O'Connor, E. J., Ryan, M., Brindal, E., Zajac, I. T., Kakoschke, N. (2025). Lifestyle behavioural and socio-demographic predictors of distress and wellbeing among Australian adults. *International Journal of Wellbeing*, *15*(2), 4537, 1-33. https://doi.org/10.5502/ijw.v15i2.4537

ARTICLE

Lifestyle behavioural and socio-demographic predictors of distress and wellbeing among Australian adults

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Abstract: Lifestyle behaviours including physical activity (PA), dietary intake, and sleep are increasingly prominent targets in preventive mental health research and practice. Nevertheless, previous studies have typically adopted a model of mental health that discounts the potential for psychological distress and mental wellbeing to coexist. Reliance on linear regression modelling in extant research has also limited our understanding of how lifestyle behaviours interact with socio-demographic and other factors to predict distress and wellbeing. Among a sample of Australian adults (n = 1496) decision tree modelling was used to explore cross-sectional interactions between lifestyle behavioural and socio-demographic predictors of distress and wellbeing. In these models, sleep quality and frequency of moderate to vigorous PA - but not diet - predicted both distress and wellbeing outcomes. In contrast, higher self-reported health predicted wellbeing, but not distress. Overall, lifestyle behaviours interacted in complex ways with mental health variables and socio-demographic factors, with the predictors of distress often distinct from those of wellbeing. Our results align with a bivariate conceptualisation of mental health in which distress and wellbeing are overlapping but distinct continua. Preventive mental health research should adopt a bivariate conceptualisation to facilitate more precise and generative insights regarding the lifestyle behavioural correlates of mental health.

Keywords: physical activity; sleep; diet; mental health; dual-continuum; distress; wellbeing; lifestyle behaviour

1. Introduction

Common mental health disorders including depression and anxiety are among the leading contributors to the global burden of disease (GBD 2019 Diseases and Injuries Collaborators, 2020; GBD 2019 Mental Disorders Collaborators, 2022). In Australia, one in five people are affected every year, with mental health and substance use disorders constituting 13% of the national disease burden with an economic cost of approximately $70 billion (AIHW, 2021; Productivity Commission, 2020). Increased expenditure on treatment has largely failed to reduce the burden of mental health disorders or very high psychological distress (Jorm, 2018; Jorm et al., 2017), leading to a greater emphasis on prevention both globally and in Australia (Australian Government, 2021; Australian Government Department of Health and Aged Care, 2021; WHO, 2021). Population-level improvements in modifiable lifestyle behaviours have been proposed as an important target for prevention (Jacka et al., 2012; Schuch & Vancampfort, 2021). The focus on lifestyle behaviours is based on substantial evidence for physical activity (PA) (Firth et al., 2020;

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Schuch & Vancampfort, 2021), diet (Mujcic & Oswald, 2016; Ocean et al., 2019; O'Neil et al., 2014), and sleep (Blackwelder, 2021; Freeman et al., 2017) as significant correlates of mental health outcomes. Greater engagement in moderate to vigorous PA has been robustly established as a protective factor against incident mental health disorders (Choi et al., 2019; Firth et al., 2020; Pearce et al., 2022; Schuch et al., 2018, 2019; Schuch & Vancampfort, 2021). For example, an inverse curvilinear dose-response relationship between PA volume and risk of depression has been observed (Pearce et al., 2022). In other words, as minutes of weekly PA increases risk of depression decreases, with most of the protective association realised when shifting from zero to at least some regular PA (Pearce et al., 2022). Moreover, meta-analytic evidence supports the efficacy of lifestyle behaviour interventions for reducing symptoms of common mental health disorders in both clinical and general populations (Brinsley et al., 2025; Firth et al., 2019; Scott et al., 2021; Singh et al., 2023). Scott et al (2021) found that randomised controlled trials of interventions targeting sleep that improved sleep quality also resulted in significant, medium-sized reductions in symptoms of depression and anxiety, respectively. Importantly, studies were excluded from this review if interventions targeted mental health directly (e.g., cognitive behavioural therapy for management of distress symptoms), providing stronger evidence for lifestyle behavioural change as a potential causal factor in improving mental health outcomes. A meta-analysis (of effect sizes from 97 systematic reviews of randomised controlled trials) also found medium-sized effects favouring PA interventions for reducing depression and anxiety symptoms (Singh et al., 2023).

1.1 Lifestyle behaviours and bivariate conceptualisations of mental health

In line with the broader psychological literature, most research focusing on lifestyle behaviours has assumed a bipolar conceptualisation of mental health (Westerhof & Keyes, 2010). The bipolar model describes a single continuum, anchored by mental ill-health at one end and mental wellbeing at the other (Zhao & Tay, 2023). Using this bipolar approach, mental ill-health is typically operationalised as symptoms of common mental health disorders (i.e., anxiety or depression) or transdiagnostic psychological distress (Drapeau et al., 2012). In contrast to this deficit-based view of mental health, mental wellbeing is often defined simply as 'feeling good and functioning well' (Ruggeri et al., 2020), though a lack of conceptual and definitional clarity in the field is well-noted (see Iasiello, Agteren, et al., 2023; Park et al., 2023). Lomas, Pawelski and VanderWeele (2024) provide a helpful framing here, with mental wellbeing referring to the relative presence of a personal subjective state of quality, with more specific constructs such as happiness nested within this broader dimension. Of importance to the present research, the bipolar model assumes that distress and wellbeing are intrinsically coupled, with increases in one dimension necessarily corresponding with reductions in the other (Cacioppo & Berntson, 1994; Iasiello, van Agteren, et al., 2023). As a result, studies employing a bipolar model of mental health typically only measure one aspect of this single spectrum (i.e., distress or wellbeing), with constructs that are inversely associated with mental ill-health assumed to be positively associated with wellbeing. In a longitudinal context, reductions in symptoms are analogous to improved wellbeing (and vice-versa). However, a growing body of research suggests that distress and wellbeing represent related but distinct continua, with both overlapping and unique antecedents and correlates (Iasiello et al., 2020; Keyes, 2005; Kinderman et al., 2015; Kraiss et al., 2023).

In contrast to bipolar models, bivariate conceptualisations such as the dual-continua model of mental health recognise that high (and low) levels of distress and wellbeing can coexist, offering a framework for operationalising mental health that aligns more closely with the lived and living experiences of many individuals (Keyes, 2005). Returning to Lomas, Pawelski and

VanderWeele (2024), a bivariate conceptualisation here allows for the possibility that individuals can experience the presence of both personal subjective states of quality (i.e., wellbeing) *and* the presence of personal subjective states lacking in quality (i.e., ill-being), with the character of these states differing from person to person. Bivariate models open new possibilities for investigating the factors that are important for lower symptoms of distress, those that contribute to higher wellbeing, and those that support more optimal outcomes across both spectra. In practical terms, studies employing a bivariate conceptualisation of mental health will measure *both* wellbeing *and* distress and will use each construct to better understand and predict the other. Substantial quantitative support has been established for the between- and within-individual separability of distress and wellbeing (Iasiello et al., 2020; Kraiss et al., 2023), with important implications for preventive mental health research. For example, longitudinal studies controlling for baseline distress symptoms suggest greater mental wellbeing reduces the odds of future mental ill-health occurrence (Lamers et al., 2015), while low wellbeing increases one's risk of future depression (Schotanus-Dijkstra et al., 2017; Wood & Joseph, 2010). Mental wellbeing is also increasingly considered as a protective factor in the suicide prevention literature. Specifically, it has been included as a moderator of the impact of depressive symptoms on suicidal ideation (Siegmann et al., 2018, 2019; Teismann et al., 2019; Teismann & Brailovskaia, 2020). These studies demonstrate that a) there is substantial cross-sectional variability in wellbeing across individuals with the same level of distress, and b) these individual differences in wellbeing are an important variable to consider, alongside indicators of distress, in preventive mental health research. Importantly, a bipolar conceptualisation would not recognise this interplay between distress and wellbeing in shaping future mental health-related behaviours and/or outcomes. Taken together, these results suggest that wellbeing should be considered as both a unique predictor of distress, and as an important target for preventive mental health interventions. Compared to the bipolar model, a bivariate conceptualisation allows for more nuanced examinations of positive and negative affective states, as well as their shared and unique predictors (Cacioppo & Berntson, 1994; Iasiello, van Agteren, et al., 2023; van Agteren & Iasiello, 2020).

While research has begun to characterise the relationships between lifestyle behaviours and various aspects of mental wellbeing (An et al., 2020; J. Burke & Dunne, 2022; Conner et al., 2017; Haapasalo et al., 2018; Heinsch et al., 2022; L. Zhang et al., 2021), fewer large-scale studies have investigated both distress and wellbeing in tandem. Cross-sectional associations have been observed between lifestyle behaviours (i.e., smoking, alcohol use, diet, PA, sedentary time, and sleep), lower depressive and anxiety symptoms, and greater wellbeing (Wang et al., 2023). Other research has been equivocal regarding the strength and significance of associations between individual lifestyle behaviours, distress and wellbeing (Anderson & Fowers, 2020; Battista et al., 2022; Wickham et al., 2020). For example, Wickham et al. (2020) found that sleep and, to a lesser extent, PA, significantly predicted both depressive symptoms and flourishing – referring here to a general construct composed of psychological and social wellbeing, as distinct from the overarching concept of flourishing proposed by Lomas, Pawelski and VanderWeele (2024) that additionally considers health-, environment- and systems-level factors. Consumption of raw fruits and vegetables predicted flourishing but not depressive symptoms, which suggests divergence in lifestyle behavioural correlates across the two axioms of mental health. Overall, there is a scarcity of research characterising relationships between lifestyle behaviours, distress and wellbeing. Some research has examined both distress and wellbeing outcomes (Anderson & Fowers, 2020; Battista et al., 2022; e.g., Wang et al., 2023; Wickham et al., 2020), however, these studies have not explicitly adopted a bivariate conceptualisation in which wellbeing was specified as an additional predictor in modelling distress outcomes (and vice versa). The

predominance of bipolar mental health conceptualisations in the existing literature has limited our understanding of how lifestyle behaviours relate to both negative and positive aspects of mental health. In addition, further research is required to explore how lifestyle behavioural factors interact with other variables such as wellbeing to shape distress.

1.2 Using decision trees to explore interactions between lifestyle behavioural, socio-demographic, and other predictors

Both lifestyle behaviours and mental health outcomes are impacted by an individual's socio-economic circumstances and opportunities (i.e., social determinants; Anderson et al., 2022; Short & Mollborn, 2015). Further complicating the task of characterising cross-sectional relationships between lifestyle behaviours and mental health are a range of other interrelated cultural, biological, life course, and contextual factors (Puka et al., 2023; Short & Mollborn, 2015). Typically, previous studies exploring relationships between lifestyle behaviours and mental health outcomes have included a set of socio-demographic factors (e.g., age, income, education, etc.) and other personal attributes (e.g., physical health status) as covariates in linear or logistic regression modelling (e.g., Wang et al., 2023; Wickham et al., 2020). This variable-centric approach estimates statistical associations between a behavioural exposure (e.g., PA) and a mental health outcome (e.g., distress) while holding constant all other variables. Accordingly, linear modelling is appropriate for addressing questions related to the effect size of specific associations whilst accounting for confounding variables. Nevertheless, such analyses are limited in their ability to portray more complex interactions between multiple predictors. While additional interaction terms can be specified, these may be complex, difficult to specify *a priori,* and can pose difficulties for interpretation. Finally, linear regression models are focused on testing hypotheses but are more limited in their ability to generate hypotheses regarding the risk profiles of priority groups (Venkatasubramaniam et al., 2017).

To overcome these limitations, a complementary approach commonly used in clinical research involves using decision-tree methods (Lemon et al., 2003; Venkatasubramaniam et al., 2017). Decision trees are a class of statistical methods that, based on predictors, recursively partition a sample into smaller subgroups who share greater similarity on the outcome variable. Whilst considered exploratory statistical methods used to generate hypotheses, these person-centric analyses result in an easily interpretable tree-like structure that can depict complex interactions between varied predictors, providing insights into important outcome differentiators while simultaneously identifying subgroups to whom preventive interventions may be targeted (Venkatasubramaniam et al., 2017). The advantages to using decision trees when investigating multifactorial population health data have recently been discussed (Battista et al., 2022, 2023; Lemon et al., 2003; Venkatasubramaniam et al., 2017; Wolfson & Venkatasubramaniam, 2018; Zhang et al., 2022). In addition, decision trees do not require data to meet the assumptions of the linear model, thus avoiding the need for bespoke statistical procedures often required when analysing questionnaire-derived mental health data (e.g., Kowal & Wu, 2023). For these reasons, decision-trees are becoming more common in public health and epidemiological research (Lemon et al., 2003; Venkatasubramaniam et al., 2017), including studies with a focus on mental health. Identifying priority sub-groups is important for effectively targeting health promotion and prevention initiatives. Regarding a bivariate conceptualisation of mental health, decision trees and similar partitioning analyses offer advantages for identifying target-groups and generating hypotheses in this nascent area of research. Specifically, we argue that decision trees may be a complementary analytic approach that can help to capture complex

interactions between wellbeing and distress, allowing for more nuanced understandings of shared and unique predictors beyond that which can be achieved via linear regression alone.

Importantly, few studies have directly compared decision tree and regression methods. In a recent study, Battista et al (2022) found that Canadian adolescents' PA, diet, and sleep were each significant predictors of mental ill-health (i.e., anxiety, depressive symptoms) and wellbeing (i.e., flourishing) in separate linear regression models. However, decision tree modelling suggested that lifestyle behaviours did not significantly differentiate any mental health outcome. Instead, the key differentiators of mental ill-health and wellbeing were young peoples' perceptions of having a 'happy home life' and school connectedness. Thus, the decision tree analysis provided important additional insights regarding hypotheses that preventive interventions targeting lifestyle behaviours may have negligible effects on depression, anxiety, and mental wellbeing if young peoples' perceptions of having a happy home life and being connected to their school remain unchanged. In a follow-up study, Battista et al. (2023) compared decision tree and regression models which both identified the same critical predictors for each outcome (mental ill-health and wellbeing), suggesting a general level of agreement. While the decision tree models had lower prediction accuracy, they were more parsimonious and indicated higher relative importance of key differentiating variables. To summarise, each analysis highlighted the same select group of variables as important predictors but offered different insights to the investigator. The linear regressions tested statistical effect sizes for each predictor across the entire sample, assuming that all other predictors were held constant. In contrast, results of the decision tree analyses highlighted specific subgroups in the population, providing hypothesis-generative insights regarding the most important differentiators of mental ill-health and wellbeing (respectively), both overall and within each of these specific subgroups. Nevertheless, the Battista et al. studies were conducted in adolescent samples in Canada. It remains to be determined whether decision tree approaches are useful for generating hypotheses in studies focused on mental health from a dual-continua perspective alongside lifestyle behaviours in broader samples from which priority sub-groups can be identified.

1.3 The current study

Despite the breadth of literature linking lifestyle behaviours with mental health outcomes, several critical gaps remain that may threaten the effectiveness of preventive health activities and progress toward reducing the mental health burden (Anderson et al., 2022; Firth et al., 2020). This study focuses on two research questions: 1) How is mental health best conceptualised in lifestyle behaviour-related research, and 2) What is the interplay between behavioural and socio-demographic determinants of mental health?

Our aim was to explore these questions to inform future hypotheses for preventive health initiatives targeted at specific populations. Decision tree models were used to explore interactions between lifestyle behaviours (i.e., PA, diet, and sleep), socio-demographic factors, and other personal attributes as predictors of mental health among a broad cross-section of Australian adults. Separate models were specified for distress and wellbeing, and each mental health variable was included as a predictor of its counterpart to understand the relevance of bivariate (Keyes, 2005) versus bipolar conceptualisations of mental health. Finally, to understand the outcome of using these novel methods, we aimed to compare decision tree models to traditional variable-centric linear regression models.

2. Methods

3.1 Procedure

This study used a cross-sectional design with data collected via an online survey (30-minute duration). Participants were recruited by an external market research company in June 2023. The market research company emailed a link to the survey to the online panel partner who then recruited and invited participants on their existing panel and other channels including social media and open web recruitment. Participants viewed the participant information sheet and provided informed consent prior to completing the socio-demographic questions, mental health scales, and lifestyle behaviour questionnaires. All study components were completed within the external market research company's proprietary survey platform hosted on secure servers. Specific representative quotas were set based on age, gender and geographical location to ensure a nationally representative sample.

3.2 Participants and ethical approval

Participants were adults (> 18 years) currently residing in Australia. For ethical reasons, individuals experiencing acutely elevated psychological distress were advised within the study information pack not to participate, but no eligibility criteria were formally assessed. Ethical approval for the present study was provided by the CSIRO Health and Medical Human Research Ethics Committee (2023_021_LR).

3.3 Measures

3.3.1 Socio-demographic factors

Demographic questions included age group (18-24; 25-34; 35-44; 45-54; 65-74; 75+ years), gender (female; male; non-binary; other), highest level of education, relationship and employment status, gross household income, and whether the participant identified with Aboriginal and/or Torres Strait Islander ancestry.

3.3.2 Personal attributes

Self-reported height and weight data were collected to allow for body mass index to be calculated (BMI; kg/m^2). Self-reported health was assessed using a single-item (Ware & Sherbourne, 1992), which asks "In general, would you say your health is: poor, fair, good, very good, or excellent?". Participants indicated their disability status as per the recommendations from Madden et al. (2020). This item asks whether participants experience difficulty due to a long-term health condition or impairment (e.g., physical and cognitive difficulties, or mental health conditions) in any of a range of life activities (e.g., self-care; work, education or training; communication). There are three possible response options (1 - *no difficulty*; 2 – *difficulty managed via the use of equipment, technology, assistance or other techniques*; 3 – *sometimes or always experiences difficulty even with the use of supports*). Participants also reported the current frequency of cigarette, cigar, pipe, or any other tobacco product use. Response options included '*daily*', '*at least weekly (not daily)*', '*less often than weekly*' and '*not at all*'.

3.3.3 Lifestyle behaviours

Physical activity (PA) was measured using the single-item measure of PA (Milton et al., 2011), reflecting the number of days in the past week on which at least 30 minutes of moderate to vigorous PA was completed. Acceptable measurement properties have been established,

including concurrent validity with accelerometry-based measures (Milton et al., 2013; O'Halloran et al., 2020).

Sleep quality was assessed using a validated single-item Sleep Quality Scale (Snyder et al., 2018). Participants rated the overall quality of their overnight sleep in the previous 7 days. Responses ranged from 0 (*terrible*) to 10 (*excellent*). Snyder et al. (2018) demonstrated strong performance of the single-item scale across a range of psychometric characteristics including concurrent criterion, convergent, divergent and known-groups validity.

The CSIRO (Commonwealth Scientific and Industrial Research Organisation) Healthy Diet Score survey (Hendrie, Baird, et al., 2017) was used to assess overall diet quality. Across 38 items, participants reported their habitual intake of fruits, vegetables, grains, meat and alternatives, dairy and substitutes, healthy fats, beverages, and discretionary foods. For each item, consumption frequency (i.e., *daily; weekly; monthly; never*) was indicated, before estimating the total number of serves consumed in the selected timeframe. The scoring algorithm considers data on quantity, quality and variety of dietary intake, with this scoring process explained in greater detail elsewhere (Hendrie, Baird, et al., 2017; Hendrie et al., 2018, 2021; Hendrie, Rebuli, et al., 2017). In brief, an overall 'diet score' is produced ranging from 0 to 100, providing a valid estimation of compliance with relevant Australian Dietary Guidelines (ADG; DHAC, 2019) for participant age and gender. Higher scores on this measure reflect closer compliance to dietary guidelines, namely, higher diet quality. The serves for food groups differ according to age group in the dietary guidelines based on the nutrient requirements at different stages of life, which aligns with the broad age groupings used in the recommendations (i.e., in years: 19-50; 51-70; over 70). We note here that the ADG present recommendations within age groupings that were broader than the age groupings used to capture demographic information in the current sample (i.e., in years: 18-24; 25-34; 35-44; 45-54; 65-74; 75+ years). As such, the ADG age groupings do not completely align with the age groupings used in the present study. As a result, the diet score calculations for a small proportion of participants were based on guideline compliance for an older (i.e., for those aged 18 the 19-50 ADG guidelines were used) or younger (i.e., for those aged 51-54 or 71-74 the 19-50 and 51-70 ADG guidelines were used, respectively) age group.

3.3.4 Mental health outcomes

Distress was measured using the Kessler 10-item scale (K10; $\alpha = 0.93$; Kessler et al., 2002), which assesses the frequency of various non-specific distress symptoms (e.g., "tired out for no good reason") over the previous month. Item responses range from 1 (*none of the time*) to 5 (*all of the time*). Summing across all items yields a total distress score ranging from 10 to 50 with higher scores reflecting greater distress. Although there is some debate about the dimensionality of the scale (Lace et al., 2019), excellent reliability and validity of the total distress score has been extensively established (Sampasa-Kanyinga et al., 2018).

The Mental Health Continuum – Short Form (MHC-SF; $\alpha = 0.91$; Lamers et al., 2011) was used to measure wellbeing. The MHC-SF comprises three subscales tapping emotional ($\alpha = 0.88$), psychological ($\alpha = 0.84$), and social wellbeing ($\alpha = 0.80$) dimensions. Participants report the frequency of feelings (e.g., "that your life has a sense of direction or meaning to it") over the previous month using a 6-point scale (*never; once or twice; about once a week; about 2 or 3 times a week; almost every day; every day*). Wellbeing was operationalised using a total wellbeing score by summing across all items. Possible scores ranged between 0 and 70, with higher scores reflecting greater wellbeing. The psychometric properties of the MHC-SF have been established in both general and clinical populations (for review, see Iasiello et al., 2022).

3.4 Data cleaning and analysis

All data handling and analyses were conducted in *R* version 4.2.2 (R Core Team, 2022). Initially, BMI was calculated for each participant and operationalised categorically (i.e., underweight, normal range, overweight, or obese) according to established cutoffs (AGDHC, 2021). A 'smoker status' categorical variable was also created from smoking frequency responses with '*daily*', '*irregular*' (i.e., at least weekly (not daily); or, less often than weekly), and 'non-smoker' (i.e., not at all) levels.

A priori sample size estimation is not typically conducted for decision tree analyses, although simulation studies suggest that prediction accuracy and specificity of subgroup identification improves with larger samples (Venkatasubramaniam et al., 2017). The few studies that have used decision trees to predict mental health outcomes have ranged in sample sizes from fewer than 400 to over 70,000 participants (Battista et al., 2023; T. A. Burke et al., 2018). To align with recent surveys investigating behavioural correlates of distress and wellbeing (S.-R. Wickham et al., 2020), and to allow the data to be split into training and test samples, we aimed to achieve a final sample size of approximately 1500 individuals.

In total, n = 2000 participants completed the survey. As per standard CSIRO Healthy Diet Score data cleaning protocols (Hendrie et al., 2021), n = 2 participants with biologically implausible anthropometric data (i.e., BMI less than 13 or greater than 97 kg/m^2, height less than 1 metre or greater than 3 metres) were removed. In line with Battista et al. (2022, 2023), only complete cases were taken forward, resulting in a final sample of n = 1496 participants. The *rsample* package (v1.2.0; Frick et al., 2023) was used to split the sample into training (n = 1269, 85%) and testing (n = 227, 15%) datasets stratifying by age group, following the splitting rule suggested by Joseph (2022). Although we focused on hypothesis generation, we employed a testing and training split of the data to gain an understanding of how well the identified models predicted out-of-sample observations.

Employment status was significantly associated with all other categorical variables based on pairwise chi-square tests with Bonferroni adjustments to correct for multiple comparisons (Bonferroni, 1936) and was not included as a predictor in subsequent models. All other categorical variables had at least one non-significant pairwise association and thus were retained. The final set of predictors included these categorical variables as well as PA, diet score and sleep quality (PA, diet score and sleep quality showed no evidence of significant multi-collinearity). Models for distress also featured the total wellbeing score as a predictor, and vice versa for wellbeing models.

Two complementary modelling approaches were undertaken. Conditional inference trees (CTREE; Hothorn et al., 2006) were conducted as the primary analysis using the *partykit* package (Hothorn & Zeileis, 2015). A type of decision tree, CTREE works by recursively partitioning the sample into smaller, distinct subgroups that share incrementally greater similarity in the dependent variable. Each splitting decision involves a two-step process (Hothorn et al., 2006; Venkatasubramaniam et al., 2017). First, a regression model appropriate to the class of outcome is fitted, and the predictor most strongly associated with the outcome is selected as the splitting variable. Second, the best binary split point of the predictor variable is determined to ensure that the two resulting groups (i.e., child nodes) are maximally differentiated on the outcome variable. Splitting continues until there are no predictors significantly associated with the outcome variable. As an additional stopping rule, we specify that a split would only occur if the child nodes each contained at least 20% of the data from the parent node; this produced visually interpretable trees from the model. Separate CTREEs were generated for distress and wellbeing, respectively.

Separate linear regression models for distress and wellbeing were also fit using the lm function, with backwards stepwise selection performed using the AIC criterion (Akaike, 1998) as per Battista et al. (2022, 2023). These variable-centric analyses contributed to investigating the shared and unique predictors of distress and wellbeing, however the primary purpose was to provide a comparison to CTREE results. All models were trained using the training data, with out of sample prediction accuracy investigated using the testing data. CTREE models were visualised using *partykit* and *ggparty* (v1.0.0; Borkovec & Madin, 2019). Prediction accuracy was estimated for each model using root mean squared error (RMSE) and R^2, with these values extracted using the *yardstick* package (v1.2.0; Kuhn et al., 2023). The total number of unique variables included in CTREE and final backwards selected linear models was evaluated as an indicator of model parsimony.

3. Results

3.1 Sample characteristics

Characteristics of the full sample are summarised in Table 1 (see Table A1 in the appendix for separate training and testing sample characteristics). The sample showed moderate-high average distress (mean K10 < 23) and good wellbeing (mean MHC-SF > 42). Compared with Australian population data from the 2021 Census (ABS, 2021), the sample had a slightly younger age distribution and a higher proportion of female respondents (55% female in present sample vs 50.7% in population). The sample broadly mirrored the broader population regarding relationship status, BMI category, employment, education and Aboriginal and/or Torres Strait Islander status. One in six participants (16.8%) accumulated 30 minutes or more of PA on five or more days, less than the national average (ABS, 2022). Average sleep quality was similar to previous non-clinical samples (Snyder et al., 2018). Diet scores were highly variable and were lower than recent estimates (n = 235,268, mean = 55.0; *SD* = 11.7; Baird & Hendrie, 2023).

3.2 CTREE modelling of distress and wellbeing

3.2.1 Distress

Eight unique variables were used to segment the sample into 18 subgroups, ranging from 28 (Nodes 18) to 111 (Node 31) participants (Figure 1; below). The first splitting variable was disability status, with lower distress found among participants reporting no disability. Wellbeing featured prominently as a differentiator of distress scores at multiple levels, with sleep quality and age emerging in multiple locations as splitting variables. Notably, lifestyle behaviours (PA) and personal attributes (smoking status) only differentiated distress for people without a reported disability, whereas distress in people with a reported disability was determined by their wellbeing and socio-demographics (age, gender, and relationship status). The highest distress scores were found among people living with a disability and with low wellbeing (i.e., MHC-SF <21; Node 23; mean = 32.8, *SD* = 8.54). In contrast, lowest distress scores were middle-aged to older adults (> 35 years) who reported no disability, greater wellbeing (MHC-SF > 50) and sleep quality greater than 7 (Node 20; mean = 13.6; *SD* = 1.79). Distress scores were also low among participants with a disability, aged over 55 years, who reported greater wellbeing (Node 35; mean = 14.4; *SD* = 3.24). When applied to predict distress outcomes in the test data, the CTREE model had an adjusted R^2 of 0.33, and RMSE of 7.63.

Table 1. Sample characteristics

Variable	N = 1,496[1]
Mental health outcome	
Mental wellbeing	42.54 (15.01)
Psychological distress	22.70 (9.06)
Socio-demographics	
Age	
18-24	168 (11%)
25-34	312 (21%)
35-44	310 (21%)
45-54	245 (16%)
55-64	206 (14%)
65-74	153 (10%)
75+	102 (6.8%)
Gender	
Female	822 (55%)
Male	674 (45%)
Other	0 (0%)
Relationship status	
Married	624 (42%)
Not married	872 (58%)
Employment status	
Casual	80 (5.3%)
Don't know	1 (<0.1%)
Full-time employed (permanent or contract) including self-employed	576 (39%)
Part-time employed (permanent or contract) including self-employed	266 (18%)
Prefer not to say	6 (0.4%)
Retired	272 (18%)
Stay-at-home parent/carer	89 (5.9%)
Student	44 (2.9%)
Unable to work	71 (4.7%)
Unemployed but seeking work	84 (5.6%)
Volunteer work	7 (0.5%)
Income	
< $12k	44 (2.9%)
$12k - $20k	60 (4.0%)
$20k - $40k	222 (15%)
$40k - $60k	217 (15%)
$60k - $80k	217 (15%)
$80k - $100k	177 (12%)
$100k - $150k	259 (17%)
$150k - $200k	139 (9.3%)
> $200k	68 (4.5%)
Prefer not to say	72 (4.8%)
Don't know	21 (1.4%)
Education	
Secondary education - Years 9 and below	40 (2.7%)

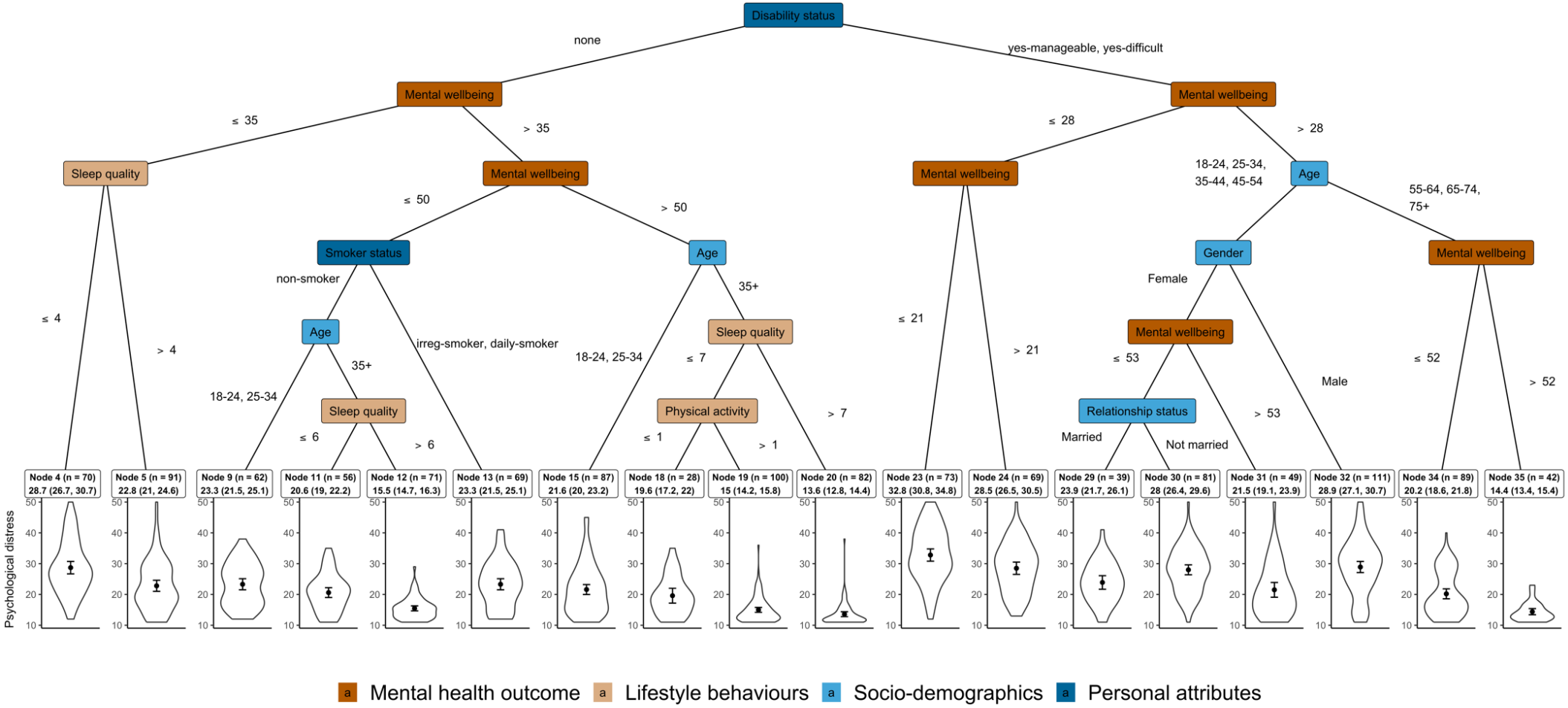
Secondary education - Year 1 and 11	141 (9.4%)
Secondary education - Year 12	236 (16%)
Certificate I & II level	29 (1.9%)
Certificate III & IV level	258 (17%)
Advance diploma and diploma level	159 (11%)
Bachelor's degree level	388 (26%)
Graduate diploma and graduate certificate level	89 (5.9%)
Postgraduate degree level	156 (10%)
Personal attributes	
Self-reported health	
Poor	69 (4.6%)
Fair	314 (21%)
Good	642 (43%)
Very good	353 (24%)
Excellent	118 (7.9%)
Difficulty due to long term health condition	
None	851 (57%)
Yes - Manageable	444 (30%)
Yes - Difficult	201 (13%)
BMI category	
Healthy Weight	587 (39%)
Obese	394 (26%)
Overweight	484 (32%)
Underweight	31 (2.1%)
Smoker status	
Non-smoker	1,034 (69%)
Irregular smoker	177 (12%)
Daily smoker	285 (19%)
Lifestyle behaviours	
Sleep quality	5.64 (2.41)
Diet score	44.93 (12.35)
PA days	3.00 (2.22)

[1]Mean (SD); n (%); Mental wellbeing = Total wellbeing score on Mental Health Continuum - Short Form; Distress = Total score on K10 scale.

3.2.2 Wellbeing

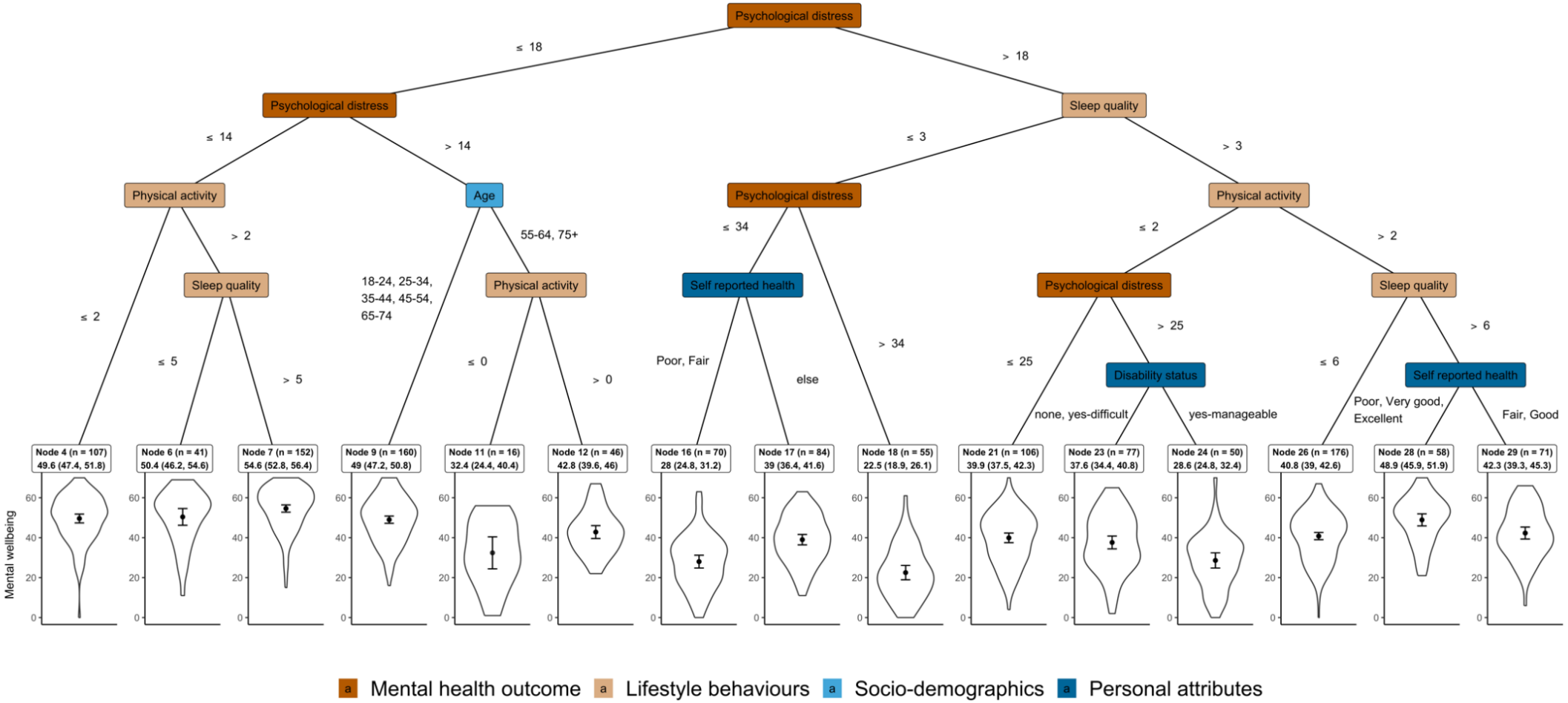
The wellbeing CTREE (Figure 2; below) identified 15 subgroups, with splits made using six unique predictors. Final subgroups ranged in size from 16 (Node 11) to 176 (Node 26). Distress was the primary splitting variable, with a K10 cutoff of 18 selected as the best differentiator of wellbeing scores at the first level of the tree. Sleep quality, PA and self-reported health appeared in multiple locations throughout the tree. For people with mild-to-low distress (K10 < 18), age and lifestyle behaviours were influential in distinguishing levels of wellbeing, whereas for people with high distress lifestyle behaviours and socio-demographics best separated wellbeing. The highest wellbeing scores were reported by those with the lowest distress, good amounts of PA, and good sleep quality (Node 7; mean = 55.6; *SD* = 11.10). However, higher wellbeing was also observed in a subgroup with higher distress (i.e., K10 > 18 at first split) who reported greater

Figure 1. Conditional inference tree (CTREE) for severity of psychological distress as measured by Kessler 10-item scale total score



Note. Numbers presented in boxes above terminal node plots represent the subgroup mean distress score with 95% confidence intervals presented in parentheses. These figures are visualised in the terminal node plots.

Figure 2. Conditional inference tree (CTREE) for mental wellbeing as measured by the Mental Health Continuum – Short Form total wellbeing score



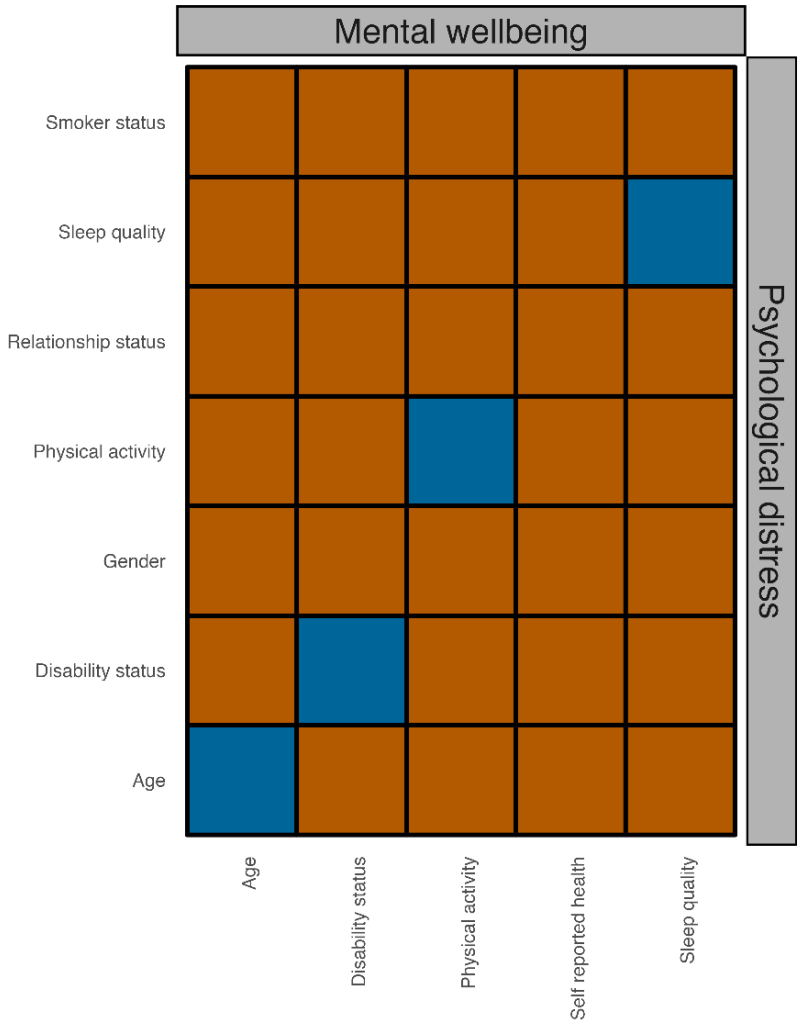
Note. Numbers presented in boxes above terminal node plots represent the subgroup mean wellbeing score with 95% confidence intervals presented in parentheses. These figures are visualised in the terminal node plots.

sleep quality, PA, and self-reported health (Node 28; mean = 58.9; *SD* = 11.42); almost paradoxically, people with high distress, good sleep quality and good PA, but poorer self-reported health also exhibited strong wellbeing. Node 18 reported the lowest wellbeing scores (mean = 22.5; *SD* = 13.35). This subgroup was characterised by higher distress (K10 > 34), and poorer sleep quality. Regarding out of sample prediction accuracy, the wellbeing CTREE achieved an adjusted R^2 of 0.36, and RMSE of 12.31.

3.3 Shared and unique predictors of distress and wellbeing

Shared and unique predictors of distress and wellbeing were evaluated by comparing the splitting variables from the CTREEs for each outcome. Wellbeing (i.e., MHC-SF total score) was a significant predictor of psychological distress (i.e., K10 total score), and vice versa. Age, disability status, sleep quality, and PA featured as splitting variables in both CTREEs (Figure 3). On each occasion that sleep quality and PA functioned as the splitting variable, greater scores on these lifestyle behavioural measures resulted in child nodes with better mental health (i.e., lower distress, or higher wellbeing). Self-reported health differentiated wellbeing scores, but not distress. Conversely, gender and smoker status differentiated distress but did not feature in the CTREE for wellbeing. Despite being included in both models, income, education, BMI and diet score did not appear as explanatory splitting variables in this sample.

Figure 3. Shared and unique predictors of distress and wellbeing based on splitting variables appearing in each respective CTREE model



Note. Blue indicates variable was significant predictor of both outcomes. Rows without blue indicate variable significant only for distress. Columns without blue indicate variable only significant for wellbeing.

3.4 Comparison of CTREE with linear regression models

The final distress linear model featured ten unique predictor variables (Table B2 in the appendix) including every predictor except PA from the CTREE predictors plus three additional variables (i.e., income, education, self-reported health). Inspection of plotted residuals revealed issues with non-linearity at the lower bound of distress scores and violations of normality at higher levels of distress (Figure B1 in the appendix). We decided not to perform any further data handling as linear regression analyses were intended to provide a comparison to CTREE analyses rather than informing generalisable conclusions. Overall, model coefficients were in expected directions across all predictors including lifestyle behaviours, however, these results should be viewed with a degree of caution as the model failed to meet assumptions. The distress linear model outperformed CTREE in terms of prediction accuracy, with a higher adjusted R^2 (0.41) and lower RMSE (7.12), although CTREE offered greater parsimony.

The linear model for predicting wellbeing met all assumptions as determined by visual inspection of the residuals, with mild non-linearity and non-normality at the tails (Figure B2 in the appendix). This model featured nine unique predictors suggesting the CTREE is more parsimonious (Table B2 in the appendix). Relationship status, education, BMI, and diet score were predictors in the linear model but did not appear in the CTREE, while disability status was a splitting variable in the CTREE but did not feature in the linear model. Otherwise, each modelling approach highlighted the same set of significant predictors. Increasing sleep ($\beta = 1.06$, 95% CI: 0.75, 1.37), diet score ($\beta = 0.13$, 95% CI: 0.07, 0.18), and PA ($\beta = 0.88$, 95% CI: 0.56, 1.21) each predicted greater wellbeing, while greater psychological distress predicted lower wellbeing ($\beta = -0.57$, 95% CI: -0.66, -0.49). Wellbeing was also higher among married participants, and those with greater self-reported health. Compared to CTREE, out of sample prediction accuracy was slightly worse for the wellbeing linear model (adjusted $R^2 = 0.33$; RMSE = 12.44).

4. Discussion

This cross-sectional study explored interactions between lifestyle behavioural and socio-demographic predictors of distress and wellbeing using conditional inference trees (CTREE; Hothorn et al., 2006), a relatively novel method in population mental health research. Consistent with most extant literature (Firth et al., 2020), lifestyle behaviours emerged as important differentiators of each mental health outcome. Specifically, PA and sleep quality were represented as splitting variables in CTREE modelling of both distress and wellbeing outcomes. In contrast, self-reported health was included as a differentiator of wellbeing, but not for distress, and diet was not included in either model.

The results for lifestyle behaviours differ from previous studies indicating that PA, diet and sleep did not feature as splitting variables in decision tree analyses (Battista et al., 2022, 2023). These divergent results may be partially explained by differences in study samples. Battista and colleagues' sample were adolescent school students whereas the present study included a broad spectrum of adults. Compared with adults, it is possible that some aspects of mental health are more strongly associated with external factors for adolescents, whose lives are often characterised by intense interpersonal pressures and who have limited autonomy in deciding the contexts in which they live and learn. In contrast, engagement in lifestyle behaviours may be more influential in shaping mental health outcomes among adults. Recent research aims to better characterise the most important predictors of distress and wellbeing within specific age groups such as among children and adolescents (Lereya et al., 2022; Patalay & Fitzsimons, 2016, 2018), although further research is needed to explore the key differentiators of distress and wellbeing across the lifespan.

Regarding specific lifestyle behaviours, our results presented a consistent signal for sleep quality as an important predictor of both wellbeing and distress. In line with previous research (Wickham et al., 2020), sleep quality was a significant predictor of distress and wellbeing in both CTREE and linear modelling. Thus, results suggest a strong association between sleep and optimal outcomes across the two mental health axioms. This finding is unsurprising given that impaired sleep is causally implicated in the aetiology of numerous mental health disorders, while poor mental health also has deleterious effects on sleep quality (Scott et al., 2021). Conversely, better sleep is associated cross-sectionally with optimal wellbeing (Smith & Lee, 2022), and longitudinal improvements in sleep result in improved depression, anxiety, psychotic experiences, and wellbeing (Freeman et al., 2017).

In contrast to sleep, the results for other lifestyle behaviours were equivocal. For example, PA featured only once as a splitting variable in the distress CTREE but appeared multiple times in the wellbeing CTREE. The latter finding partly supports previous literature that has repeatedly supported PA as a significant predictor of both distress and wellbeing in a range of observational and interventional research studies (Marconcin et al., 2022; Singh et al., 2023; Wickham et al., 2020). Following the interpretation of Battista and colleagues (2022), it could be that other factors such as age, sleep and diet quality are more strongly associated with distress than PA as an individual health behaviour that has typically been investigated in isolation. Indeed, in the current study PA only appeared as a splitting variable among participants without a reported disability indicating that the relationship between increased PA and reduced distress may vary depending on socio-demographic differences. Finally, diet quality did not feature in the CTREE models but was an important differentiator in the linear model for wellbeing with higher diet quality predicting greater wellbeing. This finding partly aligns with prior research, which found that fruit and vegetable intake predicted wellbeing, but not distress (Wickham et al., 2020). The discrepant findings may be explained by differences in samples as the previous study focused on young adults aged 18-25 while the current study included a broader sample of adults. Furthermore, the present study used a more comprehensive measure of overall dietary quality, which considered both 'protective' (e.g., fruit and vegetable intake) and 'risky' (e.g., discretionary intake) dietary behaviours. In contrast, previous research focused only on 'protective' dietary behaviours. Thus, the inclusion of discretionary intake in the current study may have tapped into the positive correlation evident between this dietary behaviour and psychological distress in previous work (Grieger et al., 2022).

Finally, in relation to lifestyle behaviours, inspection of the wellbeing CTREE revealed two major branches. Psychological distress functioned as the primary splitting variable, with greater wellbeing observed among those with low to moderate distress. As previously mentioned, the subgroup with the highest wellbeing was found on this low distress branch of the tree. Despite higher levels of distress, individuals with sufficient sleep quality and who did $\geq$30 minutes PA on at least 3 days per week maintained good levels of wellbeing especially in those with very good or excellent self-reported health. While these cross-sectional CTREE results should be viewed as exploratory, this pattern of interacting predictors suggests that engaging in a broad range of healthy lifestyle behaviours may allow individuals to maintain high levels of wellbeing in the presence of elevated distress. This latter point is consistent with literature describing the clustering of health-related behaviours, with healthier behavioural profiles promoting favourable mental health outcomes (Di Benedetto et al., 2020; Mahon et al., 2022). Greater wellbeing could also be functioning as a protective resource by buffering against the detrimental effects of distress on the ability to engage in health behaviours (Stenlund et al., 2021; Steptoe & Fancourt, 2019). Bi-directional relationships are perhaps even more likely, wherein health

behaviours and wellbeing are mutually reinforcing (Stenlund et al., 2022; Steptoe & Fancourt, 2020). Regardless of directionality, this observation underlines the utility of CTREE models to depict complex interactions between multiple predictors in an easily interpretable fashion.

4.1 Implications for bivariate conceptualisations of mental health

In the CTREE models, distress was arguably the most important differentiator of wellbeing and vice versa. For example, in the wellbeing CTREE, the highest levels of wellbeing were observed in the subgroup characterised by very low distress, good PA, and good sleep quality. Similarly, the pattern of predictors for the subgroup with the lowest wellbeing was also simple, featuring two splits on the distress variable interspersed by sleep quality. These patterns suggest that under conditions of very high or low distress, the relationship between wellbeing and distress could arguably best be described as bipolar (Zhao & Tay, 2023). Nevertheless, other results more consistently indicate a bivariate relationship between distress and wellbeing. First, in the wellbeing CTREE, the relationships between the two mental health outcomes were more complex and interrelated with lifestyle behavioural, demographic, and health-related predictors at moderate levels of distress. Similarly, wellbeing was a prominent splitting variable in the distress CTREE, but subgroup identification occurred via pathways in which wellbeing interacted with lifestyle behaviours, socio-demographics and personal attributes.

Consistent with previous research (Kinderman et al., 2015; Patalay & Fitzsimons, 2016), the predictors of distress were often different to those of wellbeing. Indeed, self-reported health was an important differentiator of wellbeing, but not of distress. In contrast, gender and smoker status did not feature in the wellbeing CTREE. Finally, several subgroups were identified that should not exist under a bipolar conceptualisation of mental health. This includes the group described above who reported favourable profiles of sleep, PA, and self-reported health, as well as high levels of wellbeing and higher distress. In addition, the highest mean distress score of any group was found in a subgroup of people with a disability and low wellbeing, whereas individuals with similar wellbeing but no disability reported smaller amounts of distress. In sum, these results align with a bivariate conceptualisation of mental health, wherein wellbeing and distress are overlapping but distinct constructs with both shared and unique predictors.

The current findings have identified some specific priority sub-groups and the target mechanisms for intervention. For example, for individuals without a reported disability, it may be warranted to focus interventions on lifestyle behaviours including PA, sleep and smoking to improve distress outcomes, while for those with a disability, interventions focused on targeting wellbeing or interpersonal relationships may be more effective.

4.2 Strengths, limitations and future directions

A key strength of the present study was the bivariate conceptualisation of mental health, combined with a decision tree analysis approach. These features facilitated a nuanced exploration of interacting lifestyle behavioural, socio-demographic, and other predictors of distress and wellbeing; however, several limitations should be considered when interpreting findings. First, while the final analytical sample approximately mirrors the Australian population on several important socio-demographic variables, the mental health and lifestyle behavioural variables are possibly under-represented due to the small sample size. Recruiting a larger sample would improve representativeness and confidence in generalisability of the findings. In addition, future research may benefit from the inclusion of additional, more granular measures or study designs that allow for observed rather than self-reported health measures. For example, we used a measure of 'disability status' that included an array of long-term health conditions impacting

one's functioning, including physical and mental health conditions. More specific measures of current and historical mental health diagnoses would be beneficial, as well as a more comprehensive set of predictors (for example, see Rothenberg et al., 2023). Similarly, the use of global measures of distress and wellbeing may also belie more complex relationships occurring at the subdomain level (Mason Stephens et al., 2023). Future research may consider implementing separate depression and anxiety scales in addition to gain a better understanding of important differentiators of these common mental health presentations, and how they relate to different dimensions of wellbeing. To add a temporal and contextual dimension to this work, further research investigating distress and wellbeing changes following stressful life events (e.g., Cleland et al., 2016) and/or lifestyle behavioural interventions would be welcomed. Finally, the focus of the current exploration was on individual factors and therefore does not include complex social and cultural factors associated with psychological distress (Lomas et al., 2024; Mittelmark et al., 2004). As with all cross-sectional studies, we cannot determine causality, reverse causality, or other more complex reciprocal relationships between the variables specified here as outcomes and predictors. Accordingly, we should not assume that lifestyle behavioural improvements will necessarily lead to optimised mental health. Our results are largely supportive of lifestyle behaviours as important differentiators of distress and wellbeing, and meta-analyses of randomised controlled trials support the effectiveness of interventions targeting lifestyle behaviours to reduce mental health symptoms (Brinsley et al., 2025; Firth et al., 2020; Singh et al., 2023). However, evidence for lifestyle behavioural interventions to improve aspects of wellbeing is more limited (e.g., Brinsley et al., 2025). Further longitudinal research is required to develop our understanding of the lifestyle behavioural intervention characteristics that are effective in reducing distress and/or improving wellbeing, and the individual differences that moderate these outcomes. Such evidence will be essential to inform preventive mental health initiatives targeting lifestyle behaviours.

Another strength of this study involved the use of decision tree analysis as an interpretable and exploratory method for hypothesis generation. Although decision trees are known to lack generalisability and have poor predictive power (Abdulhafedh, 2022; Hastie, Tibshirani, Friedman, & Friedman, 2009), the current examination of the predictive accuracy of the CTREE analysis using a training and testing split of our data indicated that the decision trees performed similarly to the linear models. Cross validation may be more appropriate to measure the out-of-sample prediction of our models, but this was deemed inappropriate due to the instability of decision trees in small samples (Hastie et al., 2009). To improve the predictive power of CTREE approaches, future studies may consider using more generalisable methods such as random forests (Breiman, 2001). Random forests were not considered here as decision trees are more interpretable, and the underlying bootstrapping procedure employed in a random forest inflates the potential biases already present in the sample. Future research using a larger and more representative sample should aim to refine the hypothesis generation procedure by using a random forest approach as a feature selection method to identify the key predictors of distress and wellbeing, but feed only those predictors into the more interpretable decision tree analysis.

4.3 Conclusion

Modifiable lifestyle behaviours are important predictors of both psychological distress and mental wellbeing and should continue to be targeted in preventive mental health efforts. Our decision tree analyses positioned sleep quality as a prominent differentiator of both distress and wellbeing. Greater engagement in moderate to vigorous physical activity and overall diet quality had more nuanced associations. Lifestyle behaviours interacted in complex ways with other

mental health variables, as well as other factors such as age, disability status and self-reported health and decision tree modelling offered easily interpretable presentation. Decision trees could provide preventive mental health researchers with a complementary analytical approach that highlights priority sub-groups. For example, our analysis illustrated the relevance of disability status. Use of person-centric methods such as decision trees alongside traditional hypothesis testing (e.g., using regression methods) may provide more in-depth approach to intervention design.

Results from this study suggest that future preventive mental health research should adopt a bivariate framework to generate greater insights about the relationship between wellbeing and mental ill-health, and to sharpen investigations of lifestyle behavioural initiatives aimed at protecting and promoting mental health.

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Funding

This research was internally funded by the CSIRO Human Health program.

Conflict of interest statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Data availability statement

De-identified data are available on reasonable request from the corresponding author.

AI statement

AI was not used in the production of this manuscript.

Acknowledgements

The authors would like to thank Dr Gilly Hendrie and Megan Rebuli for their support with accessing and scoring the CSIRO Healthy Diet Score Survey.

Publishing Timeline

Received 4 November 2024
Revised version received 2 May 2025
Accepted 23 May 2025
Published 31 May 2025

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Appendices

Appendix A: Characteristics of overall, training, and testing samples

Table A1. Full sample, testing and training sample characteristics

Variable	Overall N = 1,496[1]	Testing N = 1,269[1]	Training N = 227[1]
Mental health outcome			
Mental wellbeing	42.54 (15.01)	42.59 (14.95)	42.32 (15.39)
Psychological distress	22.70 (9.06)	22.59 (9.01)	23.30 (9.34)
Socio-demographics			
Age			
18-24	168 (11%)	140 (11%)	28 (12%)
25-34	312 (21%)	266 (21%)	46 (20%)
35-44	310 (21%)	260 (20%)	50 (22%)
45-54	245 (16%)	208 (16%)	37 (16%)
55-64	206 (14%)	174 (14%)	32 (14%)
65-74	153 (10%)	130 (10%)	23 (10%)
75+	102 (6.8%)	91 (7.2%)	11 (4.8%)
Gender			
Female	822 (55%)	693 (55%)	129 (57%)
Male	674 (45%)	576 (45%)	98 (43%)
Other	0 (0%)	0 (0%)	0 (0%)
Relationship status			
Married	624 (42%)	525 (41%)	99 (44%)
Not married	872 (58%)	744 (59%)	128 (56%)
Employment status			
Casual	80 (5.3%)	65 (5.1%)	15 (6.6%)
Don't know	1 (<0.1%)	1 (<0.1%)	0 (0%)
Full-time employed (permanent or contract) including self-employed	576 (39%)	488 (38%)	88 (39%)
Part-time employed (permanent or contract) including self-employed	266 (18%)	225 (18%)	41 (18%)
Prefer not to say	6 (0.4%)	6 (0.5%)	0 (0%)
Retired	272 (18%)	231 (18%)	41 (18%)
Stay-at-home parent/carer	89 (5.9%)	75 (5.9%)	14 (6.2%)
Student	44 (2.9%)	36 (2.8%)	8 (3.5%)
Unable to work	71 (4.7%)	63 (5.0%)	8 (3.5%)
Unemployed but seeking work	84 (5.6%)	73 (5.8%)	11 (4.8%)

Volunteer work	7 (0.5%)	6 (0.5%)	1 (0.4%)
Income			
< $12k	44 (2.9%)	38 (3.0%)	6 (2.6%)
$12k - $20k	60 (4.0%)	54 (4.3%)	6 (2.6%)
$20k - $40k	222 (15%)	186 (15%)	36 (16%)
$40k - $60k	217 (15%)	183 (14%)	34 (15%)
$60k - $80k	217 (15%)	193 (15%)	24 (11%)
$80k - $100k	177 (12%)	144 (11%)	33 (15%)
$100k - $150k	259 (17%)	226 (18%)	33 (15%)
$150k - $200k	139 (9.3%)	113 (8.9%)	26 (11%)
> $200k	68 (4.5%)	55 (4.3%)	13 (5.7%)
Prefer not to say	72 (4.8%)	60 (4.7%)	12 (5.3%)
Don't know	21 (1.4%)	17 (1.3%)	4 (1.8%)
Education			
Secondary education - Years 9 and below	40 (2.7%)	34 (2.7%)	6 (2.6%)
Secondary education - Year 10 and 11	141 (9.4%)	121 (9.5%)	20 (8.8%)
Secondary education - Year 12	236 (16%)	199 (16%)	37 (16%)
Certificate I & II level	29 (1.9%)	23 (1.8%)	6 (2.6%)
Certificate III & IV level	258 (17%)	220 (17%)	38 (17%)
Advance diploma and diploma level	159 (11%)	133 (10%)	26 (11%)
Bachelor's degree level	388 (26%)	325 (26%)	63 (28%)
Graduate diploma and graduate certificate level	89 (5.9%)	75 (5.9%)	14 (6.2%)
Postgraduate degree level	156 (10%)	139 (11%)	17 (7.5%)
Personal attributes			
Self-reported health			
Poor	69 (4.6%)	55 (4.3%)	14 (6.2%)
Fair	314 (21%)	269 (21%)	45 (20%)
Good	642 (43%)	539 (42%)	103 (45%)
Very good	353 (24%)	299 (24%)	54 (24%)
Excellent	118 (7.9%)	107 (8.4%)	11 (4.8%)
Difficulty due to long term health condition			
None	851 (57%)	716 (56%)	135 (59%)
Yes - manageable	444 (30%)	384 (30%)	60 (26%)
Yes - difficult	201 (13%)	169 (13%)	32 (14%)
BMI category			
Healthy Weight	587 (39%)	496 (39%)	91 (40%)
Obese	394 (26%)	338 (27%)	56 (25%)
Overweight	484 (32%)	405 (32%)	79 (35%)
Underweight	31 (2.1%)	30 (2.4%)	1 (0.4%)

Smoker status			
Non-smoker	1,034 (69%)	876 (69%)	158 (70%)
Irregular smoker	177 (12%)	155 (12%)	22 (9.7%)
Daily smoker	285 (19%)	238 (19%)	47 (21%)
Lifestyle behaviours			
Sleep quality	5.64 (2.41)	5.64 (2.42)	5.62 (2.36)
Diet score	44.93 (12.35)	44.87 (12.34)	45.26 (12.47)
PA days	3.00 (2.22)	3.01 (2.19)	2.99 (2.36)

[1]Mean (SD); n (%); Mental wellbeing = Total wellbeing score on Mental Health Continuum - Short Form; Distress = Total score on K10 scale.

Appendix B. Linear regression model summaries and diagnostic plots

Table B1. Backwards selection linear regression results

	Distress			Wellbeing		
Variable	**Beta**	**95% CI[1]**	**p-value**	**Beta**	**95% CI[1]**	**p-value**
Mental health outcome						
Mental wellbeing^	-.19	-.21, -.16	<0.001			
Psychological distress				-0.57	-.66, -.49	<0.001
Socio-demographics						
Age^, #						
18-24	—	—		—	—	
25-34	-1.9	-3.4, -.45	0.011	-0.59	-3.2, 2.0	0.7
35-44	-4.6	-6.2, -3.1	<0.001	-3.6	-6.3, -.95	0.008
45-54	-5.8	-7.4, -4.2	<0.001	-4.0	-6.8, -1.2	0.005
55-64	-8.3	-10, -6.6	<0.001	-5.5	-8.6, -2.5	<0.001
65-74	-9.1	-11, -7.2	<0.001	-1.7	-5.0, 1.5	0.3
75+	-12	-14, -9.7	<0.001	-2.0	-5.6, 1.6	0.3
Gender^						
Female	—	—				
Male	1.2	0.33, 2.0	0.006			
Relationship status^						
Married	—	—		—	—	
Not married	-0.71	-1.6, .15	0.10	-1.9	-3.3, -.43	0.011
Income						
< $12k	—	—				
$12k - $20k	-3.5	-6.4, -0.59	0.018			
$20k - $40k	-4.2	-6.6, -1.7	0.001			
$40k - $60k	-3.0	-5.5, -0.52	0.018			
$60k - $80k	-3.9	-6.4, -1.5	0.002			
$80k - $100k	-4.2	-6.7, -1.7	<0.001			
$100k - $150k	-4.6	-7.0, -2.2	<0.001			
$150k - $200k	-5.4	-8.0, -2.8	<0.001			
> $200k	-5.9	-8.8, -3.0	<0.001			
Prefer not to say	-6.7	-9.5, -3.8	<0.001			
Don't know	-5.5	-9.5, -1.5	0.007			
Education						
Secondary education - Years 9 and below	—	—		—	—	
Secondary education - Year 10 and 11	.33	-2.3, 3.0	0.8	-1.3	-5.9, 3.3	0.6

Secondary education - Year 12	-2.2	-4.7, 0.39	0.10	0.67	-3.8, 5.1	0.8
Certificate I & II level	-.23	-3.9, 3.4	>0.9	2.5	-3.9, 8.9	0.4
Certificate III & IV level	-1.5	-4.0, 1.1	0.3	0.57	-3.8, 5.0	0.8
Advance diploma and diploma level	-1.0	-3.7, 1.6	0.4	1.8	-2.8, 6.4	0.4
Bachelor's degree level	-.80	-3.3, 1.7	0.5	2.4	-2.0, 6.7	0.3
Graduate diploma and graduate certificate level	0.96	-1.9, 3.8	0.5	4.4	-.52, 9.4	0.079
Postgraduate degree level	0.10	-2.6, 2.8	>0.9	4.3	-.35, 8.9	0.070
Personal attributes						
Self-reported health[#]						
Poor	—	—		—	—	
Fair	-2.9	-4.9, -0.81	0.006	0.55	-3.0, 4.1	0.8
Good	-3.3	-5.4, -1.3	0.001	3.1	-.41, 6.7	0.083
Very good	-3.4	-5.6, -1.2	0.002	6.6	2.8, 10	<0.001
Excellent	-1.5	-4.0, 0.88	0.2	6.9	2.6, 11	0.002
Difficulty due to long term health condition[^, #]						
None	—	—				
Yes - Manageable	3.6	2.6, 4.5	<0.001			
Yes - Difficult	1.9	0.74, 3.1	0.001			
Smoker status[^]						
Non-smoker	—	—				
Irregular smoker	2.5	1.2, 3.7	<0.001			
Daily smoker	2.1	1.0, 3.1	<0.001			
BMI category						
Healthy weight				—	—	
Obese				0.91	-.88, 2.7	0.3
Overweight				-0.08	-1.7, 1.6	>0.9
Underweight				6.5	2.0, 11	0.005
Lifestyle behaviours						
Sleep quality[^, #]	-0.45	-0.62, -0.27	<0.001	1.1	.76, 1.4	<0.001
Diet score				0.13	.07, .18	<0.001
PA days[^, #]				0.88	.56, 1.2	<0.001

[1]CI = Confidence Interval; Mental wellbeing = Total wellbeing score on Mental Health Continuum - Short Form; Distress = Total score on K10 scale. ^predictor in distress CTREE. #predictor in wellbeing CTREE.

Figure B1. Psychological distress LM diagnostic plots

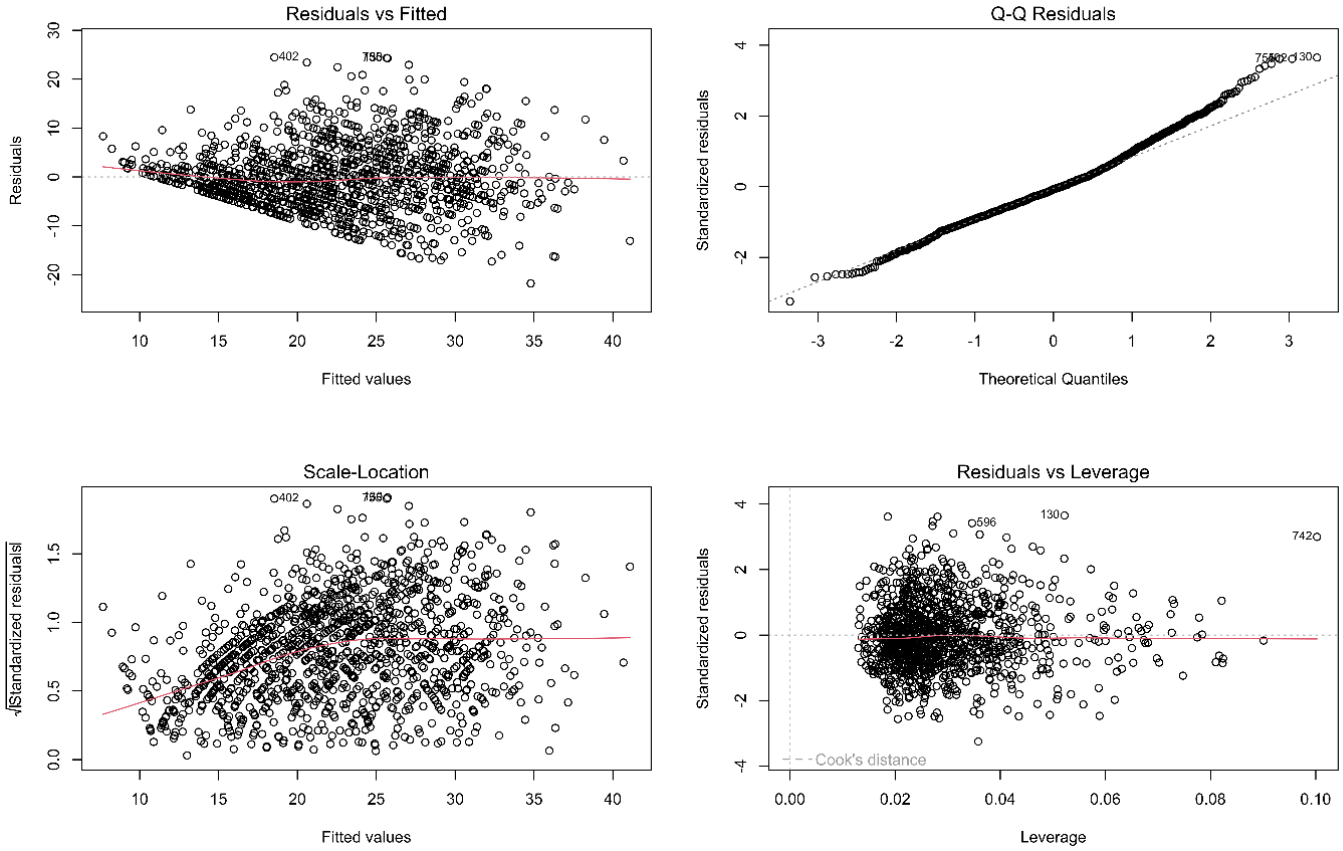

Figure B2. Mental Wellbeing LM diagnostic plots