One slope does not fit all: Longitudinal trajectories of quality of life in older adulthood

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Abstract

Purpose: Maintaining or improving quality of life (QoL) in later life has become a major policy objective. Yet we currently know little about how QoL develops at older ages. The few studies that have modelled QoL change across time for older adults have used 'averaged' trajectories. However, this ignores the variations in the way QoL develops between groups of older adults.

Methods: We took a theoretically informed 'capabilities approach' to measuring QoL. We used four waves of data, covering six years, from the New Zealand Health, Work and Retirement Study (NZHWR) (N = 3223) to explore whether distinct QoL trajectories existed. NZHWR is a nationally representative longitudinal study of community-dwelling adults aged 50+ in New Zealand. Growth mixture modelling was applied to identify trajectories over time and multinomial regressions were calculated to test baseline differences in demographic variables (including age, gender, ethnicity, education and economic living standards).

Results: We found five QoL trajectories: 1) high and stable (51.94%); 2) average and declining (22.74%); 3) low and increasing (9.62%); 4) low and declining (10.61%); 5) low and stable (5.09%). Several differences across profiles in baseline demographic factors were identified, with economic living standards differentiating between all profiles.

Conclusions: The trajectory profiles demonstrate that both maintaining and even improving QoL in later life is possible. This has implications for our capacity to develop nuanced policies for diverse groups of older adults.

Keywords: capabilities approach; CASP; latent class growth analysis; longitudinal; quality of life; trajectory analysis

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The Vienna International Plan of Action on Ageing was a watershed document identifying quality of life (QoL) as “no less important than longevity” in global efforts to respond to rapid population ageing [1, p. 5]. For over three decades, the improvement of QoL has been a critical indicator of the success of healthy ageing policies [2-5]. While there is ample evidence to indicate we have succeeded in increasing longevity, there is still a considerable lack of evidence as to whether QoL is improving and, if so, for whom [6].

The Vienna Plan and subsequent strategy documents recognise that the QoL of older adults is a heterogeneous, rather than a homogeneous, experience [2-3]. However, two main aspects of our current approach to QoL research in later life hamper this exploration of heterogeneity. First, there is concern that much social science research still focuses on the ‘averaged experience’ [7], which fails to recognise the diverse pathways that individuals can take as they age. Second, despite the inherent multidimensionality of the QoL experience reflecting an “amorphous, multi-layered and complex concept with a wide range of components” [8, pp. 3], research on the QoL of older populations has been dominated by single-dimension indicators of health or functional status [9]. There is a growing call for the use of ‘agentic’ QoL measures that focus less on older adults’ health status and more on their “freedom to do the things they want to do without restriction” [10, pp. 827].

A Capabilities-based Conceptualisation of QoL in Old Age

Many previous QoL studies have employed a deficit-based medical model conceptualizing QoL in terms of physical health and absence of disease [11-14]. This approach to QoL equates good health with good QoL, and poor health with poor QoL. Yet a growing body of work demonstrates that health status is not a reliable proxy for QoL [15-17].

Further, the assumption that poor health reflects poor QoL discriminates against those with a lived experience of anything other than perfect health [18-19].

Critical scholarship on QoL at older age has been shifting towards a model based on the ‘capabilities approach’ [20-21], which locates the potential for good QoL not in one’s health status but in one’s ability to live according to valued goals [22]. Thus, the capabilities approach acknowledges that people experience their QoL in different ways, and that diversity in achieving good QoL is underpinned by the opportunities people have throughout the lifespan to access resources [23-24]. These include opportunities that afford a person to have freedom to live according to their values, to have control over decisions, to engage in activities they enjoy, and to flourish.

Importantly, what people value changes as they transition through different life stages and so does the way they experience their QoL [25]. Conceptualizing QoL in terms of capabilities to live a life one has reason to value can account for this diversity and enable comparisons across the life course and social contexts. The capabilities approach provides a theoretical framework for understanding QoL “without restricting the scope of study into specific types of outcomes” [26, pp. 6] and, thus, it offers a social justice approach to developing policies and interventions to promote QoL that take into account inequalities and diverse needs.

We conceptualize QoL within the capabilities framework. Accordingly, we have used a measure developed which captures an older adult’s capacity for control and autonomy, self-realization and pleasure in their lives. This is known by the acronym CASP [27]. The CASP has rapidly gained a foothold in QoL research globally as an older adult specific QoL measure. It is a core indicator of QoL in many population studies on ageing, such as the English Longitudinal Study on Ageing (ELSA), the Irish Longitudinal Study on Ageing (TILDA), the Study of Health, Ageing and Retirement in Europe (SHARE), or the New Zealand Health, Work and Retirement Study (NZHWR) [28]. The inclusion of the CASP in longitudinal studies around the world offers opportunities for comparative analyses and evaluation of evidence across datasets on the shared and/or unique expressions of capabilities-based QoL across cultures and the identification of social and environmental contexts underpinning those trajectories.

Trajectories of QoL in Older Adulthood

Alongside its importance for policymakers, QoL has become a major focus for research on ageing, with a growing interest in factors associated with differences in QoL among older adults. Previous studies have mainly concentrated on exploring associations between QoL and indicators of social, economic, mental and physical wellbeing [29-34]. These investigations have led to a greater understanding of the nomological network of QoL, but at the same time have propagated a relatively static view of QoL in later life by taking QoL at a certain age as an endpoint through which to understand differences across individuals. They tell us little about *how* QoL develops as older people age and whether there are different trajectories for different groups of older people. This gap in our knowledge is remarkable given the evidence of increasing diversity and inequalities within the older population [35].

From the few studies that have explored trajectories of QoL in later life we can see that: i) QoL changes with age, but that this is not a linear decline, and ii) there is individual heterogeneity in the rate of change in QoL. Data from the first three waves of TILDA revealed an inverted-U shaped pattern for those aged 50 and over, with QoL reaching its peak at age 68 [36]. Conversely, data from ELSA showed a slow decline in QoL up to about age 75 and a more rapid decline thereafter [37]. Similarly, Asakawa and colleagues [38] found that the typical life-course trajectory of QoL in Canada followed a concave pattern with a slow decline until the age of 60 and a more rapid decline as people transitioned into older age. Finally, a study of trajectories of QoL amongst residents of senior housing in the United States found a steady decline with age [39]. This variability between countries suggests that there is no 'natural' rate of age-related change in QoL, but that it is conditioned by socio-cultural contexts.

However, a key limitation of existing research on trajectories of QoL in later life is the assumption that a single population pattern accurately describes the lived experience of older adults. Assuming population homogeneity around a common trajectory may not be the most appropriate method by which to estimate trajectories of QoL. For example, both Zaninotto and colleagues [37] and Ward and colleagues [36] show heterogeneity in the rate of change in QoL between individuals, whilst Szabo and colleagues [40] found significant variation in the rate of change amongst older homeowners in the NZHWR. This heterogeneity suggests that change in QoL in later life might be better described by different types of trajectories. However, conventional latent growth curve modelling cannot identify unobserved groups. In response to this limitation, a growing number of researchers are turning to growth-mixture modelling (GMM) techniques [41-42], which combine latent growth and latent profile analyses and allow the identification of unobserved subgroups in the data based on longitudinal change in one or more variables. A small but growing body of researchers in related fields have begun to employ these methods, including explorations of variation in trajectories in retirement adjustment [41], perinatal depression [43], subjective well-being [44] and physical and mental health [45]. In all cases, authors were able to identify subgroups with heterogeneous trajectories. For example, in relation to subjective well-being, Moreno-Agostino and colleagues found three distinct latent trajectories among those aged 50+ living in Spain. Burns and colleagues were able to show, contrary to studies that use latent growth curve models, that most people experience relatively stable physical and mental health in the years preceding death. Authors from these studies reported the advantages of using GMM to identify trajectory sub-groups which would have otherwise been missed or, in the case of Burns and colleagues, to show that supposed population level trajectories can sometimes be driven by a small, but significant, minority.

Therefore, to understand better how QoL develops in later life, we need to use methods that allow us to identify unobserved trajectories underlying the data, rather than relying on average scores, to see what patterns exist within the older adult population and what factors are associated with the different trajectories. The purpose of the present study is to demonstrate the utility of data analytic techniques that can illuminate this heterogeneity in samples to advance research on QoL. Specifically, we will use GMM to identify homogenous subgroups of individuals who demonstrate distinct change trajectories in QoL over time in a large and heterogenous sample of older New Zealanders.

Method

Design and Sample

Data were drawn from the NZHWR, a prospective longitudinal cohort study of New Zealanders aged 50 and older [46]. The NZHWR commenced in 2006 and has surveyed participants biennially with the exception of an off-year survey in 2013. In 2006, a random sample of 13,044 adults aged 55-70 was selected from the New Zealand electoral roll and invited for participation via a postal survey. The survey was returned by *n* = 6,662 participants (51% response rate), of whom 46% (*n* = 3,065) agreed to be re-approached for longitudinal assessments. To maintain the capacity of the study to represent people aged 55 years and older, the participant pool was refreshed in 2009/2010 (*n* = 2548), 2014 (*n* = 773), and 2016 (*n* = 1,272) using the same procedure outlined above. Further details on the design, sampling and response rates can be found elsewhere [46-47].

Analyses reported in the current study were based on data collected from those who participated in 2010, which was the first year QoL was administered using the CASP. In 2010, *n* = 3311 responses were received (*n* = 1985 from the original 2006 cohort and *n* = 1326 from the refresh cohort). Of these respondents, *n* = 3223 provided data on QoL and thus were included in the analyses. The average age of the analytic sample was 64.35 years (*SD* = 8.07 years). Participants were resurveyed in 2012 (*n* = 2691), 2013 (*n* = 1186), 2014 (*n* = 2035) and 2016 (*n* = 1927); however, the 2013 survey was only administered to the original 2006 cohort (not the refresh cohort). Demographic description of the analytic sample across data collection waves is reported in Table 1. Attrition was linked to QoL scores with dropouts scoring lower on the CASP compared to those who remained in the study across each wave. Further information on attrition is provided in Table 2.

Measures

Socio-demographic variables

Demographic information included age, sex (male versus female), Māori[1] descent (of Māori descent versus not of Māori descent), and education (no formal education versus formal education). The Short-Form Economic Living Standards Index was used to assess participants' economic wellbeing. It is a multi-dimensional measure of material well-being assessing self-perceived standard of living, adequacy of income to meet needs, the need for cost-cutting and economising behaviours, restrictions in social engagement due to costs, and access to basic household items [48]. Scores can range from 0 to 31 with higher scores indicating greater economic wellbeing.

QoL

[1] Indigenous population of Aotearoa/New Zealand

QoL was measured with the CASP-12, an older adult specific measure of QoL assessing agency for control and autonomy, self-realization, and pleasure [49]. It has been validated in numerous cultural contexts, including New Zealand [50]. Items, such as 'I feel that what happens to me is out of my control' (control and autonomy), 'I feel that the future looks good for me' (self-realisation) and 'I feel that my life has meaning' (pleasure) were rated on a 4-point scale (anchored at '0' never and '3' often). A composite score was derived by summing all items (range: 0-36). The CASP yielded good internal consistency with Cronbach's alpha scores ranging from .84 to .86 across time.

Data Analysis

To identify QoL trajectories, unconditional GMMs were performed on the CASP scores in Mplus8.5 [51]. GMM is a combination of latent growth and latent profile analysis that allows for the identification of unobserved groups in the data and the modelling of longitudinal change within each unobserved group. We used GMM to model QoL trajectories as assessed by the CASP over a 6-year period. The CASP had a negatively skewed distribution with a median of 30 out of 36, and this was consistent across waves. Therefore, we modelled T-distribution in the GMM. Models with increasing numbers of classes were compared using 40 random start. Intercepts (baseline levels of QoL) and linear slopes (longitudinal change in QoL) were allowed to vary within latent classes.

Models were assessed based on a combination of indicators. First, we examined changes in the Bayesian and adjusted Bayesian information criteria (BIC and aBIC), two commonly applied criteria for model selection. They apply a penalty based on the number of parameters included in the model to avoid overfitting. Higher scores indicate greater penalty; therefore, lower BIC and aBIC are preferred with a reduction of >10 between models considered to indicate improved fit [52]. Second, the Lo-Mendell-Rubin likelihood ratio test

(LMR-LRT) was calculated. The LMR-LRT compares the fit of the k-class model against the k-1 class model (e.g., a 4-class model versus a 3-class model). A significant LMR-LRT indicates that the model with *k* number of classes shows improvements in fit compared to the model with *k*-1 number of classes [53-54]. Further, entropy and posterior class membership probabilities were evaluated. These indices provide information regarding classification uncertainty. Values closer to 1 indicate less uncertainty and a greater separation between the emerging trajectory groups [55]. Finally, we have considered the size and interpretability of the classes to ensure that each group accounted for at least 5% of the sample and that they represented meaningful and theoretically relevant trajectories [56]. Baseline characteristics of trajectory groups were estimated with multinomial regressions using a 3-step (R3STEP) approach in MPlus8.5. In the first step, the latent trajectory model is estimated. Next, based on the posterior probabilities, the most likely class membership is determined. In the third step, this latent class indicator is used for calculating relationships with auxiliary variables. This approach accounts for measurement error when estimating the association between predictors and latent trajectory groups [57]. It has been shown to outperform other methods and provides a useful way to examine predictors of trajectory groups in models where participants cannot be assigned into their most likely trajectory group due to classification uncertainty [58].

Results

Model fit improved until the 5-class solution (Table 3). The 6-class solution resulted in a non-significant LMR-LRT, an increased BIC and a reduction of less than 10 in the aBIC, indicating that the addition of the sixth profile did not significantly improve fit to the data compared with the 5-class solution. The entropy of this model was acceptable and similar to the entropy of models with 3 and 4 classes. Each class accounted for more than 5% of the sample and they were interpretable and theoretically relevant. Consequently, we retained the 5-profile solution (Figure 1). The largest profile (*n* = 1674, 51.94%) consisted of participants with consistently high levels of QoL (0.5 SD above the mean). We labelled this trajectory 'high and stable'. The next profile (*n* = 733, 22.74%) included older adults with average levels of QoL, which significantly declined over time. We labelled this trajectory 'average and declining'. The third profile (*n* = 310, 9.62%) was characterized by low initial levels of QoL (1 SD below the mean) and a significant increase over time. We labelled this trajectory 'low and increasing'. The fourth profile (*n* = 342, 10.61%), likewise, had low initial levels of QoL (1 SD below the mean) but displayed a significant decline over time. We labelled this trajectory 'low and declining'. Finally, the fifth profile (*n* = 164, 5.09%) showed consistently very low levels of QoL across time (2.5 SD below the mean) and no significant change over time. We labelled this trajectory 'very low and stable'. The entropy of this model was .64 and posterior membership probabilities ranged from .61 to .88, indicating more uncertainty in the classification of participants into the 'low and declining' (.63), the 'low and increasing' (.61) and the 'average and declining' (.66) trajectories and less uncertainty in classifying the 'very low and stable' (.70) and 'high and stable' (.88) trajectories.

Baseline demographic description of the trajectories is presented in Table 4. Results (odds ratios and confidence intervals) from the multinomial regression analysis are presented in Table 5. There were significant differences across all trajectory groups in economic living standards. The 'high and stable' profile scored significantly higher on economic living standards than any of the other profiles. Conversely, those in the 'low and stable' profile reported a significantly lower economic living standards than the rest of the profiles. There were no differences between the 'low and increasing' and 'average and declining' profiles in terms of economic living standards. The 'low and declining' profile scored significantly higher on economic living standards than the 'low and stable' profile but reported poorer economic living standards than the other three profiles. Some differences emerged in age, ethnicity and gender between trajectory groups. Those in the 'average and declining' and 'low and declining' and 'very low and stable' profiles were slightly older and more likely to be men than those in the 'high and stable' and the 'low and increasing' groups. Those in the 'very low and stable' group were less likely to be of Māori descent than those in the 'average and declining', 'low and increasing', 'high and stable' groups. Education was not significantly associated with the trajectory groups.

Discussion

Most research on QoL in older age has been carried out with single-dimension, health-related measures, under the assumption that people follow a uniform QoL trajectory with a general decline in later life [36-38]. By coupling a capabilities-based indicator of QoL with GMM, an analytical technique capable of identifying diverse longitudinal trajectories, the findings of the present study suggest that there is substantial heterogeneity in older adults' QoL experiences and that improvements in QoL are possible in later life.

Five Emerging Trajectories

For the majority, QoL was high and stable over time, suggesting that most New Zealanders feel in control of their lives and find opportunities for self-realization and pleasure as they become older. Another quarter of the participants reported good QoL initially, which slowly declined over time – a pattern commonly identified in studies investigating average level trends [36, 38]. Although this group indicated some potential difficulties arising with age, QoL remained within the average range even after six years. This is in stark contrast with the group that reported very low QoL consistently throughout the study. Although they accounted for a much smaller proportion of the sample, the size of this profile was substantial; suggesting that 1-in-20 older adults in New Zealand may have persistent vulnerabilities when it comes to their QoL.

The remaining two profiles displayed opposing longitudinal trajectories. Participants in these groups started out with poor QoL, and while half of them further deteriorated, the other half demonstrated major improvements with time. After three years, those in the improving trajectory profile reported better QoL than their peers in the 'average and declining' trajectory, and after six years, they were approaching the level of QoL reported by the 'high and stable' group. These two opposing groups were similar in size, but those in the improving trajectory were somewhat younger, more likely to be Māori and reported better economic wellbeing. Understanding how these divergent trajectories develop and identifying psychosocial factors that drive and maintain them can provide a unique opportunity for health promotion and policy development and a focus for further research into QoL.

Although it is difficult to draw direct comparisons with other studies that have used GMM to identify heterogeneous trajectories in other domains, our findings are similar to those of Burns and colleagues and Wang [41; 45]. Like our study, they also identified five types of trajectories, both for physical and mental health, and, for mental health, they identified a group that started with relatively low levels and improved over time. Similarly, although Wang found fewer trajectories, he was able to identify two groups that showed improvements in psychological well-being following retirement, as well as a group that maintained high levels of well-being throughout.

Contributions of GMM to QoL Research

The chief objective of the present study was to demonstrate the potential for GMM to be used to advance theory and research on QoL. Previous studies have mostly focused on modelling average level change in QoL and exploring the correlates of such change across older adulthood. Undeniably, these investigations have provided important insights into population level trends on how QoL develops in the 'average older person'. These analyses aim to identify a trajectory that best describes the highest number of participants and thus, by design, ignore the heterogeneity within the sample [42]. Anyone with an 'other than typical' experience is considered an outlier, but outliers may provide valuable information. They can signal vulnerability (i.e., constantly low) and individuals at risk (i.e., low and declining), or groups who display reverse trends (i.e., low and improving). In population level analyses, however, the experiences of these groups are swamped by the experiences of the 'average' participants. Instead of disregarding these cases as 'noise', research should focus on identifying non-typical trajectories and exploring the heterogeneity that exists within samples. This would advance not only theorizing on QoL, but also the development of interventions that target vulnerable older adults and policy making that aims to cater for all older people. Our study provides an example of how GMM can be used to gain a more nuanced understanding of the diverse ways in which QoL develops as people age.

Limitations

In a longitudinal cohort study, people with poor health and fewer resources are more likely to experience barriers to long-term participation. Unequal loss of participants can result in a longitudinal sample that is healthier and wealthier than the general population [59]. The CASP scores in the data were negatively skewed, indicating a sample of older adults whose QoL was relatively high. Analyses corrected for the non-normal distribution of the scale, which allowed us to identify smaller groups of people who experienced less optimal QoL. This, however, did not account for the size of the trajectory groups, which means that groups with initially high QoL are likely to be over-estimated, while the size of more vulnerable groups is likely to be underestimated.

The entropy indicated uncertainty regarding the classification of participants into groups. The posterior membership probabilities suggested high confidence assigning participants into groups characterized by stable (high or low) trajectories. However, there was more uncertainty in the classification of participants into profiles with change trajectories that crossed over time. This does not refute the usefulness of the model, as the emerging groups are meaningful and describe distinct trajectories. Further, simulation studies have found the entropy to be less reliable in detecting the correct number of classes compared with other fit criteria, such as the LMR-LRT or the BIC [60]. However, when entropy is low, classifying participants for further analyses into observed groups based on most likely class membership becomes problematic [55]. It is important to note that trajectory profiles are sample specific and that these models are prone misspecification; therefore, whether the five profiles identified in our analyses replicate in other contexts and samples is a question for future research.

Policy Implications

To enhance QoL, we need to identify social and psychological mechanisms of QoL that are amenable to policy. One such potential determinant is socioeconomic status. Material wellbeing and accumulation of resources support QoL among older adults by enabling them to maintain control over decision-making as they age [61]. New Zealand has a system of universal superannuation (i.e., state pension for New Zealand citizens and residents aged 65+) that contributes to a reduction of socioeconomic inequalities in older age [62]. However, inequalities accumulate over the life course and many arrive at older age in poor economic conditions. Retirement policies might be effective for some, but for those most disadvantaged it might not be enough to reverse the QoL impact of economic inequalities accumulated over the life span [63-65]. The trajectory groups showed large differences at baseline both in QoL and SES, suggesting existing disparities. This highlights the need for interventions across the life course, such as Universal Social Protection, to reduce inequalities and promote QoL as people age [66].

Conclusions

There is concern that increasing longevity without adding quality to the years gained has adverse consequences for individuals and societies [67]. We need to find ways to improve QoL as people transition into older adulthood. This requires a move away from analyses that model changes in QoL only at the sample/population level and directing efforts to identifying diverse experiences of QoL and mechanisms that drive positive change. We identified a small group of older adults who arrived at older age in poor QoL, but substantially improved as they became older. This demonstrates that although many older adults experience declining QoL, it does not have to be the norm. By understanding for whom and under what conditions QoL improves in older adulthood, we can design inclusive policies that not only promote longevity but also ensure that quality is added to peoples' lives.

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Table 1. *Demographic description of the sample across data collection waves*

	2010	2012	2013	2014	2016
Age: M (SD)	64.35 (8.07)	66.40 (7.87)	67.49 (4.51)	67.64 (6.11)	69.69 (6.12)
Gender					
Male	44.93%	44.85%	45.62%	45.36%	44.42%
Female	55.07%	55.15%	54.38%	54.64%	55.58%
Māori descent					
Māori descent	37.33%	35.12%	39.97%	35.33%	34.09%
Not of Māori descent	62.67%	64.88%	60.03%	64.67%	65.91%
Education					
No formal education	26.14%	22.26%	24.07%	25.52%	24.96%
Formal education	73.86%	77.74%	75.93%	74.48%	75.04%

Table 2. *Attrition analysis across biennial waves and its association with the CASP scores*

	Longitudinal Sample	Dropouts	Difference test
2010-2012			
%	82	18	
CASP: M (SD)	28.30 (5.35)	27.04 (5.77)	$t(3221) = 4.97$, $p < .001$, $d = .23$
2012-2014			
%	76	24	
CASP: M (SD)	28.76 (5.35)	27.26 (5.77)	$t(2603) = 6.36$, $p < .001$, $d = .27$
2014-2016			
%	95	5	
CASP: M (SD)	28.84 (5.38)	27.40 (6.69)	$t(1981) = 3.46$, $p = .001$, $d = .24$

Table 3. *Fit indices of the growth mixture model for quality of life as measured by the CASP using a model with T-distribution*

	Size of profiles	LMR-LRT	BIC	aBIC	Entropy	Posterior membership probabilities
1 group	3223	NA	63200	63165	NA	1
2 groups	894; 2329	606.68^{***}	62607	62560	.73	.91; .93
3 groups	619; 301; 2303	110.15	62527	62467	.69	.72; .66; .92
4 groups	1954; 591; 240; 438	118.80^{***}	62407	62334	.66	.90; .67; .73 .65
5 groups	342; 310; 164; 1674; 733	63.20^{*}	62375	62289	.64	.63; 61; .70; .88; .66
6 groups	1169; 283; 362; 170; 777; 432	27.17	62379	62280	.59	.82; .61; .65; .74; .60; .60

Note. ***, $p < .001$; **, $p < .01$; * $p < .05$; NA = not applicable LMR–LRT = Lo-Mendell-Rubin likelihood ratio test; BIC = Bayesian Information Criterion; aBIC = sample size adjusted BIC

Table 4. *Demographic description of the quality of life trajectory profiles at baseline*

	High and stable	Average and declining	Low and increasing	Low and declining	Very low and stable
Age at baseline: M (SD)	63.81 (7.75)	65.24 (8.32)	64.25 (8.16)	64.90 (8.45)	64.00 (9.06)
Gender					
Male	43.55%	47.75%	40.32%	48.54%	46.34%
Female	56.45%	52.25%	59.68%	51.46%	53.66%
Māori descent					
Māori Descent	35.13%	39.56%	42.58%	39.77%	34.15%
Not of Māori Descent	64.87%	60.44%	57.42%	60.23%	65.85%
Education					
No formal qualification	21.60%	28.69%	31.48%	34.21%	31.68%
Formal qualification	78.40%	71.31%	68.32%	65.79%	68.32%
Economic living standards: M (SD)	25.91 (4.52)	22.63 (5.94)	21.68 (6.19)	18.46 (7.81)	14.41 (8.35)

Table 5. *Multinomial regression analysis of the relationship between baseline demographic variables and quality of life longitudinal trajectory profiles using a 3-step (R3STEP) approach*

	Age		Male		Māori descent		Formal education		Economic living standards	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Reference: High and stable										
Average and declining	1.06	1.03; 1.09	1.57	1.08; 2.25	0.88	0.59; 1.31	1.00	0.65; 1.54	0.81	0.77; 0.84
Low and increasing	0.99	0.96; 1.03	0.91	0.55; 1.49	1.26	0.76; 2.08	0.81	0.47; 1.41	0.84	0.80; 0.88
Low and declining	1.08	1.03; 1.12	2.48	1.45; 4.24	0.59	0.33; 1.05	0.69	0.40; 1.17	0.72	0.69; 0.76
Very low and stable	1.04	0.99; 1.10	2.22	1.16; 4.25	0.34	0.16; 0.69	0.83	0.42; 1.65	0.67	0.63; 0.70
Reference: Average and declining										
Low and increasing	0.93	0.89; 0.98	0.58	0.29; 1.15	1.43	0.71; 2.86	0.80	0.38; 1.69	1.04	0.98; 1.10
Low and declining	1.02	0.97; 1.06	1.60	0.92; 2.78	0.67	0.37; 1.20	0.68	0.39; 1.20	0.90	0.86; 0.94
Very low and stable	0.99	0.93; 1.04	1.43	0.76; 2.67	0.38	0.19; 0.76	0.83	0.43; 1.61	0.83	0.79; 0.86
Reference: Low and increasing										
Low and declining	1.08	1.02; 1.15	2.74	1.19; 6.31	0.47	0.20; 1.13	0.84	0.36; 2.01	0.86	0.81; 0.92
Very low and stable	1.05	0.98; 1.13	2.45	1.07; 5.62	0.27	0.11; 0.65	1.02	0.42; 2.52	0.80	0.75; 0.84
Reference: Average and declining										
Low and declining	1.02	0.97; 1.06	1.60	0.92; 2.78	0.67	0.37; 1.20	0.68	0.39; 1.20	0.90	0.86; 0.94
Very low and stable	0.99	0.93; 1.04	1.43	0.76; 2.67	0.38	0.19; 0.76	0.83	0.43; 1.61	0.83	0.79; 0.86
Reference: Low and declining										
Very low and stable	0.97	0.90; 1.04	0.90	0.39; 2.04	0.57	0.24; 1.38	1.21	0.55; 2.69	0.92	0.87; 0.97

Note. OR = odds ratio; CI = Confidence interval

Figure 1. Longitudinal quality of life trajectory profiles from 2010 to 2016. The Y axis depicts standardized scores with M = 0 and SD = 1. Error bars represent standard error of the mean.