INT'L. J. AGING AND HUMAN DEVELOPMENT, Vol. 79(2) 131-156, 2014

UNDERSTANDING HETEROGENEITY IN ADAPTATION TO RETIREMENT: A GROWTH MIXTURE MODELING APPROACH

ALEXA M. MURATORE

JOANNE K. EARL

CATHERINE G. COLLINS

University of New South Wales, Australia

ABSTRACT

Previous research has shown that as people transition to retirement they display heterogeneous growth in outcomes. Typically three subgroups are observed, in which people either increase, decrease, or maintain their scores over time. Extending this research, this study investigates whether subgroups exist independent of the retirement event and compares growth in two outcome measures—retirement adjustment and life satisfaction. Survey data were collected from 360 retirees across three time points. For life satisfaction, growth mixture modeling identified three distinctly growing subgroups. The majority maintained their scores over time, and two smaller groups showed increases and decreases in life satisfaction over time. No subgroups were identified for retirement adjustment. Implications of these results are discussed and suggestions are made for future research.

Throughout their lifespan, people are likely to experience many changes which require adjustment or adaptation (Schlossberg, 1981). Such changes can be labeled as life transitions and are described as experiences that change the individual's appraisal of themselves and their world, that require adaptive thought or

doi: http://dx.doi.org/10.2190/AG.79.2.c
http://baywood.com

behavior, and that can either promote or retard development (Schlossberg, 1981). Retirement is a transition in later life that confronts the individual with new circumstances and environmental demands inherent in altered relationships, routines, time, assumptions, and roles (Jonsson, Borell, & Sadlo, 2000; Perren, Keller, Passardi, & Scholz, 2010). Adjustment to these changes is a dynamic and highly individual process (Atchley, 1976; Shultz & Wang, 2011; Wang & Shultz, 2010). Yet, researchers who rely on methodologies that assume a single homogenous population, for example regression and latent growth curve modeling, neglect individual variation in adaptive processes.

Accordingly, the appropriate investigative framework must include a theoretical model and statistical method that account for both the dynamic and individual characteristics of an adaptive process. First, the resource-based dynamic perspective posits a general mechanism that can explain heterogeneous patterns of change, namely, that if an individual's resources fluctuate, so do their outcomes in a similar direction (Wang, Henkens, & van Solinge, 2011). Note that outcome change is driven by resource change, and therefore could be indirectly impacted by any form of life transition. However, previous research has typically applied this framework to explain changing outcomes over the retirement transition only (e.g., Pinquart & Schindler, 2007, 2009; Wang, 2007). The present article further tests the application of a resource perspective by investigating heterogeneity in outcome change independent of the retirement event. Second, growth mixture modeling (Muthén, 2004) provides a statistical model that can identify heterogeneous patterns of change. This is important, because the diversity present in the older population (O'Rand & Henretta, 1999) means that retirees may not exhibit the same changes in resources and outcomes at the same time. Despite this, very little research has appeared that uses this method to understand heterogeneity in retirement (see for exceptions; Pinquart & Schindler, 2007, 2009; Wang, 2007). In the future, this investigative framework can be applied to other adaptation processes that occur throughout the life span, helping researchers and practitioners to better understand how humans adapt to change.

HETEROGENEITY AND THREE PATTERNS OF CHANGE

Retirement adaptation is an individual process. As early as 1976, Atchley proposed that adjusting to retirement was a process that developed in stages and that individuals may recycle through these stages depending on their unique experiences (Atchley, 1976). Individuals have distinct lifestyles, experience diverse life events, and age differently. They continue to develop, enhance, or rediscover roles (Schau, Gilly, & Wolfinbarger, 2009; Wang, 2007). A number of life events, such as death or illness of a spouse or abrupt changes in financial situation or health status, may occur that can upset adjustment or wellbeing (Lo & Brown, 1999; Noone, Stephens, & Alpass, 2009; Szinovacz, 2003). Aging itself can present gradual changes in functioning that require adjustment, and the timing and impact of such changes are unique to individuals (Jex, Wang, & Zarubin, 2007; Stein & Moritz, 1999; Yaffe, Fiocco, Lindquist, Uittinghoff, Simonsick, Newman, et al., 2009). In short, personal opportunities and constraints confronting older individuals vary greatly (O'Rand & Henretta, 1999). Perhaps as a consequence, empirical research is yet to establish "a general pattern of retirement transition and adjustment" (Wang & Shultz, 2010, p. 189).

Researchers who are alert to this heterogeneity typically observe three groups with distinct patterns of change in retirement outcomes. Wang (2007) modeled wellbeing curves for over 2000 individuals as they transitioned into retirement. He found that one group maintained their wellbeing over the transition, one showed an increase in wellbeing over time (e.g., release from a stressful job), and one showed a decline and then increase over time (e.g., recovering from a poor transition or unmet expectations). Pinquart and Schindler (2007) observed a similar pattern using life satisfaction, with the majority of participants showing a small increase, a second group showing a large increase, and a third group showing a large decrease immediately after retirement. Similar patterns were found in leisure satisfaction over the retirement transition (Pinquart & Schindler, 2009). These studies have all investigated changes over the retirement transition, at the expense of investigating change later in retirement. Research conducted after retirement has shown that groups of individuals demonstrated similar patterns of change in life satisfaction. Older individuals displayed low, moderate, and high levels of life satisfaction with approximately 20% moving up a category and 20% moving down a category over 2 years (Han & Hong, 2011). However, this study did not use growth curves to model change and therefore could not describe the shape of the growth curve after retirement. Accordingly, the present article will add to this research by investigating the potential for heterogeneous growth after retirement. The investigation is expected to replicate earlier results by identifying three subgroups that display different patterns of growth within the retiree population and to extend earlier results by showing that these subgroups exist within a population who have been retired for varying lengths of time.

The resource-based dynamic perspective (Wang et al., 2011) easily accounts for the existence of these subgroups. Resources represent the capacity an individual has to meet core needs and can be physical, cognitive, motivational, financial, social, and emotional (Wang, 2007). Consequently, an increase, decrease, or stability in outcomes (e.g., adjustment or life satisfaction) is a result of an improvement, depletion, or maintenance of resource level (Wang et al., 2011). Significantly, according to this theory, outcome change may be observed at any time there is a resource change and as such can be independent of the retirement event. The design of the present article provides a test of this premise.

Observing subgroups that display distinct growth has become possible through the development of more sophisticated and flexible analysis techniques, for example Growth Mixture Modeling (GMM; Muthén, 2001, 2004). Growth mixture models represent an extension of the basic growth model, called a latent growth curve model (LGM; Bollen & Curran, 2006), that specifies two latent variables to capture change. One represents initial status and the other represents growth trajectory. The means of these latent factors represent group averages and the variances of these factors describe individual differences (Bollen & Curran, 2006). Although the LGM captures both interindividual and intraindividual differences in growth parameters, it assumes that only a single homogeneous population is present in the sample (Duncan, Duncan, & Strycker, 2006; Wang & Bodner, 2007). In the GMM, expected heterogeneity in the population is captured by including a variable indicating latent class membership (Duncan et al., 2006; Preacher, Wichman, MacCallum, & Briggs, 2008; Wang & Bodner, 2007). Growth factors are regressed on this categorical variable, so that intercept and slope means are estimated for each group (Duncan et al., 2006; Preacher et al., 2008). Therefore, different growth parameters can be estimated for a given number of subgroups in a sample.

This method is being more frequently applied within a number of disciplines (Huang, Brecht, Hara, & Hser, 2010). For example, growth mixture modeling has demonstrated that subgroups exist in individuals' responses to drug treatments, development of alcohol abuse and other problems, academic achievement, and socialization in organizational groups (Feldman, Masyn, & Conger, 2009; Gueorguieva, Mallinckrodt, & Krystal, 2011; Hodis, Meyer, McClure, Weir, & Walkey, 2011; Qureshi & Fang, 2011). GMM has successfully identified multiple patterns of growth within retiree populations (e.g., Pinquart & Schindler, 2007, 2009; Wang & Bodner, 2007), offering an explanation for previously inconsistent results regarding positive or negative change after retirement (Wang & Bodner, 2007).

CONTRIBUTIONS: TESTING A PREMISE OF THE RESOURCE PERSPECTIVE AND COMPARING OUTCOME MEASURES

Previous research that uses GMM has typically only investigated changes over the retirement transition (Pinquart & Schindler, 2007, 2009; Wang, 2007). Yet, according to a resource perspective, heterogeneity in outcome-change can occur at any time, because it is driven by resource change rather than the retirement event per se. Therefore, further evidence for this theory can be provided if subgroups are shown to exist independent of the retirement event. Accordingly, the purpose of this article is to test for heterogeneous growth in a sample of retirees that have been retired for various lengths of time. This will show that subgroups exist independent of the retirement event, in accordance with the resource-based dynamic perspective (Wang et al., 2011).

A variety of different measures have been used to measure outcomes related to retirement adaptation, including happiness, psychological wellbeing, retirement satisfaction, life satisfaction, and depression (van Solinge & Henkens, 2008; Wang et al., 2011). The many different outcome measures used across retirement research impede its consolidation (Floyd, Haynes, Doll, Winemiller, Lemsky, Burgy, et al., 1992; Reitzes & Mutran, 2004). Researchers can seek consolidation by comparing the performance of different outcome measures in single studies (Wang et al., 2011). As research interest grows and the number of studies using the same measures multiplies, it will be possible to combine data across studies through meta-analyses. To advance this goal, the present article compares retirement adjustment and global life satisfaction.

Retirement adjustment serves as an index of how well an individual adjusts or adapts to the retirement transition and evaluates retirement on a number of dimensions such as finances, lifestyle, and other changes (Wells, de Vaus, Kendig, Quine, & Petralia, 2006). The construct is measured both by enjoyment of retired life and a sense of purpose or meaning (Wells et al., 2006). It reflects the process through which a retiree adapts to post-retirement changes and gradually becomes comfortable with his or her life in retirement (Wang & Shultz, 2010). The measure should not be confused with retirement satisfaction which is described as the level of contentment with one's life in retirement (van Solinge & Henkens, 2008). Price and Balaswamy (2009) proposed that retirement satisfaction reflects an individual's evaluation of his or her retirement experience. These conceptual differences are also reflected in operational measures, although only retirement adjustment is included in our study. We chose instead to measure life satisfaction based on overall positive evaluations of life (Lent, 2004). Retirement adjustment specifically evaluates retirement experiences, whereas life satisfaction is a global measure of positive experience. Retirement specific measures versus general measures may lead to different conclusions (Taylor & Doverspike, 2003). For example, the pattern of predictors for retirement satisfaction and life satisfaction were different (Taylor, Goldberg, Shore, & Lipka, 2008). Further, gender differences were found in a comparative evaluation of retirement but not in overall life satisfaction (Quick & Moen, 1998).

HYPOTHESES AND ANALYSIS STEPS

The present article draws on longitudinal data to investigate change in outcomes. Longitudinal studies improve precision, because these are able to untangle cohort effects and stable individual differences from development effects (Hedeker & Gibbons, 2006; Lucas, Clark, Georgellis, & Diener, 2003). Since each subject serves as his or her own control (Hedeker & Gibbons, 2006), tests are more sensitive and powerful. Two outcomes (retirement adjustment and life satisfaction) are investigated. The literature reviewed previously has highlighted that the retirement process is dynamic and heterogeneous. Accordingly, further evidence for heterogeneity is sought in the form of differently developing subgroups within the sample. The hypothesis for the present article is that three subgroups of retirees will be observed. The majority of individuals will show no change in outcomes over time, and two smaller groups will show positive and negative changes over time similar to those reported by Wang (2007). Extending the results of Wang (2007), who explored these patterns over the retirement transitions, the present study draws on a sample of individuals who have been retired for varying lengths of time.

METHOD

Participants and Procedure

Participants were recruited from the National Seniors Australia (NSA) database. The first round was distributed in May 2009. New South Wales members aged 45 years and over, who nominated themselves as having permanently left full-time work, were invited to complete an online or paper survey. At the end of this survey, interested individuals were asked to identify themselves for follow-up surveys. For completing all three rounds, participants were offered a summary report of results and a chance to win one of three $100 gift vouchers.

A total of 433 individuals volunteered for future research and were invited to participate in subsequent rounds (distributed in January and September 2010). Of these, 367 responded to all three rounds, yielding an overall response rate of 85%. Consent to participate was indicated by a returned complete survey; therefore, only data from individuals who responded to all three rounds were used. Individuals who completed all rounds ($N = 367$) were compared to individuals who completed only the first round ($N = 44$). A series of t-tests showed that these groups did not differ significantly on retirement adjustment and life satisfaction, suggesting that there were no differences on these variables due to attrition. At each round, over 77% of the sample responded online. T-tests showed that on retirement adjustment and life satisfaction, data from paper surveys did not differ from that collected online and, therefore, these data were analyzed together.

Participants who indicated their status as "not retired" and who reported engaging in full-time work that was paid at any of the three rounds were screened from the study (similar to established criteria used by Reitzes & Mutran, 2004). Accordingly, six individuals were excluded using this criteria and an additional individual was excluded for substantially missing data. For at least one round, 21 individuals responded that they were not retired, however, were not excluded because they did not meet the paid working criteria described above. Univariate outliers were screened from the study (Tabachnick & Fidell, 2007). Means of variables were compared with 5% trimmed means to confirm that any remaining univariate outliers would not have an undue influence on analysis (Tabachnick & Fidell, 2007). After excluding seven outliers, the sample included 353 individuals.

Nine cases needed to be excluded due to missing data in models that included covariates (please refer to Explanation of Analysis). Following recommendations (Tabachnick & Fidell, 2007), one multivariate outlier and two cases with missing data for all time points were excluded from the retirement adjustment models ($n = 342$), and three multivariate outliers were excluded from the life satisfaction models ($n = 341$). The proportion of missing data on any variable was no more than 7%, with complete data for 253 individuals for three time points (refer to Table 1 on p. 141). For detail on how this missing data was addressed, please refer to Explanation of Analysis.

Materials

Demographics and Retirement Information

Information on age, gender, education, occupation, gross household income, age retired, and years retired were collected. Information is reported below for participants who responded to all three rounds.

Retirement Outcomes

Retirement adjustment was measured using the 13-item scale from the Healthy Retirement Project (Wells et al., 2006). Participants rated their agreement from 1 strongly disagree to 5 strongly agree to statements such as "I am well adjusted to the changes" and "people don't respect me as much now that I'm retired." Total adjustment score was calculated as the sum of ratings across the 13 items, such that higher scores indicated better adjustment. The scale has shown high internal consistency (Cronbach α coefficient = .81 and .83; Wells et al., 2006; Wong & Earl, 2009). In the present study, the measure showed high reliability at each of the three rounds: Cronbach α coefficients = .89, .89, .89.

Given the demands of our longitudinal design, we used several one item measures, a common approach for such designs (Pinquart & Schindler, 2007; Wanous, Reichers, & Hudy, 1997) demonstrated to have reliable results (Lucas & Donnellan, 2011). Life satisfaction was rated using a single item, "Overall, how satisfied are you nowadays with your life as a whole?" from 1 completely dissatisfied to 10 completely satisfied. Similar measures with 7 or more scale points have produced sufficient variability for investigation and have the advantage of reducing the possibility of overloading the participants (de Vaus, Wells, Kendig, & Quine, 2007; Easterlin, 2009).

Variables Selected to Improve the Accuracy of GMM Estimation

Muthén (2004) warns that an unconditional GMM is inappropriate when covariates directly influence either of the growth factors (intercept or slope). In such cases, a conditional GMM can be estimated with greater accuracy than an unconditional GMM, because including the covariates provides additional information on class membership (Huang et al., 2010; Lubke & Muthén, 2007).

Further, it is critical to note that the single class models have only one degree of freedom, which would require a sample of 3000 or more to be evaluated accurately (MacCallum, Browne, & Sugawara, 1996). Therefore, including covariates in the LGM increased the degrees of freedom and consequently provided greater opportunity to reject the model.

Research suggests that finances, health, relationship, and mastery are correlated with retirement outcomes (Hobfoll, 2002; Rijs, Cozijnsen, & Deeg, 2012; Rohwedder, 2006; van Solinge & Henkens, 2008). Finances were measured by a single item (1 not enough or just enough money or 2 comfortably well off), as was current physical health (1 poor to 5 excellent). Relationship was measured by status and satisfaction, and a new variable was created to represent both of these. Based on preliminary analysis, five categories were created and ordered such that outcome means for each of the categories was higher than the previous category (1 partnered dissatisfied, 2 partnered satisfied, 3 no partner, 4 partnered highly satisfied, 5 partnered completely satisfied). Finally, Mastery was measured using the Mastery Scale (Pearlin & Schooler, 1978). In the present study, the Cronbach α coefficient was .88. Preliminary analysis confirmed that covariates were correlated with the outcomes of interest and therefore they should be included when identifying classes (Muthén, 2004).[1]

Explanation of Analysis

To review, the hypothesis is that any sample drawn from a population of retirees will contain three different subgroups that display growth, maintenance, and decline that is representative of the retirement experience (Wang, 2007). Therefore, the analysis method needs to be able to capture growth and heterogeneity. To do this, a Growth Mixture Model (GMM; Muthén, 2001, 2004) was used. The model captures growth using latent constructs that represent initial status and growth trajectory. Heterogeneity is captured using a latent class variable that allows initial status and growth trajectory to be estimated for a given number of subgroups. A non-technical description of the GMM is shown in Figure 1.

[1] We acknowledge that there are many variables expected to influence outcomes in retirement, for example, age (by enabling access to government support or by its association with declining health), paid and volunteer work, and time in retirement (McKelvey, 2009; Reitzes & Mutran, 2004; Rohwedder, 2006; Wong & Earl, 2009; Yaffe et al., 2009; Zhan, Wang, Liu, & Shultz, 2009). In the present study, age, retirement age, years in retirement, work hours (more than 35 hours or less than 35 hours), volunteer status, work status (full time, part time, or casual/contract) were also examined for their effect on retirement adjustment and life satisfaction, however, were not significantly correlated with these outcomes. Future researchers should continue to consider a range of variables in their model estimation as well as examining potential relationships amongst resources (for example, these variables may be antecedents of key resources such as health, finances, and mastery) and investigating alternative influences on growth (for example, these variables may predict turning points in growth).

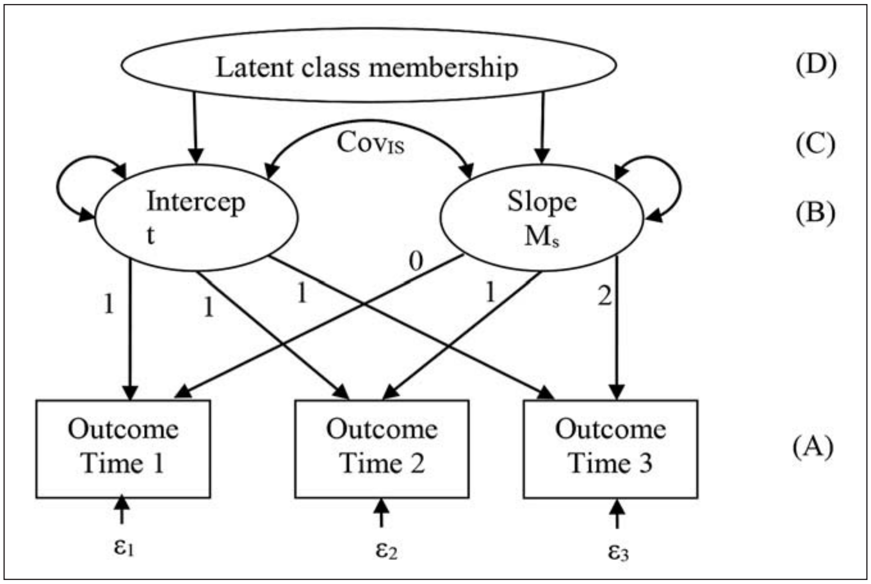


Figure 1. Basic GMM for the present study.
(A) Outcome Time 1-Time 3 represent observed variables (adjustment or satisfaction) measured at three time points; $\varepsilon_{1\text{-}3}$ represent error.
(B) Variance in Outcome Time 1-Time 3 is explained by two growth factors. The mean of the *intercept* (M_i) describes average starting point for the population and its variance (represented by a double headed arrow) describes individual differences in starting point; factor loadings fixed to 1 represent its constant value across all time points (Duncan et al., 2006; Wang & Bodner, 2007). The mean of the *slope* (M_a) describes average growth rate for the population and its variance (represented by a double headed arrow) describes the degree to which individuals vary around the average growth rate; factor loadings are fixed to 0, 1, 2, representing linear growth over three equally spaced time points (Preacher et al., 2008).
(C): Cov$_{IS}$ describes the **covariance** between growth factors.
(D): **Latent class membership** represents the number of subgroups. Growth factors are regressed on class membership so that the estimated intercept and slope means can differ across subgroups.

For further technical detail, readers are referred to recent research (Bollen & Curran, 2006; Muthén, 2004).

Analyses were conducted in Mplus 6.12 (Muthén & Muthén, 2010). Following recommendations (Preacher et al., 2008; Wang & Bodner, 2007), full information maximum likelihood (FIML) was chosen to deal with missing data in the growth models. As recommended, the MLR estimator was used (Byrne, 2012; Sass, 2011). Note that observed covariates have no distributional assumptions, and therefore FIML cannot address missing data on these variables (Muthén & Muthén, 1998-2010). Accordingly, cases with missing data on covariates were excluded from the analysis. Growth models were estimated for each of the outcomes by, first, fitting an unconditional LGM (a basic growth model without covariates) followed by conditional LGM (a basic growth model with covariates) to establish the validity of the single-class model, and then, fitting a conditional GMM to identify the number of classes (Huang et al., 2010; Lubke & Muthén, 2007; Muthén, 2004).

For the LGM models, recommended fit statistics criteria were used (Hancock & Mueller, 2006; Preacher et al., 2008), with adequate fit shown by comparative fit index >.90 (CFI), Tucker-Lewis coefficient >.90 (TLI), root mean square error of approximation <.08 with a confidence interval upper limit of <.08 (RMSEA with CI 90%), and standardized root mean square residual of <.08 (SRMR).

For the GMMs, the goal is to identify the model with the number of classes that best fits the data. Following recommendations (Duncan et al., 2006; Lubke & Muthén, 2007; Tofighi & Enders, 2008), better fit was indicated by lower values of Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC), and sample-size adjusted BIC (ABIC), an entropy value closer to 1 (which indicates distinction among classes), and a significant Lo-Mendell-Rubin likelihood ratio test (LMR). In addition, as recommended (Bauer & Curran, 2003b; Muthén, 2004), model selection was closely guided by theory, successful model convergence, and whether class differences have substantive meaning.

RESULTS

Slightly more males (54%) than females (46%) participated, with an average age of 64.28 years (*SD* = 5.24). Participants retired at the average age of 58.85 (*SD* = 4.73) and had spent an average of 5.36 (*SD* = 5.04) years in retirement. Approximately 19% of the sample had spent a year or less in retirement. The median income bracket of the entire sample was $52,000-$63,399. Participants were highly educated, with 59% holding a bachelor degree or above (including 20% with a postgraduate degree). The majority of participants held managerial (31%), professional (37%), or clerical or administrative (19%) roles prior to retirement. Participants reported an average score on finances of 1.48 (*SD* .50), health of 3.36 (*SD* 1.03), relationship of 3.47 (*SD* 1.26), and mastery of 11.02 (*SD* 1.96). Descriptive statistics for outcomes across the three time points are shown in Table 1. Also shown in Table 1, skew and kurtosis values were within acceptable ranges for SEM-based models (Hancock & Mueller, 2006).

Following guidelines for GMM analyses (Brown, 2006; Muthén, 2004; Wang & Bodner, 2007), the analyses were conducted in three steps. First, as recommended measurement invariance of adjustment was tested to establish that this multiple-item construct was measured equivalently over time (Brown, 2006;

Table 1. Missing Data, Mean, Standard Deviation, Variance, Skew and Kurtosis Values for Outcomes Across the Time Points

	Time	*N*	% missing	Mean	Standard deviation	Variance	Skew	Kurtosis
Adjustment[a]	1	332	6%	9.29	1.79	3.19	–0.69	0.37
	2	331	6%	9.33	1.73	2.98	–0.71	0.85
	3	330	7%	9.34	1.66	2.75	–0.69	0.43
Life satisfaction	1	353	0%	7.85	1.83	3.33	–1.70	2.68
	2	352	1%	7.83	1.79	3.19	–1.88	4.52
	3	349	1%	7.87	1.70	2.90	–1.75	3.22

Note: Missing data was rounded to the nearest whole percent.
[a]The variable was rescaled so that variances would fall between 1 and 10, in line with Mplus developers' recommendations (Muthén & Muthén, 1998-2010).

Chan, 1998). Second, two single-class unconditional and conditional models were specified to test that growth model specification was appropriate for adjustment and satisfaction growth. Third, two conditional GMMs were run to identify potential subgroups within adjustment and satisfaction growth.

Step 1: Establishing Measurement Invariance of Retirement Adjustment Measure

Measurement invariance analysis should be established for multiple-item measures (Brown, 2006). Accordingly, measurement invariance of retirement adjustment was tested in the present study. The analysis is conducted by imposing increasingly stringent equality constraints on a structural equation model that tests whether factors, factor loadings, and intercepts are similar across each time point. These models are nested, thus a chi-square difference test is used to determine if the increasingly demanding equality constraints necessary to conclude measurement invariance are being met; a non-significant chi-square test is needed to demonstrate a similar factor structure across the time points (Brown, 2006). First, a model specifying the same adjustment factor structure at each time point showed adequate fit. Imposing the additional constraint of equal factor loadings across the time points did not significantly degrade model fit (Change $\chi^2_{(24)} = 19.39$, $p > .05$). Finally, imposing equal indicator intercepts did not significantly degrade model fit (Change $\chi^2_{(24)} = 48.81$, $p > .05$). Therefore, adequate measurement invariance was established for the retirement adjustment measure in the present study, so longitudinal analysis can be meaningfully conducted (Chan, 1998). Details of model fit and chi-square tests are shown in Table 2.

Table 2. Longitudinal Invariance of a Measurement Model for Retirement Adjustment

	$\chi^2_{(df)}$	N $\chi^2_{(df\ diff)}$	RMSEA (90% CI)	CFI	TLI	SRMR
Retirement adjustment						
Equal form	$1603.82_{(660)}$		.06 (.06 to .07)	.89	.87	.08
Equal factor loadings	$1622.34_{(684)}$	$19.39_{(24)}$	.06 (.06 to .07)	.89	.88	.08
Equal indicator intercepts	$1671.57_{(708)}$	$48.81_{(24)}$	.06 (.06 to .07)	.89	.88	.08

Note: N $\chi^2_{(df\ diff)}$ = scaled χ^2 difference and degrees of freedom difference; RMSEA = root mean square error of approximation; 90% CI = 90% confidence interval for RMSEA; CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean square residual. All scaled χ^2 differences were non-significant at $p < .001$.

Step 2: Latent Growth Models (single class)

Following recommendations, a valid single class model was identified prior to GMM analysis (Muthén, 2004). Unconditional (without predictors) and then conditional (with predictors) LGMs were specified for each of the outcomes in line with recommendations. Modification indices were used to identify additional pathways between growth parameters and resources that should be included.

The goal was to estimate a well-fitting single class model on which reliable estimations of multiple classes (step 3 below) can be performed. Accordingly, model fit was the focus and so parameter estimates were checked to confirm that their values were within expected ranges, but were not interpreted. Furthermore, the same model of predictors was used for both outcomes—retirement adjustment and life satisfaction—in the interest of comparing the behavior of different outcomes. The resulting LGMs established well-fitting models on which to base GMMs. Results suggested that the covariates best used may differ according to the outcome under investigation. However, in the interest of comparing the behavior of different outcomes, the same model was used to estimate classes for each outcome.

Single-Class Retirement Adjustment Model

First, an unconditional, linear growth curve model was estimated for adjustment. Fit statistics showed acceptable model fit: MLR $\chi^2_{(1)} = .505$ ($p > .05$), RMSEA = .00 (90% CI .00 to .125), CFI = 1.00, TLI = 1.00, SRMR = .01.

Second, a conditional growth curve model was estimated, by adding covariates (finances, health, relationship, and mastery) to predict initial status. Results of this initial model were inadmissible, because the estimated variance of the slope was negative (variance = –.01, $p > .05$). Therefore, the model was re-estimated with slope variance fixed at 0 to identify the cause of model misfit (fit statistics for this model follow: MLR $\chi^2_{(11)} = 9.75$ ($p > .05$), RMSEA = .00 (90% CI .00 to .05), CFI = 1.00, TLI = 1.00, SRMR = .04). Modification indices suggested that slope should also be predicted by mastery (modification index of 4.20 and an unstandardized expected parameter change of –.03). A scaled difference in chi-squares test (Brown, 2006) confirmed that adding this path significantly improved fit (Change $\chi^2_{(1)} = 3.98$, $p < .05$). With mastery predicting slope, slope variance estimated normally. A further scaled difference in chi-squares test confirmed that removing the restriction on slope variance did not significantly worsen fit (Change $\chi^2_{(2)} = .79$, $p > .05$).[2] The final conditional model showed good fit: MLR $\chi^2_{(8)} = 4.78$ ($p > .05$), RMSEA = .00 (90% CI .00 to .04), CFI = 1.00, TLI = 1.00, SRMR = .01. On average, the group did not grow significantly (intercept = 9.28, $p < .001$; slope = .04, $p > .05$). All covariates except health ($p = .053$) showed a significant influence on growth factors.

Single-Class Life Satisfaction Model

First, an unconditional, linear growth curve model was estimated for life satisfaction. Fit statistics were acceptable: MLR $\chi^2_{(1)} = .09$ ($p > .05$), RMSEA = .00 (90% CI .00 to .10), CFI = 1.00, TLI = 1.00, SRMR = .00.

Second, a conditional growth curve model was estimated, by adding covariates (finances, health, relationship, and mastery) to predict initial status. Initial model fit was acceptable: MLR $\chi^2_{(9)} = 10.47$ ($p < .05$), RMSEA = .02 (90% CI .00 to .07), CFI = 1.00, TLI = 1.00, SRMR = .03. Modification indices suggested that slope should be predicted by health (modification index of 5.28 and standardized expected parameter change of –.20). However, for the sake of consistency with the adjustment model, a pathway between slope and mastery was added instead. A scaled difference in chi-squares test (Brown, 2006) showed that adding this pathway did not significantly improve model fit (Change $\chi^2_{(1)} = 1.69$, $p > .05$), however, with the path included modification indices did not suggest any further changes. The final conditional model showed good fit: MLR $\chi^2_{(8)} = 8.67$ ($p > .05$), RMSEA = .02 (90% CI .00 to .07), CFI = 1.00, TLI = 1.00, SRMR = .02. On average, the group did not grow significantly (intercept = 7.86, $p < .001$; slope = .01, $p > .05$). All covariates showed significant relationship with the intercept factor; however, mastery did not significantly predict the slope factor.

[2]Note that the degrees of freedom changed by 2, because when slope variance was estimated, covariance between intercept and slope could also be estimated.

Step 3: GMM—Identifying Whether Multiple Growth Classes Exist

Having identified an acceptable single-class LGM model for each outcome, GMM analysis could proceed (Jung & Wickrama, 2008; Muthén, 2004). In the present study, three growth classes for each outcome were expected. Namely, a group that maintained their outcome level over time, a group that increased, and a group that decreased in outcome level over time. To identify the most appropriate number of classes, growth mixture models with one, two, three, and four classes were fit for each outcome and evaluated using criteria described previously. User-defined start values were entered to facilitate model convergence (Duncan et al., 2006). Between 500 and 1000 sets of random start values with 50 final stage optimizations were used to ensure that models converged at global rather than local maxima (Muthén, 2004; Wang & Bodner, 2007). Analysis stopped if the models displayed convergence problems or the LMR became non-significant (Jung & Wickrama, 2008).

Adjustment

The one class model was retained in favor of a two class model, because LMR likelihood ratio test for the two-factor model was non-significant; that is, the more parsimonious model was retained since it was not a significantly worse fit. Therefore, no further models were estimated, and the hypothesis that subgroups exist in adjustment growth was rejected. For fit statistics, please refer to Table 3.

Table 3. Fit Information for Multiple-Class Retirement Adjustment and Life Satisfaction Models

	AIC	BIC	ABIC	Entropy	LMR	*N*
Adjustment						
1-class	2672.16	2722.01	2680.77			342
2-class	2645.83	2722.53	2659.09	.79	39.36	63, 279
Satisfaction						
1-class	3226.06	3275.88	3234.64			341
2-class	3024.71	3101.35	3037.91	.98	210.20***	42, 299
3-class	2965.13	3068.60	2982.95	.97	99.17*	42, 19, 280
4-class	2857.50	2987.78	2879.93	.98	118.73	31, 20, 12, 278

Note: ABIC = sample size adjusted BIC; LMR = Lo-Mendell-Rubin adjusted likelihood ratio test; *N* = estimated number of individuals in each class.

Life Satisfaction

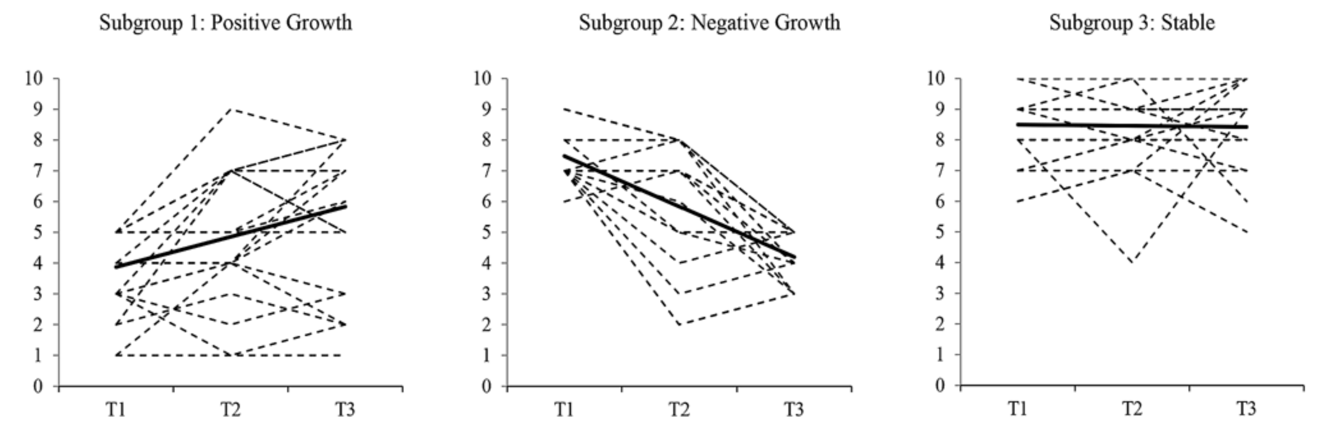
At four classes, the LMR was non-significant (118.73, $p > .05$), indicating that a three class solution should not be rejected in favor of a four class solution. Selection of the three class model was also supported by significant LMR (99.17, $p < .05$), information criteria, and high entropy (Jung & Wickrama, 2008).[3] For fit statistics, please refer to Table 3.

The sample characteristics of the three subgroups for life satisfaction are shown in Figure 2. Subgroup 1 included 42 individuals with a moderate starting point (4.57, $p < .001$) and positive growth (1.02, $p < .001$). Subgroup 2 included 19 individuals with a higher starting point (7.93, $p < .001$) and negative growth (–1.62, $p < .001$). Subgroup 3 included 280 individuals with the highest starting point (8.36, $p < .001$) and non-significant growth (–.05, $p > .05$). The negative growth group had the highest proportion of females (58%) and the highest average number of years retired (8.19, $SD = 6.08$).

DISCUSSION

Longitudinal analysis has the potential to answer many of the questions still clouding our understanding of retirement. Indeed, empirical and theoretical knowledge on the temporal nature of retirement-related processes is highly sought (Calvo, Haverstick, & Sass, 2009; Rohwedder, 2006; Shultz & Wang, 2011). To answer this demand, the present article investigated outcome growth during retirement. Extending previous research, we conducted a GMM to identify subgroups independent of the retirement event, providing further support for the resource perspective (Wang et al., 2011), and compared a general and a specific measure of retirement adaptation to identify whether these constructs captured the change process equivalently.

[3]Note that additional parameters such as variances, growth factor covariance, and the influence of covariates on growth factors can be freed among classes. There are not yet definitive guidelines about which of these produce the greatest precision, although they can be expected to produce different results (Huang et al., 2010). In the present study, freeing variance parameters produced convergence problems and so these were fixed to equality across classes (Huang et al., 2010). Inspection of graphs did not suggest that variance needed to be freed across classes (Jung & Wickrama, 2008; Muthén, 2004) and freeing variances when class separation is low can cause problems (Lubke & Muthén, 2007). Freeing growth factor covariance and the influence of covariates on growth factors produced slightly different class counts (44, 21, 276 and 37, 28, 281); however, these classes supported the same conclusions regarding growth means. Further, fit statistics of these models did not suggest that freeing these parameters substantially improved fit. Therefore, results of the more parsimonious model with these parameters fixed across classes is reported, but it is recommended that future researchers be aware of and explore the potential for differences when additional parameters are freed across classes.



	Average (*SE/SD*)	Average (*SE/SD*)	Average (*SE/SD*)
N	42	19	280
Intercept	4.57 (.21)***	7.93 (.31)***	8.36 (.05)***
Slope	1.02 (.13)***	-1.62 (.20)***	-0.05 (.03)
Female	50%	58%	45%
Age	65.92 (5.58)	65.51 (5.62)	63.88 (5.13)
Years retired	6.41 (5.51)	8.19 (6.08)	5.04 (4.91)

Figure 2. Mean growth of subgroups and observed growth of 20 randomly selected subgroup members for life satisfaction growth. In each group the participants with the lowest and highest growth factor means were also included. The tables present number of individuals in each subgroup (*N*), intercept and slope means, and key demographics. *SE* = standard error; *SD* = standard deviation.

Presence of Subgroups

The hypothesis was partially supported by three subgroups that displayed different growth patterns for life satisfaction, providing support for the premise of the resource perspective (Wang et al., 2011) that these subgroups should exist independent of the retirement event. A larger group showed non-significant change over time, and two smaller groups showed negative and positive changes in outcomes over time. This result adds to our knowledge on subgroups by replicating previous findings of three subgroups that display different growth patterns (e.g., Pinquart & Schindler, 2007; Wang, 2007), and improves our understanding of these subgroups by showing that they exist independent of the retirement event. As a consequence, interventions that aim to improve satisfaction with retired life may be appropriate well beyond the retirement event. Profiles of the groups suggest that the negative growth group had the highest average number of years spent in retirement (but also the highest standard deviation), and were mostly female. However, females generally live longer (Humpel, O'Loughlin, Wells, & Kendig, 2010) and may be more willing to report negative experiences (Yong, Saito, & Chan, 2011), so this result does not necessarily imply that women are predisposed to negative retirement experiences. Future researchers should continue to consider how the composition of these groups may differ in terms of gender, age, and years retired.

Contrary to expectations, the best-fitting models for retirement adjustment specified a single population with no change. Van Solinge and Henkens (2008) describe adjustment to retirement as a multidimensional process requiring efforts directed "along two tracks"—one requires adjustment to the workforce exit and the other requires creation of a satisfying life postretirement. Applied to the present results, this suggests that the retirement adjustment measure captured the first part of this process, in line with research that suggests early retirement offers greater adjustment challenges and then most retirees adjust with time (Taylor & Doverspike, 2003; Wong & Earl, 2009). Indeed, several items on the adjustment scale directly refer to adjustment to life without work. On the other hand, the life satisfaction measure appears to capture the second part of this process, the creation of a satisfying life that is a dynamic and ongoing process (Jonsson et al., 2000; Sterns & Subich, 2004) and is logically more likely to be affected by resource change.

Note, however, that different lengths of time between longitudinal waves can produce different conclusions (Collins, 2006). Therefore, further research is recommended using shorter and longer periods between measurement occasions to confirm that the stability observed in the present study in adjustment represents reality, discussed in more detail later.

Comparing Outcome Measures

Wang and colleagues (2011) suggested that measuring multiple outcomes simultaneously may reveal important differences among them. In the present study, linear growth in life satisfaction differed from adjustment, such that subgroups were observed in life satisfaction, but not in adjustment. First, it is possible that subgroups were not identified due to the restriction of a linear trend, discussed further under limitations. However, it is also possible that these outcomes are different. For example, van Solinge and Henkens (2008) observed a greater effect of health and loss of partner on satisfaction than on how difficult it was for the individual to adjust. Taylor and Doverspike (2003) noted that retirement satisfaction and life satisfaction are more strongly associated earlier in retirement than later in retirement. Life satisfaction may be more sensitive to resource change than retirement adjustment. Opportunities for such comparisons among outcomes are limited because most studies measure only one outcome (Wang et al., 2011). Nevertheless, present results caution against the temptation to assume that because outcome measures capture similar or related constructs that they will equivalently characterize an adaptive processes.

Limitations and Future Research

As with all research, there are limitations to the inferences that can be drawn from results. First, observed in Table 1, most people reported positive outcomes (maximum possible score for life satisfaction was 10 and for scaled-adjustment was 13). Future researchers need to draw on diverse populations; for example, those who report negative outcomes and those from different strata of society and cultures (Chi, 2011; Humpel, O'Loughlin, Wells, & Kendig, 2009; Stephan, Fouquereau, & Fernandez, 2008). Second, to corroborate self-report data and provide ideal data for SEM-based models, future researchers need to draw on measures with multiple items and domains, objective measures, and reports from others (Brown, 2006; Floyd et al., 1992; Menard, 2008).

In the present sample, based on their resources and reported outcomes, slightly more females than males were classified into the declining group. We acknowledge that different career opportunities, roles, and life events may produce differences in the way men and women anticipate and adjust to retirement (Beehr & Bennett, 2007; Elgán, Axelsson, & Fridlund, 2009; Everingham, Warner-Smith, & Byles, 2007; Price, 2003), and recommend that future researchers investigate this possibility. Further, some resources are equally valued by both genders, but others, such as finances and social contacts, may be more important to a particular gender (Kubicek, Korunka, Raymo, & Hoonakker, 2011). If results can be replicated, there may be a need for tailored support for men and women (e.g., Jacobs-Lawson, Hershey, & Neukam, 2004) and future researchers should investigate this possibility.

In the present study, resources were used to improve the precision with which heterogeneity in outcome growth could be identified. However, as future researchers begin the next step of identifying contributing factors of growth, decline, and maintenance patterns, the question of relative importance of resources, including protective effects of a high level of resources (Hobfoll, 2002), and processes of recovery (e.g., selective optimization with compensation; Baltes & Baltes, 1990) will be important. Accordingly, future researchers may benefit from the inclusion of more detailed measures of resources. Leung and Earl (2012) developed a new measure known as the Retirement Resources Inventory incorporating the Wang et al. (2011) resource based dynamic model. Resources predicted retirement adjustment and retirement satisfaction in the following order: finances and health, followed by social resources, and lastly emotional, cognitive, and motivational resources.

Growth mixture modeling represents a leap forward in flexible hypothesis testing, but these methods are relatively new and formal guidelines on model specification and selection still need to be developed (Duncan et al., 2006). Results should be interpreted and generalized cautiously (Bauer & Curran, 2003a; Muthén, 2003). An incorrect number of classes may be identified if observed variables are nonnormal, if within-class models are misspecified, or if trajectories are non-linear (Bauer & Curran, 2003a; Duncan et al., 2006). Like SEM, good fit of a model does not prove that it is the only model that explains results (Muthén, 2004). The three class model accepted for life satisfaction above does not prove that there are three subgroups, just as the well-fitting single trajectory LGM does not prove that adjustment growth is homogeneous (Preacher et al., 2008). Consequently, further testing of models is suggested and recommendations are made here.

For accurate hypothesis testing, a high correspondence between the question of interest and the model is necessary (Collins, 2006). Achieving this correspondence is possible with the flexibility of SEM-based models, however, depends on particular characteristics of the data set (Preacher et al., 2008). Sample size, number of, timing of, and space between waves dictate which models can be specified and how they are interpreted (Bollen & Curran, 2006; Duncan et al., 2006; Preacher et al., 2008).

Three measurement occasions in the present article were only sufficient to test a linear model, but quadratic or cubic models may more accurately represent outcome growth. A quadratic growth factor can be added to the model using squared factor loadings (Bollen & Curran, 2006; Brown, 2006). Whereas the linear slope represents the constant growth rate in the outcome per unit of time, the quadratic term reveals whether this growth rate is increasing or decreasing over time. To specify non-linear growth, at least four waves of data are needed to provide the necessary degrees of freedom (Bollen & Curran, 2006). Increasing the number of measurement occasions should also increase the accuracy of the longitudinal model (Bollen & Curran, 2006; Preacher et al., 2008).

The interval between waves has important consequences for interpretation, because it can determine whether change is observed in the phenomenon of interest. Research on appropriate spacing of waves is limited, and based on present results recommendations may differ according to the outcome measure used. Insights from the normative aging study suggested that an 8-month interval may capture important changes, as the study showed that recent retirees (0 to 6 months) had the highest level of life satisfaction, while those retired for 18 months reported the lowest levels of satisfaction (Ekerdt, Bosse, & Levkoff, 1985). The interval of 8 months used in the present study was sufficient to observe linear changes in life satisfaction, but not in adjustment. It is not possible to determine whether this was due to true stability in adjustment scores, non-linear growth averaged by the linear model, or inappropriate intervals between waves, and so further research is needed. Determining the optimal timing between waves to detect changes is a recognized challenge of longitudinal research (Selig & Preacher, 2009) and so longitudinal models should be tested in studies using different spacing between waves (Calvo et al., 2009; Collins, 2006; Ployhart & Vandenberg, 2010). Therefore, in addition to further longitudinal research on the relevance/accuracy of the model, the authors recommend future researchers also consider the implications of spacing between the waves in mapping and measuring adaptation processes particularly where measures of adjustment are included.

In the present study, money perception was a dichotomous measure, and health and relationship were measured by five ordered categories. Such measures may suffer from floor or ceiling effects or be insensitive to changes that occur within categories (Gunasekara, Carter, & Blakely, 2012; Wells et al., 2009). Accordingly, future researchers should consider replacing dichotomous items and categorical measures used in the study with multi-item and continuous measures when available. These measures will be more reliable, more sensitive, and allow parsimonious SEM-based models to be constructed (Calvo et al., 2009; Floyd et al., 1992; Muthén & Muthén, 1998-2010). In addition, multiple-item measures enable researchers to test for measurement invariance, improving our understanding of the longitudinal behavior of these constructs. We note, however, that single item measures have the advantage of investigating more variables while managing participants' fatigue. Managing time and fatigue in longitudinal research is critical and it is common for one item measures to be used with such research designs (Pinquart & Schindler, 2007). Furthermore one item measures of life satisfaction are reported to have a mean reliability of 0.72 across four large representative samples over time (Lucas & Donnellan, 2011). Similarly, Scarpello and Campbell (1983) reported that global indices of job satisfaction can be more valid than facet-based measures, since these enable participants to respond to the facet of satisfaction that resonates with them the most.

CONCLUSION

The present article supports the use of GMM to identify subgroups in retiree populations. Our understanding of outcome growth was improved, because subgroups were found independent of the retirement event and this evidence is promising for applying the resource perspective (Wang et al., 2011) to other adaptive processes. In the future, the investigative framework presented in the article may be used to test for heterogeneity in a broader range of processes that are prompted by other life events throughout the life span. For example, recent research acknowledges between-person differences in trajectories of depressive symptoms in response to life events (Infurna, Gerstorf, & Ram, 2012; Liang, Xu, Quiñones, Bennett, & Ye, 2011). Results presented here suggest that comparison of various outcome measures is also warranted. For researchers and practitioners, these results highlight the possibility that if we continue to use theory and analysis that assumes homogenous growth in response to life transitions we may overlook those people who need the most help.

REFERENCES

Atchley, R. C. (1976). *The sociology of retirement*. Cambridge, MA: Schenkman.

Baltes, P. B., & Baltes, M. M. (Eds.). (1990). *Successful aging: Perspectives from the behavioral sciences.* New York, NY: Cambridge University Press.

Bauer, D. J., & Curran, P. J. (2003a). Distributional assumptions of growth mixture models: Implications for overextraction of latent trajectory classes. *Psychological Methods, 8*(3), 338-363. doi: 10.1037/1082-989x.8.3.338

Bauer, D. J., & Curran, P. J. (2003b). Overextraction of latent trajectory classes: Much ado about nothing? Reply to Rindskopf (2003), Muthén (2003), and Cudeck and Henly (2003). *Psychological Methods, 8*(3), 384-393. doi: 10.1037/1082-989X.8.3.384

Beehr, T. A., & Bennett, M. M. (2007). Examining retirement from a multi-level perspective. In K. S. Shultz & G. A. Adams (Eds.), *Aging and work in the 21st century* (pp. 277-302). London, UK: Erlbaum Associates.

Bollen, K. A., & Curran, P. J. (2006). *Latent curve models: A structural equation perspective*. New Jersey: John Wiley & Sons.

Brown, T. A. (2006). *Confirmatory factor analysis for applied research*. New York, NY: Guilford Press.

Byrne, B. M. (2012). *Structural equation modeling with Mplus: Basic concepts, applications, and programming*. New York, NY: Taylor & Francis.

Calvo, E., Haverstick, K., & Sass, S. A. (2009). Gradual retirement, sense of control, and retirees' happiness. *Research on Aging, 31*(1), 112-135. doi: 10.1177/0164027508324704

Chan, D. (1998). The conceptualization and analysis of change over time: An integrative approach incorporating Longitudinal Mean and Covariance Structures Analysis (LMACS) and Multiple Indicator Latent Growth Modeling (MLGM). *Organizational Research Methods, 1*(4), 421-483. doi: 10.1177/109442819814004

Chi, I. (2011). Cross-cultural gerontology research methods: Challenges and solutions. *Ageing & Society, 31*(3), 371-385. doi: 10.1017/S0144686X10000942

Collins, L. M. (2006). Analysis of longitudinal data: The integration of theoretical model, temporal design, and statistical model. *Annual Review of Psychology, 57*(1), 505-528. doi: 10.1146/annurev.psych.57.102904.190146

de Vaus, D., Wells, Y., Kendig, H., & Quine, S. (2007). Does gradual retirement have better outcomes than abrupt retirement? Results from an Australian panel study. *Ageing & Society, 27*(5), 667-682. doi: 10.1017/S0144686X07006228

Duncan, T. E., Duncan, S. C., & Strycker, L. A. (2006). *An introduction to latent variable growth curve modelling: Concepts, issues and applications*. New Jersey: Lawrence Erlbaum Associates.

Easterlin, R. A. (2009). Lost in transition: Life satisfaction on the road to capitalism. *Journal of Economic Behavior & Organization, 71*(2), 130-145. doi: 10.1016/j.jebo.2009.04.003

Ekerdt, D. J., Bosse, R., & Levkoff, S. (1985). An empirical test for phases of retirement: Findings from the Normative Aging Study. *Journal of Gerontology, 40,* 95-101.

Elgán, C., Axelsson, Å., & Fridlund, B. (2009). Being in charge of life: Perceptions of lifestyle among women of retirement age. *Scandinavian Journal of Caring Sciences, 23*(4), 730-735. doi: 10.1111/j.1471-6712.2008.00671.x

Everingham, C., Warner-Smith, P., & Byles, J. (2007). Transforming retirement: Re-thinking models of retirement to accommodate the experiences of women. *Women's Studies International Forum, 30*(6), 512-522. doi: 10.1016/j.wsif.2007.09.006

Feldman, B. J., Masyn, K. E., & Conger, R. D. (2009). New approaches to studying problem behaviors: A comparison of methods for modeling longitudinal, categorical adolescent drinking data. *Developmental Psychology, 45*(3), 652-676. doi: 10.1037/a0014851

Floyd, F. J., Haynes, S. N., Doll, E. R., Winemiller, D., Lemsky, C., Burgy, T. M., et al. (1992). Assessing retirement satisfaction and perceptions of retirement experiences. *Psychology and Aging, 7*(4), 609-621. doi: 10.1037/0882-7974.7.4.609

Gueorguieva, R., Mallinckrodt, C., & Krystal, J. H. (2011). Trajectories of depression severity in clinical trials of duloxetine: Insights into antidepressant and placebo responses. *Archives of General Psychiatry, 68*(12), 1227-1237. doi: 10.1001/archgenpsychiatry.2011.132

Gunasekara, F. I., Carter, K., & Blakely, T. (2012). Comparing self-rated health and self-assessed change in health in a longitudinal survey: Which is more valid? *Social Science and Medicine, 74*(7), 1117-1124. doi: doi:10.1016/j.socscimed.2011.11.038

Han, C.-K., & Hong, S.-I. (2011). Assets and life satisfaction patterns among Korean older adults: Latent class analysis. *Social Indicators Research, 100*(2), 225-240. doi: 10.1007/s11205-010-9613-8

Hancock, G. R., & Mueller, R. O. (Eds.). (2006). *Structural equation modeling: A second course*. Greenwich, CT: Information Age Publishing.

Hedeker, D., & Gibbons, R. D. (2006). *Longitudinal data analysis*. New Jersey: John Wiley & Sons.

Hobfoll, S. E. (2002). Social and psychological resources and adaptation. *Review of General Psychology, 6*(4), 307-324. doi: 10.1037/1089-2680.6.4.307

Hodis, F. A., Meyer, L. H., McClure, J., Weir, K. F., & Walkey, F. H. (2011). A longitudinal investigation of motivation and secondary school achievement using growth mixture modeling. *Journal of Educational Psychology, 103*(2), 312-323. doi: 10.1037/a0022547

Huang, D., Brecht, M.-L., Hara, M., & Hser, Y.-I. (2010). Influences of covariates on growth mixture modeling. *Journal of Drug Issues, 40*(1), 173-194.

Humpel, N., O'Loughlin, K., Wells, Y., & Kendig, H. (2009). Ageing baby boomers in Australia: Evidence informing actions for better retirement. *The Australian Journal of Social Issues, 44*(4), 399-415.

Humpel, N., O'Loughlin, K., Wells, Y., & Kendig, H. (2010). The health of Australian baby boomers. *Australasian Journal on Ageing, 29*(1), 8-13. doi: 10.1111/j.1741-6612.2010.00412.x

Infurna, F. J., Gerstorf, D., & Ram, N. (2012). The nature and correlates of change in depressive symptoms with cancer diagnosis: Reaction and adaptation. *Psychology and Aging*, doi: 10.1037/a0029775

Jacobs-Lawson, J. M., Hershey, D. A., & Neukam, K. A. (2004). Gender differences in factors that influence time spent planning for retirement. *Journal of Women & Aging, 16*(¾), 55-69.

Jex, S. M., Wang, M., & Zarubin, A. (2007). Aging and occupational health. In K. S. Shultz & G. A. Adams (Eds.), *Aging and work in the 21st century* (pp. 199-223). London, UK: Erlbaum Associates.

Jonsson, H., Borell, L., & Sadlo, G. (2000). Retirement: An occupational transition with consequences for temporality, balance and meaning of occupations. *Journal of Occupational Science, 7*(1), 29-37.

Jung, T., & Wickrama, K. A. S. (2008). An introduction to latent class growth analysis and growth mixture modeling. *Social and Personality Psychology Compass, 2*(1), 302-317. doi: 10.1111/j.1751-9004.2007.00054.x

Kubicek, B., Korunka, C., Raymo, J. M., & Hoonakker, P. (2011). Psychological well-being in retirement: The effects of personal and gendered contextual resources. *Journal of Occupational Health Psychology, 16*(2), 230-246. doi: 10.1037/a002233

Lent, R. W. (2004). Toward a unifying theoretical and practical perspective on well-being and psychosocial adjustment. *Journal of Counseling Psychology, 51*(4), 482-509. doi: 10.1037/0022-0167.51.4.482

Leung, C. S. Y., & Earl, J. K. (2012). Retirement resources inventory: Construction, factor structure and psychometric properties. *Journal of Vocational Behavior, 81*(2), 171-182.

Liang, J., Xu, X., Quiñones, A. R., Bennett, J. M., & Ye, W. (2011). Multiple trajectories of depressive symptoms in middle and late life: Racial/ethnic variations. *Psychology and Aging, 26*(4), 761-777. doi: 10.1037/a0023945

Lo, R., & Brown, R. (1999). Stress and adaptation: Preparation for successful retirement. *Australian & New Zealand Journal of Mental Health Nursing, 8*(1), 30-38.

Lubke, G., & Muthén, B. O. (2007). Performance of factor mixture models as a function of model size, covariate effects, and class-specific parameters. *Structural Equation Modeling: A Multidisciplinary Journal, 14*(1), 26-47. doi: 10.1080/10705510709 336735

Lucas, R. E., Clark, A. E., Georgellis, Y., & Diener, E. (2003). Reexamining adaptation and the set point model of happiness: Reactions to changes in marital status. *Journal of Personality and Social Psychology, 84*(3), 527-539. doi: 10.1037/0022-3514.84.3.527

Lucas, R. E., & Donnellan, M. B. (2011). Estimating the reliability of single-item life satisfaction measures: Results from four national panel studies. *Social Indicators Research, 105*, 323-331.

MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods, 1*(2), 130-149. doi: 10.1037/1082-989x.1.2.130

McKelvey, J. B. (2009). Globalization and ageing workers: Constructing a global life course. *International Journal of Sociology and Social Policy, 29*(½), 49-59.

Menard, S. (2008). *Handbook of longitudinal research: Design, measurement, and analysis*. London, UK: Academic Press.

Muthén, B. (2001). Second-generation structural equation modeling with a combination of categorical and continuous latent variables: New opportunities for latent class-latent growth modeling. In L. M. Collins & A. G. Sayer (Eds.), *New methods for the analysis of change. Decade of behavior* (pp. 291-322). Washington, DC: American Psychological Association.

Muthén, B. (2003). Statistical and substantive checking in growth mixture modeling: Comment on Bauer and Curran (2003). *Psychological Methods, 8*(3), 369-377. doi: 10.1037/1082-989x.8.3.369

Muthén, B. (2004). Latent variable analysis: Growth mixture modeling and related techniques for longitudinal data. In D. Kaplan (Ed.), *Handbook of quantitative methodology for the social sciences* (pp. 345-368). Newbury Park, CA: Sage.

Muthén, L. K., & Muthén, B. O. (1998-2010). *Mplus user's guide* (6th ed.). Los Angeles, CA: Muthén & Muthén.

Muthén, L. K., & Muthén, B. O. (2010). *Mplus (Version 6.12)* [Computer program]. Los Angeles, CA: Muthén & Muthén.

Noone, J. H., Stephens, C., & Alpass, F. M. (2009). Preretirement planning and well-being in later life: A prospective study. *Research on Aging, 31*(3), 295-317. doi: 10.1177/0164027508330718

O'Rand, A. M., & Henretta, J. C. (1999). *Age and inequality: Diverse pathways through later life*. Boulder, CO: Westview Press.

Pearlin, L. I., & Schooler, C. (1978). The structure of coping. *Journal of Health and Social Behavior, 19*(1), 2-21. doi: 10.2307/2136319

Perren, S., Keller, R., Passardi, M., & Scholz, U. (2010). Well-being curves across transitions: The development of a retrospective measure. *Swiss Journal of Psychology, 69*(1), 15-29. doi: 10.1024/1421-0185/a000003

Pinquart, M., & Schindler, I. (2007). Changes of life satisfaction in the transition to retirement: A latent-class approach. *Psychology and Aging, 22*(3), 442-455.

Pinquart, M., & Schindler, I. (2009). Change of leisure satisfaction in the transition to retirement: A latent-class analysis. *Leisure Sciences, 31*(4), 311-329. doi: 10.1080/01490400902988275

Ployhart, R. E., & Vandenberg, R. J. (2010). Longitudinal research: The theory, design, and analysis of change. *Journal of Management, 36*(1), 94-120. doi: 10.1177/0149206309352110

Preacher, K. J., Wichman, A. L., MacCallum, R. C., & Briggs, N. E. (2008). *Latent growth curve modelling*. Los Angeles, CA: Sage.

Price, C. A. (2003). Professional women's retirement adjustment: The experience of reestablishing order. *Journal of Aging Studies, 17*(3), 341-355. doi: 10.1016/s0890-4065(03)00026-4

Price, C. A., & Balaswamy, S. (2009). Beyond health and wealth: Predictors of women's retirement satisfaction. *International Journal of Aging and Human Development, 68,*195-214.

Quick, H. E., & Moen, P. (1998). Gender, employment and retirement quality: A life course approach to the differential experiences of men and women. *Journal of Occupational Health Psychology, 3*(1), 44-64.

Qureshi, I., & Fang, Y. (2011). Socialization in open source software projects: A growth mixture modeling approach. *Organizational Research Methods, 14*(1), 208-238. doi: 10.1177/1094428110375002

Reitzes, D. C., & Mutran, E. J. (2004). The transition to retirement: Stages and factors that influence retirement adjustment. *International Journal of Aging and Human Development, 59*(1), 63-84.

Rijs, K. J., Cozijnsen, R., & Deeg, D. J. (2012). The effect of retirement and age at retirement on self-perceived health after three years of follow-up in Dutch 55-64-year-olds. *Ageing & Society, 32*(2), 281-306.

Rohwedder, S. (2006). *Self-assessed retirement outcomes: Determinants and pathways* (WP 2006-141). Retrieved from University of Michigan, Michigan Retirement Research Center website: http://www.mrrc.isr.umich.edu/publications/papers/pdf/wp141.pdf

Sass, D. A. (2011). Testing measurement invariance and comparing latent factor means within a confirmatory factor analysis framework. *Journal of Psychoeducational Assessment, 29*(4), 347-363. doi: 10.1177/0734282911406661

Scarpello, V., & Campbell, J. P. (1983). Job satisfaction: Are all the parts there? *Personnel Psychology, 36,* 577-600.

Schau, H. J., Gilly, M. C., & Wolfinbarger, M. (2009). Consumer identity renaissance: The resurgence of identity-inspired consumption in retirement. *Journal of Consumer Research, 36*(2), 255-276. doi: 10.1086/597162

Schlossberg, N. K. (1981). A model for analyzing human adaptation to transition. *Counseling Psychologist, 9*(2), 2-18. doi: 10.1177/001100008100900202

Selig, J. P. & Preacher, K. J. (2009). Mediation models for longitudinal data in developmental research. *Research in Human Development, 6*(2-3), 144-164.

Shultz, K. S., & Wang, M. (2011). Psychological perspectives on the changing nature of retirement. *American Psychologist, 66*(3), 170-179. doi: 10.1037/a0022411

Stein, C., & Moritz, I. (1999). *A life course perspective of maintaining independence in older age* (WHO/HSC/AHE/99.2). Retrieved from World Health Organization website: http://whqlibdoc.who.int/hq/1999/WHO_HSC_AHE_99.2_life.pdf

Stephan, Y., Fouquereau, E., & Fernandez, A. (2008). The relation between self-determination and retirement satisfaction among active retired individuals. *The International Journal of Aging and Human Development, 66*(4), 329-345. doi: 10.2190/AG.66.4.d

Sterns, H. L., & Subich, L. M. (2004). Counseling for retirement. In S. D. Brown & R. W. Lent (Eds.), *Career development and counseling: Putting theory and research to work* (pp. 506-521). Hoboken, NJ: John Wiley & Sons.

Szinovacz, M. E. (2003). Contexts and pathways: Retirement as institution, process, and experience. In G. Adams & T. Beehr (Eds.), *Retirement: Reasons, processes and results* (pp. 6-52). New York, NY: Springer.

Tabachnick, B. G., & Fidell, L. S. (2007). *Using multivariate statistics* (5th ed.). Boston, MA: Pearson Education.

Taylor, M. A., & Doverspike, D. (2003). Retirement planning and preparation. In G. Adams & T. Beehr (Eds.), *Retirement: Reasons, processes and results* (pp. 53-82). New York, NY: Springer.

Taylor, M. A., Goldberg, C., Shore, L. M., & Lipka, P. (2008). The effects of retirement expectations and social support on post-retirement adjustment: A longitudinal analysis. *Journal of Managerial Psychology, 23*(4), 458-470.

Tofighi, D., & Enders, C. K. (2008). Identifying the correct number of classes in growth mixture models. In G. R. Hancock & K. M. Samuelsen (Eds.), *Advances in latent variable mixture models* (pp. 317-341). Greenwich, CT: Information Age.

van Solinge, H., & Henkens, K. (2008). Adjustment to and satisfaction with retirement: Two of a kind? *Psychology and Aging, 23*(2), 422-434. doi: 10.1037/0882-7974.23.2.422

Wang, M. (2007). Profiling retirees in the retirement transition and adjustment process: Examining the longitudinal change patterns of retirees' psychological well-being. *Journal of Applied Psychology, 92*(2), 455-474. doi: 10.1037/0021-9010.92.2.455

Wang, M., & Bodner, T. E. (2007). Growth mixture modeling: Identifying and predicting unobserved subpopulations with longitudinal data. *Organizational Research Methods, 10*(4), 635-656. doi: 10.1177/1094428106289397

Wang, M., Henkens, K., & van Solinge, H. (2011). Retirement adjustment: A review of theoretical and empirical advancements. *American Psychologist, 66*(3), 204-213. doi: 10.1037/a0022414

Wang, M., & Shultz, K. S. (2010). Employee retirement: A review and recommendations for future investigation. *Journal of Management, 36*(1), 172-206. doi: 10.1177/0149206309347957

Wanous, J. P., Reichers, A. E., & Hudy, M. J. (1997). Overall job satisfaction: How good are single-item measures? *Journal of Applied Psychology, 82*(2), 247.

Wells, Y., de Vaus, D., Kendig, H., & Quine, S. (2009). Health and wellbeing through work and retirement transitions in mature age: Understanding pre-post and retrospective measures of change. *International Journal of Aging and Human Development, 69*(4), 287-310. doi: 10.2190/AG.69.4.c

Wells, Y., de Vaus, D., Kendig, H., Quine, S., & Petralia, W. (2006). *Healthy retirement project: Technical report.* Retrieved from La Trobe University website: http://www.latrobe.edu.au/aipca/projects/hrp.pdf

Wong, J. Y., & Earl, J. K. (2009). Towards an integrated model of individual, psychosocial, and organizational predictors of retirement adjustment. *Journal of Vocational Behavior, 75*(1), 1-13. doi: 10.1016/j.jvb.2008.12.010

Yaffe, K., Fiocco, A. J., Lindquist, K., Vittinghoff, E., Simonsick, E. M., Newman, A. B., et al. (2009). Predictors of maintaining cognitive function in older adults. *Neurology, 72*, 2029-2035.

Yong, V., Saito, Y., & Chan, A. (2011). Gender differences in health and health expectancies of older adults in Singapore: An examination of diseases, impairments, and functional disabilities. *Journal of Cross-Cultural Gerontology, 26*(2), 189-203.

Zhan, Y., Wang, M., Liu, S., & Shultz, K. S. (2009). Bridge employment and retirees' health: A longitudinal investigation. *Journal of Occupational Health Psychology, 14*(4), 374-389. doi: 10.1037/a001528

Direct reprint requests to:

Joanne K. Earl
School of Psychology
Matthews, Room 904
University of New South Wales
Sydney NSW 2052 Australia
e-mail: j.earl@unsw.edu.au