic conditions. A linear mixed model (LMM) was used to assess the impact of comorbidities on HRQoL in individuals with PD, and additional LMM regressions were performed to examine differences based on comorbidity type and pattern.

Results The final sample included 26,991 observations (mean age 40.75 years; 58.25% female). Among individuals with PD, 31.36% had at least one comorbidity, with cardiovascular disease the most common (14.09%). The most prevalent pattern was 'cardiovascular + musculoskeletal' (9.43%). Higher numbers of comorbidities significantly worsened HRQoL, from −0.01 (95% CI −0.03, 0.01) for one comorbidity to −0.06 (95% CI −0.08, −0.03) for five comorbidities. Cancer had the greatest impact (−0.02; 95% CI −0.03, −0.02), while patterns involving cardiovascular and cancer or metabolic with multiple conditions reduced HSU by −0.03 (95% CI −0.05, −0.01) to −0.05 (95% CI −0.08, −0.02).

Conclusions The types and patterns of comorbidities significantly impact HRQoL, even with a consistent comorbidity count. Early detection and treatment of these conditions can enhance HRQoL in individuals with PD.

Keywords Psychological distress · Health-related quality of life · Comorbidities · Health state utilities · Linear mixed model

Introduction

Psychological distress (PD), a prevalent mental disorder found in both adults and seniors, poses a significant public health challenge, adding substantially to the overall burden worldwide (Charlson et al. 2019; James et al. 2018). In Australia, mental health disorders including PD are among the primary contributors to the health burden. In 2023, mental health conditions and substance use disorders climbed to the second position in the rankings, accounting for 15% of the total disease burden, second only to cancer, which accounted for 17% (AIHW 2022). Mental disorders are frequently linked with one or more chronic physical diseases, exacerbating the physical consequences for patients' overall health. Additionally, mental disorder comorbidities constitute the leading cause of mortality worldwide (Daré et al. 2019).

✉ Muhammad Iftikhar ul Husnain
Muhammadiftikharul.Husnain@usq.edu.au

Mohammad Hajizadeh
m.hajizadeh@dal.ca

Hasnat Ahmad
Hasnat.ahmad@utas.edu.au

Rasheda Khanam
Rasheda.khanam@usq.edu.au

[1] School of Business, University of Southern Queensland, , 44 Baker Street, Darling Height Toowoomba, Queensland, Australia

[2] Dalhousie University, Halifax Nova, Scotia, Canada

[3] University of Tasmania, Hobart Tasmania, Australia

[4] University of Southern Queensland, Toowoomba, Queensland, Australia

Published online: 15 May 2025

Comorbidity, defined as the simultaneous presence of two or more health conditions in an individual, significantly affects health, healthcare use, and related costs (Zulman et al. 2014), and has been found to be significantly associated with a decrease in overall quality of life (Butterly et al. 2023) and health-related quality of life (HRQoL) (Chen et al. 2015; Haagsma et al. 2011; Havens et al. 2017; Keramat et al. 2024; Lo et al. 2021; Poblador-Plou et al. 2014; Shih et al. 2006; Sundh et al. 2015; Zhao et al. 2022). Furthermore, treatments proven in clinical trials to enhance quality of life are prescribed less frequently to people with multimorbidity than to those without comorbidities (Smith et al. 2018). The effective and resource-efficient long-term management of multimorbidity is among the most significant health challenges confronting patients, healthcare providers, and society (McPhail 2016).

People with PD are more likely to have comorbidities, as previous studies have shown strong associations between PD and many diseases, including arthritis (Shih et al. 2006), cardiovascular disease (Garcia et al. 2024; Serrano Jr et al. 2011), epilepsy (Layne et al. 2009; Strine et al. 2005), diabetes (Egede and Dismuke 2012; Schmitz et al. 2008), asthma (Dunlop et al. 2004), and cancer (Banks et al. 2010), which could correlate with a reduction in HRQoL, suggesting that comorbidities should be taken into account when developing strategies to manage PD. However, the impact of overall comorbidity burden on HRQoL in PD individuals remains poorly understood.

To our knowledge, no study has examined the role of comorbidities in determining the HRQoL of individuals with PD. Previous studies focused on the role of comorbidities in determining the HRQoL of individuals with other medical conditions, including pulmonary fibrosis (Zheng et al. 2023), arthritis (Havens et al. 2017), multiple sclerosis (Lo et al. 2021; Warren et al. 2009), major depressive disorder (Mittal et al. 2006), chronic obstructive pulmonary disease (Huber et al. 2015), asthma (Chen et al. 2015), severe chronic obstructive pulmonary disease (Sundh et al. 2015), chronic medical conditions (Butterly et al. 2023), dementia (Poblador-Plou et al. 2014), mental disorders (McGrath et al. 2020), and coronary heart disease (Vynckier et al. 2023). This study aims to offer an overview of contemporary changes in HRQoL concerning the comorbidity burden among Australian adults with PD via longitudinal data from a nationally representative survey—the Household, Income and Labour Dynamics in Australia (HILDA).

This study is important for several reasons. First, clinical practice guidelines often lack comprehensive coverage of multiple concurrent conditions. Constructing care plans for patients with multiple chronic conditions based on a single-disease paradigm may be not only impractical but also potentially harmful (Wyatt et al. 2014). Therefore, there is potential for a major improvement in HRQoL through the prevention and optimal management of comorbidities. Second, identifying comorbidity groups and individual comorbidities that have a substantial impact on HRQoL aids in the targeting, prevention, and optimal treatment of individuals with PD. Third, neglecting to account for comorbidities limits the applicability of the burden of disease concept in multimorbid populations. The potential for overestimating gains from healthcare interventions becomes significant when a substantial number of patients contend with additional conditions (McPhail 2016). Finally, the incorporation of patterns as potential predictors of the HRQoL of individuals with PD can be embedded into risk stratification tools to increase their effectiveness, which may assist clinicians in reducing the functional and social impact of the disease by enhancing their assessment and clinical decision-making processes (Soh et al. 2011).

Methods

Data source and sample selection

This study utilizes information gathered from the extensive nationwide HILDA survey in Australia which commenced in 2001. This survey collects data on various aspects, including family dynamics, health, financial status, income, employment trends, and education levels, from over 17,000 Australians aged 15 or above. This information is collected through a mix of face-to-face interviews and self-completed questionnaire (SCQ) (Watson and Wooden 2021). HRQoL, comorbidities, and PD were collected in the SCQ part, achieving approximately 90% wave-on-wave response, comparable to other large longitudinal surveys in the USA and Europe (Summerfield et al. 2011). A detailed description of the HILDA survey sample design, survey response rates, and attrition rates was published elsewhere (Summerfield et al. 2023).

We used data from waves 9 (baseline), 13 (follow-up T1), 17 (follow-up T2), and 21 (follow-up T3) (collected in 2009, 2013, 2017, and 2021, respectively) since information on chronic diseases was only available in these waves. Participants were included if they met the following criteria: (i) aged 15 years and older; (ii) completed all four waves; (iii) had valid information regarding chronic diseases and outcome variable. These inclusion criteria yielded a panel of 26,991 observations. Figure 1 describes the sample selection procedure.

Outcome variable

The primary outcome variable was HRQoL, a widely used multidimensional concept for assessing an individual's health status, primarily encompassing physical and mental

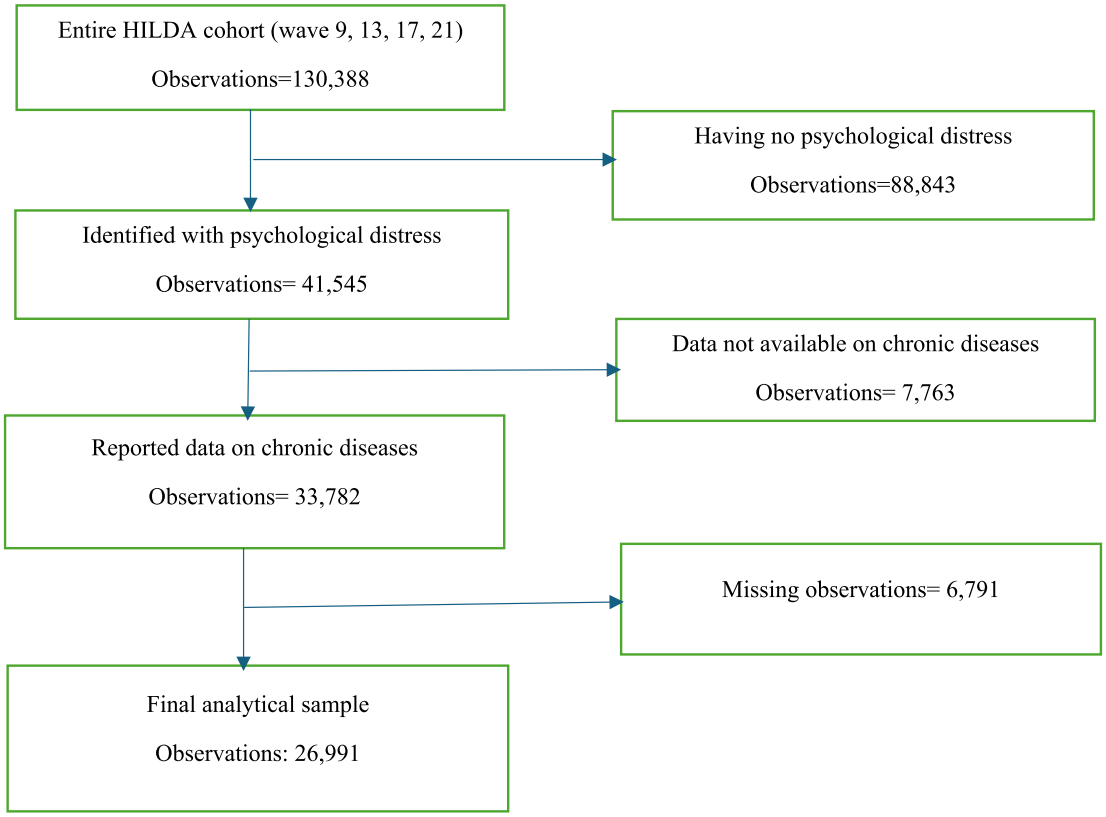

Fig. 1 Participant flow into the analytical sample and missing data

health. HRQoL is recognized as a vital core outcome in research on comorbidity (Smith et al. 2018). HRQoL is expressed as health state utilities (HSUs) derived from the Short-Form Six-Dimension (SF-6D) health survey, a widely utilized multi-attribute utility instrument (MAUI) derived from the 36-Item Short Form Survey (SF-36). The SF-36 was administered across all waves of the HILDA survey. The validity of the SF-36 data from the HILDA survey has been tested and reported elsewhere (Kharroubi et al. 2007). We valued HSUs using Norman et al.'s (2013) algorithm developed for the Australian population. These weights vary from 0.29 to 1.00, where 1.00 represents 'full health'.

Measurement of comorbidities

Comorbidity was the main exposure variable in this study. Self-reported data from participants were utilized to assess the primary exposure variable based on the information derived from the survey question asking participants whether they had been 'diagnosed with a serious illness'. The participants were presented with a showcard containing a list of 11 conditions to choose from. These conditions included hypertension, heart disease, type 1 diabetes, type 2 diabetes, chronic bronchitis/emphysema, cancer, asthma, arthritis/osteoporosis, anxiety/depression, other mental health conditions, and circulatory disease. Based on the respondents' answers regarding critical health conditions, five types of comorbidities were derived: (1) metabolic group (type 1 diabetes, type 2 diabetes); (2) cardiovascular group (heart disease, hypertension, high blood pressure); (3) respiratory group (asthma, chronic bronchitis, emphysema); (4) musculoskeletal group (arthritis/osteoporosis); and (5) cancer. Each participant's total number of comorbidities was computed to classify them into one of five groups: those with 0, 1, 2, 3, 4 or more than 4 comorbidities.

Estimation strategy

The analysis commenced by summarizing the characteristics of the study sample, employing frequencies, means, and/or percentages. Student's *t* tests and chi-squared tests were used where appropriate to compare the differences in characteristics, including age, sex, and number of comorbidities, between survey responders and nonresponders. In linear regression models, baseline HRQoL was modelled while accounting for factors including age, sex (compared with the reference group of females), and number of comorbidities (adjusted per additional comorbidity).

Our hypothesis posited that the presence of multimorbidity would have a detrimental effect on the HRQoL

of individuals with PD. To test this hypothesis, we first employed a linear mixed model (LMM) to explore the relationship between HRQoL and the number of comorbidities among participants. Our model incorporates both fixed and random effects to capture population-level patterns and individual-specific variations. Fixed effects address consistent trends across the population, while random effects account for unique, individual deviations not explained by these broader trends. This combined approach allows for a more precise and comprehensive understanding of both shared and individual influences on the outcome. Our data, like any real-world longitudinal dataset, contained missing values due to dropouts or non-responses. Linear mixed models are particularly effective in handling such issues (Lee and Shang 2022) without requiring imputations (Gabrio et al. 2022) and are effective in preventing false-positive associations caused by the sample structure in studies involving humans (Kang et al. 2010; Yu et al. 2006; Zhao et al. 2007). Furthermore, LMMs can increase the power of the test at a reasonable computational cost (Yang et al. 2014). We estimated the following three equations to analyse the effect of comorbidity counts (Eq. 1), comorbidity types (Eq. 2), and comorbidity patterns (Eq. 3) on HRQoL.

$$HRQoL_{it} = \beta_1 + \beta_2 CC_{it} + \beta_3 D_i + +\epsilon_{it}, \quad (1)$$

$$HRQoL_{it} = \beta_1 + \beta_2 CT_{it} + \beta_3 D_i + +\epsilon_{it}, \quad (2)$$

$$HRQoL_{it} = \beta_1 + \beta_2 CP_{it} + \beta_3 D_i + \epsilon_{it}, \quad (3)$$

where HRQoL, the primary outcome variable, is the health-related quality of life of individual i at multiple times t; ϵ_{it} represents unobservable determinants of HRQoL; CC, CT, and CP represent comorbidity counts, types, and patterns, respectively; and D encompasses the age and sex of the respondent. The parameters of the model (the β values) are commonly referred to as fixed effects. The error term in all equations has two components,

$$\epsilon_{it} = \gamma + \delta_{it}, \quad (4)$$

where $\gamma \sim i.i.d.(0, \sigma_u^2)$ is an individual-specific component that captures time-invariant unobserved component factors, and $\delta_{it} \sim \mathrm{N}\left(0, \sigma_\delta^2\right)$ is an individual-specific time-varying component of the error term which captures the impact of other unobserved variables that can potentially affect the HRQoL of the individual.

Initially, we assessed the association between HRQoL and the total number of comorbidities, classifying participants into five groups according to their number of comorbidities: 0, 1, 2, 3, and 4 or more. We adjusted the models for age and sex, refraining from overadjustment for other covariates, as the LMM can overcome the effects of missing data encountered in the analysis. Furthermore, these models are increasingly used to obtain longitudinal outcomes (Gabrio et al. 2022), as they can be tailored according to data features and their results are easily reproducible. Additionally, the LMM can produce robust estimates from non-normally distributed data, and this method has been found to work well in small sample sizes (Verbeke et al. 1997). In LMMs, parameter estimation is obtained by maximizing the likelihood of the full data (Patterson and Thompson 1971), which is analogous to classical linear models. Furthermore, traditional regression models may become implausible with a large number of confounders and more difficult to interpret when there are many covariates (Shi et al. 2024). It is a myth that all the confounders can be statistically adjusted, and overadjustment can potentially amplify bias and affect precision (Brookhart et al. 2006; Pearl 2011; Sainani 2011).

Next, we compiled a comprehensive list of all potential combinations of comorbidities, ranging from one to four coexisting health conditions. Specifically, we identified five options for one comorbidity, 10 options for two comorbidities, 10 options for three comorbidities, and five options for four comorbidities (for the frequency distribution of comorbidity combinations of individuals with PD and those without, see supplementary material Table S1), implying that participants with the same number of health conditions can differ greatly in terms of their disease profiles. To ensure sufficient statistical power, all comorbidity combinations with a sample size of less than 15 individuals were excluded from the analysis. Next, we determined the frequency distribution of participants with each unique combination. Given that participants with the same comorbidity count may exhibit diverse comorbidity types or combinations, we further investigated the nature and extent of any such impacts. Our key aim was to evaluate whether individuals with alternative comorbidity types/combinations, but an identical comorbidity count differed in terms of their HRQoL. We therefore conducted separate LMM regressions for each category (i.e., one, two, three, and four) of comorbidity combinations to identify potential variations in HRQoL based on the specific combination of diseases, even when the total comorbidity count remained consistent across groups. All analyses were performed using STATA for Windows (version 17.0).

Results

The demographic and health-related characteristics of the participants included in this study are described in Table 1 (for further details on the frequencies by number of comorbidities in the full sample and PD group, see supplementary material Table S2 and Table S3; for further details on the frequencies by health condition in the PD group, see supplementary material Table S4). The mean age of the respondents with PD was 40.70 years. Most of the respondents were in the 25–44-year age group (36.47%). Approximately

Table 1 Demographic and health-related characteristics of participants with psychological distress and those without

Characteristics	No psychological distress group (K10 score 10–19) (n = 88,843)	Psychological distress group (K10 score 20–50) (n = 26,991)	P-value
Average age (years)	46.84	40.75	< 0.01
Sex			
Male % (n)	48.25 (42,865)	41.75 (11,269)	
Female % (n)	51.75 (45,978)	58.25 (15,722)	< 0.01
Age group (years), % (n)			
15–24	14.48 (12,865)	23.79 (6422)	
24–44	32.29 (28,684)	36.47 (9844)	
45–64	32.81 (29,147)	27.86 (7520)	
65+	20.43 (18,147)	11.87 (3205)	< 0.01
Number of comorbidities, % (n)			
0	0.57 (502)	0.34 (93)	
1	12.89 (11,448)	15.16 (4091)	
2	5.45 (4842)	9.23 (2490)	
3	1.8 (1599)	4.43 (1196)	
≥ 4	0.48 (427)	1.77 (479)	
Not asked	28.16 (25,017)	20.31 (5481)	
Missing	50.57 (44,925)	47.99 (12,954)	< 0.01
Type of comorbidities			
Metabolic (Me) group, % (n)			
No	18.42 (16,361)	28.23 (7620)	
Yes	2.86 (2540)	3.47 (936)	
Not asked	28.16 (25,017)	20.31 (5481)	
Missing	50.57 (44,925)	47.99 (12,954)	< 0.01
Cardiovascular (Ca) group, % (n)			
No	7.23 (6424)	17.61 (4754)	
Yes	14.04 (12,477)	14.09 (3802)	
Not asked	28.16 (25,017)	20.31 (5481)	
Missing	50.57 (44,925)	47.99 (12,954)	< 0.01
Respiratory (Re) group, % (n)			
No	15.94 (14,163)	22.16 (5981)	
Yes	5.33 (4738)	9.54 (2575)	
Not asked	28.16 (25,017)	20.31 (5481)	
Missing	50.57 (44,925)	47.99 (12,954)	< 0.01
Musculoskeletal (Mu) group, % (n)			
No	12.85 (11,419)	22.27 (6012)	
Yes	8.42 (7482)	9.43 (2544)	
Not asked	28.16 (25,017)	20.31 (5481)	
Missing	50.57 (44,925)	47.99 (12,954)	< 0.01
Cancer (Can), % (n)			
No	20.9 (18,568)	27.8 (7503)	
Yes	0.37 (333)	3.9 (1053)	
Not asked	28.16 (25,017)	20.31 (5481)	
Missing	50.57 (44,925)	47.99 (12,954)	< 0.01
Comorbidity pattern			
CaMu			
No	12.85 (11,419)	22.27 (6012)	
Yes	8.42 (7482)	9.43 (2544)	
Not asked	28.16 (25,017)	20.31 (5481)	
Missing	50.57 (44,925)	47.99 (12,954)	< 0.01
CaRe			
No	19.24 (17,091)	27.88 (7525)	
Yes	2.04 (1810)	3.82 (1031)	
Not asked	28.16 (25,017)	20.31 (5481)	
Missing	50.57 (44,925)	47.99 (12,954)	< 0.01
ReMu			
No	19.87 (17,651)	28.81 (7776)	
Yes	1.41 (1250)	2.89 (780)	
Not asked	28.16 (25,017)	20.31 (5481)	
Missing	50.57 (44,925)	47.99 (12,954)	< 0.01
MeCa			
No	19.37 (17,209)	29.34 (7919)	
Yes	1.9 (1692)	2.36 (637)	
Not asked	28.16 (25,017)	20.31 (5481)	
Missing	50.57 (44,925)	47.99 (12,954)	< 0.01
MeMu			
No	20.26 (18,002)	30.23 (8160)	
Yes	1.01 (899)	1.47 (396)	
Not asked	28.16 (25,017)	20.31 (5481)	
Missing	50.57 (44,925)	47.99 (12,954)	< 0.01
MeCaRe			
No	20.98 (18,638)	30.98 (8362)	
Yes	0.3 (263)	0.72 (194)	
Not asked	28.16 (25,017)	20.31 (5481)	
Missing	50.57 (44,925)	47.99 (12,954)	< 0.01
MeReMu			
No	21.07 (18,721)	31.18 (8417)	
Yes	0.2 (180)	0.51 (139)	
Not asked	28.16 (25,017)	20.31 (5481)	
Missing	50.57 (44,925)	47.99 (12,954)	< 0.01
CaReCan			
No	21.25 (18,878)	31.17 (8414)	
Yes	0.03 (23)	0.53 (142)	
Not asked	28.16 (25,017)	20.31 (5481)	
Missing	50.57 (44,925)	47.99 (12,954)	< 0.01
CaReMuCan			
No	21.26 (18,885)	31.29 (8445)	
Yes	0.02 (16)	0.41 (111)	
Not asked	28.16 (25,017)	20.31 (5481)	
Missing	50.57 (44,925)	47.99 (12,954)	< 0.01

K10: Kessler psychological distress score. Me (metabolic); Ca (cardiovascular); Re (respiratory); Mu (musculoskeletal); Can (cancer); CaMu (cardiovascular + musculoskeletal); CaRe (cardiovascular + respiratory); ReMu (respiratory + musculoskeletal); MeCaRe (metabolic + cardiovascular + respiratory); MeReMu (metabolic + respiratory + musculoskeletal); CaReCan (cardiovascular + respiratory + cancer); CaReMuCan (cardiovascular + respiratory + musculoskeletal + cancer)

31.36% of the respondents with PD had at least one comorbidity, with cardiovascular being the most common (14.09%). Among the comorbidity patterns, 'cardiovascular + musculoskeletal' (CaMu) was the most prevalent (9.43%).

Table 2 shows the linear mixed model estimates of the impact of the comorbidity count on the HSU. The adjusted difference in the HSU between participants with zero and one comorbidity was neither statistically significant nor clinically meaningful. However, individuals with two comorbidities experienced statistically significant and clinically meaningful decreases in the HSU [−0.03 (95% CI −0.05, −0.01)] compared with those without comorbidities. Compared with those without any comorbidities, participants diagnosed with three or more comorbidities presented the most significant reduction in the mean HSU, with a decrease of −0.04 units (95% CI −0.06, −0.02). This reduction is both clinically significant and statistically noteworthy. Figure 2 shows the consistent and significant decrease in the HSU as the number of comorbidities increases to eight.

In Table 3, the age- and sex-adjusted LMM estimates of the impact of different types and patterns of comorbidities on the HSU under four schemes of comorbidities (one, two, three, and four comorbidities) are provided. Overall, the results revealed HSU differences across individuals with the same number of comorbidities. Among the combinations of two comorbidities, 'cardiovascular + cancer' was associated with the largest reduction in the HSU [−0.03 (95% CI −0.05, −0.01)]. Among the combinations of three and four comorbidities, 'cardiovascular + respiratory + cancer' and 'cardiovascular + respiratory + musculoskeletal + cancer' were associated with the greatest reductions in the HSU [−0.05 (95% CI −0.08, −0.02) and −0.04 (95% CI −0.06, −0.02), respectively]. The results were similar for the 'metabolic + cardiovascular + musculoskeletal + cancer' pattern of comorbidities.

Table 2 Linear mixed model estimates adjusted for age and sex of the impact of comorbidity counts on HRQoL

Classification 1		Classification 2	Classification 3
Number of comorbidities	Health state utilities	Health state utilities	Health state utilities
0	Reference	Reference	Reference
1	−0.01 (−0.03, 0.01)	−0.03 (−0.05, −0.01)	−0.03 (−0.05, −0.01)
2	**−0.03 (−0.05, −0.01)**	**−0.04 (−0.05, −0.01)**	**−0.04 (−0.05, −0.01)**
≥ 3	**−0.04 (−0.05, −0.01)**	**−0.05 (−0.07, −0.03)**	**−0.05 (−0.07, −0.03)**
≥ 4	**−0.05 (−0.07, −0.03)**	**−0.03 (−0.05, −0.01)**	
≥ 5	**−0.06 (−0.08, −0.03)**		
Age (years)			
15–24	Reference	Reference	Reference
25–44	−0.02 (−0.02, −0.02)	−0.02 (−0.02, −0.02)	−0.02 (−0.03, −0.02)
45–64	−0.06 (−0.06, −0.05)	−0.06 (−0.06, −0.05)	−0.06 (−0.06, −0.05)
64+	−0.10 (−0.10, −0.09)	−0.10 (−0.10, −0.09)	−0.10 (−0.10, −0.09)
Sex			
Male	Reference	Reference	Reference
Female	−0.01 (−0.02, −0.01)	−0.01 (−0.02, −0.01)	−0.01 (−0.02, −0.01)
Constant	0.69 (0.67, 0.71)	0.69 (0.67, 0.71)	0.69 (0.67, 0.71)

Note: Bold values indicate statistically significant estimates (95% CI does not include the null value)

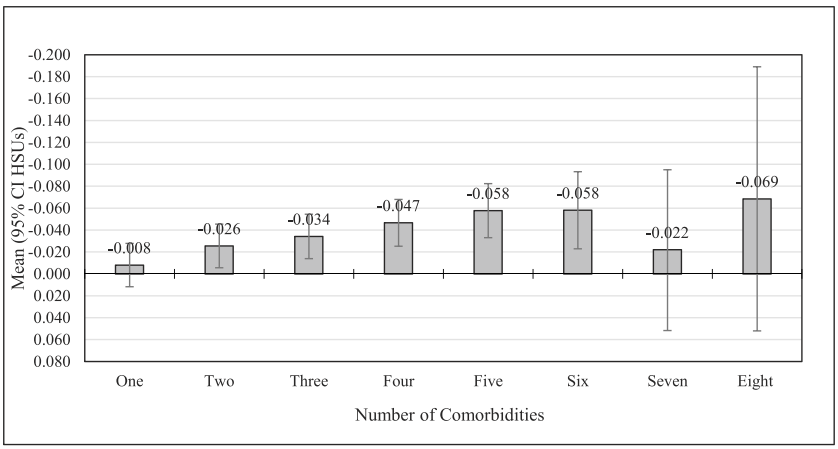

Fig. 2 Linear mixed model coefficients showing the association between the number of comorbidities and health state utilities

Table 3 Linear mixed model estimates of the impact of types/patterns of comorbidities on health state utilities of included participants with one, two, three, and four comorbidities

One comorbidity		Two comorbidities		Three comorbidities		Four comorbidities	
Type/pattern	HSUs	Type/pattern	HSUs	Type/pattern	HSUs	Type/pattern	HSUs
Me	**−0.01 (−0.01, 0.00)**	MeCa	0.00 (−0.01, 0.02)	MeCaRe	−0.01 (−0.04, 0.02)	MeCaReMu	**−0.02 (−0.04, −0.00)**
Ca	Omitted	MeRe	**−0.01 (−0.02, 0.01)**	MeCaMu	**−0.02 (−0.03, −0.01)**	MeCaReCan	−0.03 (−0.13, 0.07)
Re	Omitted	MeMu	**−0.01 (−0.03, 0.01)**	MeCaCan	0.01 (−0.04, 0.06)	MeCaMuCan	**−0.04 (−0.09, 0.00)**
Mu	**−0.02 (−0.03, −0.01)**	MeCan	0.00 (−0.02, 0.02)	MeReMu	0.03 (−0.01, 0.06)	MeReMuCan	0.10 (−0.02, 0.22)
Can	**−0.02 (−0.03, −0.02)**	CaRe	−0.00 (−0.02, 0.01)	MeReCan	−0.02 (−0.07, 0.02)	CaReMuCan	**−0.04 (−0.06, −0.02)**
		CaMu	**−0.01 (−0.02, −0.01)**	MeMuCan	0.01 (−0.05, 0.08)	MeCaReMuCan	Omitted
		CaCan	**−0.03 (−0.05, −0.01)**	CaReMu	**−0.02 (−0.03, −0.01)**		
		ReMu	−0.00 (−0.02, 0.01)	CaReCan	**−0.05 (−0.08, −0.02)**		
		ReCan	**−0.02 (−0.03, −0.01)**	CaMuCan	**−0.04 (−0.06, −0.02)**		
		MuCan	0.01 (−0.01, 0.04)	ReMuCan	0.07 (0.03, 0.11)		
Age							
15–24 years	Reference	15–24 years	Reference	15–24 years	Reference	15–24 years	Reference
25–44 years	−0.02 (−0.03, −0.02)	25–44 years	−0.02 (−0.03, −0.02)	25–44 years	−0.02 (−0.03, −0.02)	25–44 years	−0.02 (−0.03, −0.02)
45–64 years	−0.06 (−0.06, −0.06)	45–64 years	−0.06 (−0.06, −0.05)	45–64 years	−0.06 (−0.06, −0.06)	45–64 years	−0.06 (−0.06, −0.06)
64+ years	−0.20 (−0.10, −0.09)	64+ years	−0.10 (−0.10, −0.09)	64+ years	−0.10 (−0.10, −0.09)	64+ years	−0.10 (−0.10, −0.09)
Sex							
Male	Reference						
Female	−0.01 (−0.02, −0.01)	Female	−0.01 (−0.02, −0.01)	Female	−0.01 (−0.02, −0.01)	Female	−0.01 (−0.02, −0.01)
Constant	0.68 (0.67, 0.69)	Constant	0.68 (0.67, 0.69)	Constant	0.68 (0.67, 0.69)	Constant	0.68 (0.67, 0.69)

Note: Bold values indicate statistically significant estimates (95% CI does not include the null value)

Me (metabolic); Ca (cardiovascular); Re (respiratory); Mu (musculoskeletal); Can (cancer); CaMu (cardiovascular + musculoskeletal); CaRe (cardiovascular + respiratory); ReMu (respiratory + musculoskeletal); MeCa (metabolic + cardiovascular); MeMu (metabolic + musculoskeletal); MeRe (metabolic + respiratory); CaCan (cardiovascular + cancer); ReCan (respiratory + cancer); MuCan (musculoskeletal + cancer); MeCan (metabolic + cancer); CaReMu (cardiovascular + respiratory + musculoskeletal); MeCaMu (metabolic + cardiovascular + musculoskeletal); MeCaRe (metabolic + cardiovascular + respiratory); MeReMu (metabolic + respiratory + musculoskeletal); CaReCan (cardiovascular + respiratory + cancer); ReMuCan (respiratory + musculoskeletal + cancer); MeCaCan (musculoskeletal + cardiovascular + cancer); MeCaReMu (metabolic + cardiovascular + respiratory + musculoskeletal); CaReMuCan (cardiovascular + respiratory + musculoskeletal + cancer); MeCaMuCan (metabolic + cardiovascular + musculoskeletal + cancer); MeCaReCan (metabolic + cardiovascular + respiratory + cancer); MeReMuCan (metabolic + respiratory + musculoskeletal + cancer); MeCaReMuCan (metabolic + cardiovascular + respiratory + musculoskeletal + cancer

Discussion

We report the impact of the number, type, and pattern of comorbidities on HRQoL in individuals with PD in Australia. This study significantly contributes to filling a substantial evidence gap by examining the role of comorbidities in determining HRQoL in individuals with PD via longitudinal data from the HILDA survey, a nationally representative survey. Earlier studies focused mostly on the role of comorbidities in other medical conditions, whereas this study focused on PD. Results revealed that the type and pattern of comorbidities create differences in HRQoL even when the number of comorbidities is the same. The knowledge gained from this study is essential to enhancing patient care and applying a more tailored approach in the management of PD patients.

Our finding that 31.36% of the respondents with PD had at least one comorbidity is consistent with national estimates, highlighting that 47% of Australians experienced at least one chronic condition in 2020–2021 (ABS 2022), reinforcing the validity of the multimorbidity data in the HILDA survey. Our main estimates derived from the LMM showing the adverse impact of comorbidities on HRQoL are consistent with previous findings (Keramat et al. 2024). These findings not only are significant but also hold practical significance. Previous findings derived from broader populations and other medical conditions showing an inverse association between multimorbidity and HRQoL align with the results of this study (Fortin et al. 2006; Hunger et al. 2011; Makovski et al. 2019), suggesting that our findings can be confidently generalized to PD populations in other geographic locations as well.

A significant decrease in HRQoL was observed in participants as the comorbidity count increased to ≥4 comorbidities, with these individuals experiencing a clinically significant reduction of up to 0.06 HSUs over 12 years (2009–2021). We are not aware of any comparable study on the impact of comorbidities on the HRQoL of individuals with PD. However, previous studies have assessed the comorbidity burden in terms of HRQoL in other medical conditions and reported the negative impact of comorbidities on HRQoL with a disease-specific assessment of quality of life (Bárrios et al. 2013). For example, Zhao et al. (2022) reported a negative impact of the comorbidity count on the HRQoL of people with osteoarthritis, which is consistent with the results of our study. Keramat et al. (2024) demonstrated that the presence of multiple chronic conditions was negatively associated with the HRQoL of Indigenous Australians. Tušek-Bunc and Petek (2016) reported a lower HRQoL in patients with coronary heart disease with multiple comorbid chronic conditions. Comorbid conditions led to low HRQoL scores in people with dementia (Poblador-Plou et al. 2014). An increase in the comorbidity score was associated with a decrease in the HRQoL of people with asthma (Chen et al. 2015). These comorbidity-related decreases in HRQoL in different medical conditions may be because people with severe comorbid conditions have more difficulties with self-care, mobility, and managing their usual activities, pain, and mood (Nelis et al. 2019).

The most prevalent comorbidity type was cardiovascular conditions, whereas the most common comorbidity combination associated with a lower HSU was 'cardiovascular + musculoskeletal'. Similar findings were reported by Zhao et al. (2022) when they studied the impact of comorbidities on patients with osteoarthritis. These findings may help researchers conclude that non-cardiovascular and non-musculoskeletal conditions might be comorbidities that offer the greatest improvement in the HRQoL among individuals with PD when optimally managed and prevented. Our findings also highlight the importance of accounting for both the number and pattern of comorbidities when assessing HRQoL in individuals with PD. However, some studies have reported hypertension as the most frequent comorbid condition (Nelis et al. 2019).

Additionally, our findings indicating that HRQoL among individuals with PD with the same number of comorbidities may differ over time are particularly noteworthy. Among individuals with the same number of comorbidities, the comorbidity combination 'cardiovascular + cancer' significantly reduced HRQoL when compared with other combinations, which is in line with the findings of previous studies. For example, Zhao et al. (2022) reported the largest decline in HRQoL among patients with osteoarthritis and cardiovascular conditions. Similarly, heart failure as a comorbid condition was found to be a strong predictor of HRQoL in a study by Tušek-Bunc and Petek (2016).

Defining meaningful thresholds of change in an outcome measurement instrument is essential to ensuring that observed differences accurately reflect patient-relevant improvements (Klukowska et al. 2024). In this study, the threshold for a minimum clinically important difference (MCID) ranges from a 0.03- to 0.05-point reduction in HSUs. This threshold is supported by several empirical studies examining the impact of various health conditions on HRQoL across different populations using multi-attribute utility instruments such as the SF-6D. For example, in a study of an Indigenous population in Australia, MCIDs of 0.03 and 0.08 were used as a benchmark for a single and multiple chronic conditions, respectively (Keramat et al. 2024). Similarly, an MCID of 0.05 was used as a reference point for insomnia comorbidity in Australian adults (Le et al. 2024). For the US population, a cutoff value of 0.03 was reported for obesity with comorbidities as an MCID (Le and Delevry 2021). In a study examining the impact

of comorbidities on HRQoL in patients with rheumatoid arthritis, an MCID of 0.007 per additional comorbidity was applied (Gaujoux-Viala et al. 2014).

Our study bridges an important evidence gap by examining the impact of number, type, and combinations of comorbidities on HRQoL of individuals with PD in Australia. Some combinations of comorbidities were more influential in reducing HRQoL than other clusters requiring urgent health interventions. Therefore, to improve HRQoL in individuals with PD, tailored and more holistic approaches are needed to better manage more impactful combinations of comorbidities such as 'cardiovascular + cancer' in the two-comorbidity group. Integrated screening and detection programmes aimed at assessing the combined risk of cardiovascular and cancer along with targeted interventions such as the establishment of specialized 'cardiovascular + cancer' outpatient clinics could be useful. Further, more resources may be allocated to provide subsidized preventive care for this high-risk cluster.

In the presence of comorbidity, patient care complexity increases due to the more frequent and longer medical appointments than those without multimorbidity (RACGP 2023), requiring coordination across various organs of the health system. In Australia, the coordinated care for people living with morbidity is supported by programmes such as Medicare-subsidized chronic disease management services, medication reviews, and the 'MyMedicare' model. In 2022–2023, 152,000 medication review services were provided (Services Australia 2023), and 4.1 million Australian benefited from multidisciplinary care through a general practitioner chronic disease management plan (AIHW 2024). The state and tertiary governments could further enhance the capacity and efficiency of these programmes by providing additional funding and following voluntary patient registration model.

The key strength and innovation of this study is that it is the first to provide age- and sex-adjusted estimates of the burden of the number, type, and pattern of comorbidities among Australian adults experiencing PD. Second, the analyses utilized nationally representative longitudinal data with a response rate on par with many international surveys and with a sufficient number of respondents experiencing PD, enabling the tracking of individuals over time and producing estimates generalizable to other populations as well. Third, our estimates are derived from an LMM, which has been increasingly used to obtain longitudinal outcomes (Gabrio et al. 2022), as this type of model can be tailored according to data features, and the results are easily reproduced. These models incorporate both fixed effects (the factors assumed to have consistent impacts across patients) and random effects (the factors expected to vary significantly between patients) and are best suited to accommodate unbalanced data patterns even when the missing values are not completely random (Detry and Ma 2016).

Nonetheless, some limitations should be taken into consideration. First, though our applied LMM accounts for missing data, their efficacy in handling missingness in exposure variable is not reliable. This may bias our results. Second, the data lacked the granularity needed for a more detailed refinement of the comorbidity measures, such as incorporating information on disease awareness, disease duration, and treatment adherence. Additionally, several other comorbidities, such as chronic kidney disease and neurological disorders, can affect HRQoL; however, these conditions are not covered by the HILDA survey, which limits the scope of our analysis and may not fully capture the overall burden of comorbidities on HRQoL in individuals with PD. Third, we acknowledge that our reliance on patient self-reports of comorbidities may introduce misclassification bias, as study participants may underreport or overreport their health conditions due to several factors including personality traits, contextual information, beliefs, and event reappraisal (Levine et al. 2001; Robinson and Clore 2002; Safer et al. 2002). Recall bias is also a concern, as participants may have difficulty accurately recalling past events (Ben-Zeev et al. 2009; Wirtz et al. 2003) such as the onset or progression of certain health conditions. This is especially relevant for mild or subclinical diseases, which may not have been diagnosed or may not have exhibited prominent symptoms at the time of reporting (e.g., early-stage hypertension, mild cognitive impairment, or subclinical diabetes). These sources of bias may therefore have resulted in an underestimation of the prevalence and impact of these health conditions in our study. However, while self-reported data collection is subject to recall bias, it remains a common approach for collecting data in medical research (Althubaiti 2016). Furthermore, despite our relatively large sample size, some higher-order comorbidities (e.g., 'metabolic + respiratory + musculoskeletal + cancer' and 'metabolic + cardiovascular + respiratory + musculoskeletal + cancer') were underrepresented, leading to inflated confidence intervals and potentially unstable estimates, hence limiting the reliability of our conclusions in such cases. Consequently, results from comorbidity combinations with fewer than 30 participants should be interpreted with caution. The HRQoL impacts of comorbidities by PD severity were not assessed in this study due to sample size constraints. However, future work will address this when larger datasets and sample sizes are available. Moreover, we did not have data on disease severity or duration, which limited our ability to account for the severity or recency of diagnoses in our study. Even if such data had been available, the aforementioned sample size constraints would have hindered our ability to meaningfully assess these aspects with the current dataset. To validate our findings

and shed light on these issues, future studies with larger sample sizes with granular information are needed. Finally, the possibility of reverse causation and other possible biases cannot be ruled out, although the LMM used here accounts for various possible sources of confounding.

Conclusions

The relationships between HRQoL, measured as the health state utility, and the number, type, and pattern of comorbidities underscore the intricate nature of health status. This study indicates that comorbidities significantly increase the risk of poor health in individuals with psychological distress, underscoring the need for enhanced support and intervention in care provision and planning. As individuals experience an increase in comorbidities, their HRQoL often decreases. Thus, managing and preventing comorbid conditions is crucial not only for physical well-being but also for overall life satisfaction. Age- and sex-adjusted differences in HRQoL among individuals with the same number of comorbidities add another layer of complexity. These disparities highlight the multifaceted nature of health-related outcomes. Care providers often concentrate on individual conditions, but this study emphasizes the need for improved care planning and the organization of care to address multiple conditions in an integrated manner. To address morbidity effectively and efficiently, PD healthcare should be integrated with physical healthcare. Prioritizing multimorbid intervention strategies, rather than adhering to a single-disease approach, should be a key objective in research and clinical practice to increase the HRQoL of PD patients.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10389-025-02490-5.

Acknowledgements This paper uses unit record data from different waves of the Household, Income and Labour Dynamics in Australia (HILDA). The HILDA Project was initiated and is funded by the Australian Government Department of Social Services and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the authors and should not be attributed to the universities, Department of Social Services or the Melbourne Institute. The authors are responsible for all findings and views expressed in this paper.

Funding Open Access funding enabled and organized by CAUL and its Member Institutions. This study did not receive any type of funding.

Data availability The data used in this study were obtained from the Melbourne Institute of Applied Economic and Social Research (https://melburneinstitute.unimelb.edu.au/). Although the information is not openly available, appropriately qualified researchers can access the data after following their protocols and meeting their requirements. Their contact address is Melbourne Institute of Applied Economic and Social Research, the University of Melbourne, VIC 3010, Australia.

Declarations

Ethics approval This study used secondary data from de-identified existing unit records from the HILDA survey, so ethical approval was not required. However, the authors completed and signed the Confidentiality Deed Poll and sent it to ADA (https://ada@anu.edu.au) before receiving approval for their data application. The datasets analysed and/or generated during the current study are subject to the signed confidentiality deed.

Conflicts of interest The authors have no relevant financial or non-financial interests to disclose.

References

ABS (2022) Australian Bureau of Statistics. Health conditions prevalence. https://www.abs.gov.au/statistics/health/health-conditions-and-risks/health-conditions-prevalence/latest-release . Accessed 10 April 2024

AIHW (2022) Australian Institute of Health and Welfare. Australian Burden of Disease Study. https://www.aihw.gov.au/reports/burden-of-disease/australian-burden-of-disease-study-2022/contents/summary. Accessed 18 March 2024

AIHW (2024) Australian Institute of Health and Welfare. Medicare-subsidised GP, allied health and specialist health care across local areas: 2022–23. https://www.aihw.gov.au/reports/primary-health-care/medicare-subsidised-care-2022-23/contents/about. Accessed 19 April 2024

Althubaiti A (2016) Information bias in health research: definition, pitfalls, and adjustment methods. J Multidiscip Health 9:211–217. https://doi.org/10.2147/JMDH.S104807

Banks E, Byles JE, Gibson RE et al (2010) Is psychological distress in people living with cancer related to the fact of diagnosis, current treatment or level of disability? Findings from a large Australian study. Med J Aust 193:S62–S67. https://doi.org/10.5694/j.1326-5377.2010.tb03931.x

Bárrios H, Verdelho A, Narciso S, Gonçalves-Pereira M, Logsdon R, de Mendonça A (2013) Quality of life in patients with cognitive impairment: validation of the Quality of Life–Alzheimer's Disease scale in Portugal. Int Psychogeriatr 25(7):1085–1096. https://doi.org/10.1017/S1041610213000379

Ben-Zeev D, Young MA, Madsen JW (2009) Retrospective recall of affect in clinically depressed individuals and controls. Cogn Emot 23(5):1021–1040. https://doi.org/10.1080/02699930802607937

Brookhart MA, Schneeweiss S, Rothman KJ, Glynn RJ, Avorn J, Stürmer T (2006) Variable selection for propensity score models. Am J Epidemiol 163(12):1149–1156. https://doi.org/10.1093/aje/kwj149

Butterly EW, Hanlon P, Shah AS et al (2023) Comorbidity and health-related quality of life in people with a chronic medical condition in randomised clinical trials: An individual participant data meta-analysis. PLoS Med 20(1):e1004154. https://doi.org/10.1371/journal.pmed.1004154

Charlson F, van Ommeren M, Flaxman A, Cornett J, Whiteford H, Saxena S (2019) New WHO prevalence estimates of mental disorders in conflict settings: a systematic review and meta-analysis. Lancet 394(10194):240–248. https://doi.org/10.1016/S0140-6736(19)30934-1

Chen W, Lynd LD, FitzGerald JM, Marra CA, Rousseau R, Sadatsafavi M (2015) The added effect of comorbidity on health-related quality of life in patients with asthma. Qual Life Res 24:2507–2517. https://doi.org/10.1007/s11136-015-0995-6

Daré LO, Bruand PE, Gérard D, Marin B, Lameyre V, Boumédiène F, Preux PM (2019) Co-morbidities of mental disorders and chronic physical diseases in developing and emerging countries: a meta-analysis. BMC Public Health 19:1–12. https://doi.org/10.1186/s12889-019-6623-6

Detry MA, Ma Y (2016) Analyzing repeated measurements using mixed models. JAMA 315(4):407–408. https://doi.org/10.1001/jama.2015.19394

Dunlop DD, Lyons JS, Manheim LM, Song J, Chang RW (2004) Arthritis and heart disease as risk factors for major depression: the role of functional limitation. Med Care 42(6):502–511. https://doi.org/10.1097/01.mlr.0000127997.51128.81

Egede LE, Dismuke CE (2012) Serious psychological distress and diabetes: a review of the literature. Curr Psychiatry Rep 14:15–22. https://doi.org/10.1007/s11920-011-0240-0

Fortin M, Bravo G, Hudon C, Lapointe L, Almirall J, Dubois MF, Vanasse A (2006) Relationship between multimorbidity and health-related quality of life of patients in primary care. Qual Life Res 15:83–91. https://doi.org/10.1007/s11136-005-8661-z

Gabrio A, Plumpton C, Banerjee S, Leurent B (2022) Linear mixed models to handle missing at random data in trial-based economic evaluations. Health Econ 31(6):1276–1287. https://doi.org/10.1002/hec.4510

Garcia M, Moazzami K, Almuwaqqat Z et al (2024) Psychological distress and the risk of adverse cardiovascular outcomes in patients with coronary heart disease. JACC: Adv 3(2):100794. https://doi.org/10.1016/j.jacadv.2023.100794

Gaujoux-Viala C, Hosseini K, Rat AC et al (2014) THU0432 Impact of comorbidities on measuring indirect utility by the SF-6D or the EQ-5D in rheumatoid arthritis: an analysis of 962 patients enrolled in Comedra. Ann Rheum Dis 73:332. https://doi.org/10.1136/annrheumdis-2014-eular.5794

Haagsma JA, van Beeck EF, Polinder S, Toet H, Panneman M, Bonsel GJ (2011) The effect of comorbidity on health-related quality of life for injury patients in the first year following injury: comparison of three comorbidity adjustment approaches. Popul Health Metr 9:1–8. https://doi.org/10.1186/1478-7954-9-10

Havens E, Slabaugh SL, Helmick CG, Cordier T, Zack M, Gopal V, Prewitt T (2017) Peer reviewed: comorbid arthritis is associated with lower health-related quality of life in older adults with other chronic conditions, United States, 2013–2014. Prev Chronic Dis 14. https://doi.org/10.5888/pcd14.160495

Huber MB, Wacker ME, Vogelmeier CF, Leidl R (2015) Comorbid influences on generic health-related quality of life in COPD: a systematic review. PLoS ONE 10(7):e0132670. https://doi.org/10.1371/journal.pone.0132670

Hunger M, Thorand B, Schunk M, Döring A, Menn P, Peters A, Holle R (2011) Multimorbidity and health-related quality of life in the older population: results from the German KORA-age study. Health Qual Life Outcomes 9:1–10. https://doi.org/10.1186/1477-7525-9-53

James SL, Abate D, Abate KH et al (2018) Global, regional, and national incidence, prevalence, and years lived with disability for 354 diseases and injuries for 195 countries and territories, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017. Lancet 392(10159):1789–1858. https://doi.org/10.1016/S0140-6736(18)32279-7

Kang HM, Sul JH, Service SK et al (2010) Variance component model to account for sample structure in genome-wide association studies. Nat Genet 42(4):348–54. https://doi.org/10.1038/ng.548

Keramat SA, Perales F, Alam K et al (2024) Multimorbidity and health-related quality of life amongst Indigenous Australians: a longitudinal analysis. Qual Life Res 33(1):195–206. https://doi.org/10.1007/s11136-023-03500-3

Kharroubi SA, Brazier JE, Roberts J, O'Hagan A (2007) Modelling SF-6D health state preference data using a nonparametric Bayesian method. J Health Econ 26(3):597–612. https://doi.org/10.1016/j.jhealeco.2006.09.002

Klukowska AM, Vandertop WP, Schröder ML, Staartjes VE (2024) Calculation of the minimum clinically important difference (MCID) using different methodologies: case study and practical guide. Eur Spine J 33(9):3388–3400. https://doi.org/10.1007/s00586-024-08369-5

Layne MJ, Elliott JO, Lu B, Klatte ET, Charyton C (2009) Serious psychological distress among persons with epilepsy based on the 2005 California Health Interview Survey. Epilepsia 50(5):1077–1084. https://doi.org/10.1111/j.1528-1167.2008.01996.x

Le QA, Delevry D (2021) Impact of elevated BMI and types of comorbid conditions on health-related quality of life in a nationally representative US sample. Public Health Nutr 24(18):6346–6353. https://doi.org/10.1017/S1368980021003694

Le PH, Le Khanh-Dao L, Rajaratnam SM, Mihalopoulos C (2024) Quality of life impacts associated with comorbid insomnia and depression in adult population. Qual Life Res 33(12):3283–3298. https://doi.org/10.1007/s11136-024-03793-y

Lee YC, Shang J (2022) Estimation and selection in linear mixed models with missing data under compound symmetric structure. J Appl Stat 49(15):4003–4027. https://doi.org/10.1080/02664763.2021.1969342

Levine LJ, Prohaska V, Burgess SL, Rice JA, Laulhere TM (2001) Remembering past emotions: the role of current appraisals. Cogn Emot 15(4):393–417. https://doi.org/10.1080/02699930125955

Lo LMP, Taylor BV, Winzenberg T et al (2021) Estimating the relative contribution of comorbidities in predicting health-related quality of life of people with multiple sclerosis. J Neurol 268:569–581. https://doi.org/10.1007/s00415-020-10195-w

Makovski TT, Schmitz S, Zeegers MP, Stranges S, van den Akker M (2019) Multimorbidity and quality of life: systematic literature review and meta-analysis. Ageing Res Rev 53:100903. https://doi.org/10.1016/j.arr.2019.04.005

McGrath JJ, Lim C, Plana-Ripoll O et al (2020) Comorbidity within mental disorders: a comprehensive analysis based on 145,990 survey respondents from 27 countries. Epidemiol Psychiatr Sci 29:e153. https://doi.org/10.1017/S2045796020000633

McPhail SM (2016) Multimorbidity in chronic disease: impact on health care resources and costs. Risk Manag Healthc Policy 143–56. https://doi.org/10.2147/RMHP.S97248

Mittal D, Fortney JC, Pyne JM, Edlund MJ, Wetherell JL (2006) Impact of comorbid anxiety disorders on health-related quality of life among patients with major depressive disorder. Psychiatr Serv 57(12):1731–1737. https://doi.org/10.1176/ps.2006.57.12.1731

Nelis SM, Wu Y-T, Matthews FE et al (2019) The impact of co-morbidity on the quality of life of people with dementia: findings from the IDEAL study. Age Ageing 48(3):361–367. https://doi.org/10.1093/ageing/afy155

Norman R, Church J, Van Den Berg B, Goodall S (2013) Australian health-related quality of life population norms derived from the SF-6D. Aust N Z J Public Health 37(1):17–23. https://doi.org/10.1111/1753-6405.12005

Patterson HD, Thompson R (1971) Recovery of inter-block information when block sizes are unequal. Biometrika 58(3):545–554. https://doi.org/10.1093/biomet/58.3.545

Pearl J (2011) Invited commentary: understanding bias amplification. Am J Epidemiol 174(11):1223–1227. https://doi.org/10.1093/aje/kwr352

Poblador-Plou B, Calderón-Larrañaga A, Marta-Moreno J, Hancco-Saavedra J, Sicras-Mainar A, Soljak M, Prados-Torres A (2014) Comorbidity of dementia: a cross-sectional study of primary care older patients. BMC Psychiatry 14:1–8. https://doi.org/10.1186/1471-244X-14-84

RACGP (2023) Royal Australian College of General Practitioners. https://www.racgp.org.au/getmedia/122d4119-a779-41c0-bc67-a8914be52561/Health-of-the-Nation-2023.pdf Accessed 01 February 2024.

Robinson MD, Clore GL (2002) Belief and feeling: evidence for an accessibility model of emotional self-report. Psychol Bull 128(6):934. https://doi.org/10.1037/0033-2909.128.6.934

Safer MA, Levine LJ, Drapalski AL (2002) Distortion in memory for emotions: the contributions of personality and post-event knowledge. Pers Soc Psychol Bull 28(11):1495–1507. https://doi.org/10.1177/014616702237577

Sainani K (2011) The Limitations of Statistical Adjustment. PM&R 3(9):868–872. https://doi.org/10.1016/j.pmrj.2011.06.006

Schmitz N, Wang J, Lesage A, Malla A, Strychar I (2008) Psychological distress and short-term disability in people with diabetes: results from the Canadian Community Health Survey. J Psychosom Res 65(2):165–172. https://doi.org/10.1016/j.jpsychores.2008.03.004

Serrano Jr CV, Setani KT, Sakamoto E, Andrei AM, Fraguas R (2011) Association between depression and development of coronary artery disease: pathophysiologic and diagnostic implications. Vasc Health Risk Manag 159–164. https://doi.org/10.2147/VHRM.S10783

Services Australia (2023) Australian Government. Medicare Item Reports. https://medicarestatistics.humanservices.gov.au/statistics/mbs_item.html Accessed 08 November 2023

Shi AX, Zivich PN, Chu H (2024) A comprehensive review and tutorial on confounding adjustment methods for estimating treatment effects using observational data. Appl Sci 14(9):3662. https://doi.org/10.3390/app14093662

Shih M, Hootman JM, Strine TW, Chapman DP, Brady TJ (2006) Serious psychological distress in US adults with arthritis. J Gen Intern Med 21(11):1160–1166. https://doi.org/10.1111/j.1525-1497.2006.00573.x

Smith SM, Wallace E, Salisbury C, Sasseville M, Bayliss E, Fortin M (2018) A core outcome set for multimorbidity research (COSmm). Ann Fam Med 16(2):132–138. https://doi.org/10.1370/afm.2178

Soh SE, Morris ME, McGinley JL (2011) Determinants of health-related quality of life in Parkinson's disease: a systematic review. Parkinsonism Relat Disord 17(1):1–9. https://doi.org/10.1016/j.parkreldis.2010.08.012

Strine TW, Kobau R, Chapman DP, Thurman DJ, Price P, Balluz LS (2005) Psychological distress, comorbidities, and health behaviors among US adults with seizures: results from the 2002 National Health Interview Survey. Epilepsia 46(7):1133–1139. https://doi.org/10.1111/j.1528-1167.2005.01605.x

Summerfield M, Dunn R, Freidin S et al (2011) HILDA user manual–release 10. Melbourne Institute of Applied Economic and Social Research, University of Melbourne. https://research.monash.edu/en/publications/hilda-user-manual-release-10. Accessed 31 March 2025.

Summerfield M, Garrard B, Kamath R, et al (2023) HILDA User Manual–Release 22. Melbourne Institute of Applied Economic and Social Research, The University of Melbourne. https://melbourneinstitute.unimelb.edu.au/__data/assets/pdf_file/0020/4815110/HILDA-User-Manual-Release-22.0.pdf. Accessed 2 April 2025

Sundh J, Johansson G, Larsson K, Linden A, Löfdahl C-G, Janson C, Sandström T (2015) Comorbidity and health-related quality of life in patients with severe chronic obstructive pulmonary disease attending Swedish secondary care units. Int J Chron Obstruct Pulmon Dis 173–183. https://doi.org/10.2147/COPD.S74645

Tušek-Bunc K, Petek D (2016) Comorbidities and characteristics of coronary heart disease patients: their impact on health-related quality of life. Health Qual Life Outcomes 14:1–12. https://doi.org/10.1186/s12955-016-0560-1

Verbeke G, Molenberghs G, Verbeke G (1997) Linear mixed models for longitudinal data: Springer.

Vynckier P, Van Wilder L, Kotseva K et al (2023) Gender differences in health-related quality of life and psychological distress among coronary patients: Does comorbidity matter? Results from the ESC EORP EUROASPIRE V registry. Int J Cardiol 371:452–459. https://doi.org/10.1016/j.ijcard.2022.09.010

Warren SA, Turpin KV, Pohar SL, Jones CA, Warren K (2009) Comorbidity and health-related quality of life in people with multiple sclerosis. Int J MS Care 11(1):6–16. https://doi.org/10.7224/1537-2073-11.1.6

Watson N, Wooden M (2021) The household, income and labour dynamics in Australia (HILDA) survey. Jahrb Natlökonom Statistik 241(1):131–141. https://doi.org/10.1515/jbnst-2020-0029

Wirtz D, Kruger J, Scollon CN, Diener E (2003) What to do on spring break? The role of predicted, on-line, and remembered experience in future choice. Psychol Sci 14(5):520–524. https://doi.org/10.1111/1467-9280.0

Wyatt KD, Stuart LM, Brito JP et al (2014) Out of context: clinical practice guidelines and patients with multiple chronic conditions: a systematic review. Med Care 52:S92–S100. https://doi.org/10.1097/MLR.0b013e3182a51b3d

Yang J, Zaitlen NA, Goddard ME, Visscher PM, Price AL (2014) Advantages and pitfalls in the application of mixed-model association methods. Nat Genet 46(2):100–106. https://doi.org/10.1038/ng.2876

Yu J, Pressoir G, Briggs WH et al (2006) A unified mixed-model method for association mapping that accounts for multiple levels of relatedness. Nat Genet 38(2):203–208. https://doi.org/10.1038/ng1702

Zhao K, Aranzana MJ, Kim S et al (2007) An Arabidopsis example of association mapping in structured samples. PLoS Genet 3(1):e4. https://doi.org/10.1371/journal.pgen.0030004

Zhao T, Winzenberg T, Aitken D, Graaff Bd, Ahmad H, Jones G, Palmer AJ (2022) The impact of comorbidities on health-related quality of life of people with osteoarthritis over 10 years. Rheumatology 61(1):139–145. https://doi.org/10.1093/rheumatology/keab358

Zheng Q, Cox IA, de Graaff B et al (2023) The relative contribution of co-morbidities to health-related quality of life of people with idiopathic pulmonary fibrosis using the assessment of quality of life-8-dimension multi-attribute utility instrument. Qual Life Res 32(6):1609–1619. https://doi.org/10.1007/s11136-022-03331-8

Zulman DM, Asch SM, Martins SB, Kerr EA, Hoffman BB, Goldstein MK (2014) Quality of care for patients with multiple chronic conditions: the role of comorbidity interrelatedness. J Gen Intern Med 29:529–537. https://doi.org/10.1007/s11606-013-2616-9