



A life course view on depression: Social determinants of depressive symptom trajectories over 25 Years of Americans' Changing Lives

Marilyn Sinkewicz^{*}, Ola Rostant, Kara Zivin, Ryan McCammon, Philippa Clarke

University of Michigan, USA

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ABSTRACT

Objectives: This study investigates heterogeneity in trajectories of depressive symptomatology in a national sample of American adults followed over 25 years. Using an innovative combination of data and methods, we sought to illuminate how depressive symptoms change over adulthood in terms of their levels and severity across 25 years, and how the social determinants of health influence differences in those trajectory paths.

Methods: Data come from the Americans' Changing Lives (ACL) study, a national sample of 3617 adults (age 25+) followed over 25 years (1986–2011). Depressive symptoms were assessed with an 11-item abbreviated version of the Center for Epidemiologic Studies-Depression scale (CESD). A second-order growth mixture model was used to assess measurement invariance (addressing questions of different or changing meaning of depression) and latent trajectories of change (addressing questions of changing severity levels with aging) in depressive symptomatology over adulthood.

Results: Results indicate that the CESD was invariant across time, and depressive symptomatology followed a U-shaped form across the life course. Two latent trajectories of depressive symptoms were identified across the life course; one was a normative trajectory (60% of the sample) and the other (40% of the sample) had persistently high depressive symptoms over adulthood. Women, race/ethnic minorities, and those of lower socioeconomic position were more likely to be in the persistently depressed class.

Discussion: Results are consistent with those of other studies demonstrating a U-shaped form of depressive symptoms across the life course. However, a substantial sub-population with persistent depressive symptomatology over adulthood was also identified, whose predictors suggest the need to take a social determinants of health approach to disparities related to serious and persistent mental illness.

1. Introduction

Depression is the third leading cause of disease globally, and is among the top 10 most costly diseases in the US (Hall & Wise, 1995). It stands apart as the mental disorder claiming the highest percentage of disability-adjusted life years, and the highest increased risk of all-cause mortality (Eaton et al., 2008). Despite the extreme burden of the disorder, little progress has been made in understanding heterogeneity in the course of depression or the factors which differentiate levels of risk over adulthood (Insel, 2009; McMahon & Insel, 2012; Strakowski, 2012).

It is crucial to delineate and understand multiple trajectories of depression to shed light not only on people with milder symptoms that come and go with life's challenges, but also to focus on a potentially more vulnerable and underserved group that experiences serious and

persistent mental illness (SPMI) over time. This latter group is particularly important from a health and social policy perspective, since they are at risk of becoming trapped in a revolving door of high utilization across the health, social service (homelessness), and criminal legal systems (Milgram, Brenner, Wiest, Bersch, & Truchil, 2018). There is a deficit of empirical evidence to inform policies and programs that effectively address the complex needs of this high-priority sub population, which may explain why families and advocates continue to decry the challenges they face and the lack of support they receive.

Life course research shows that the relationship between age and depressive symptomatology is typically represented by a U-shape, non-linear curve, falling steeply during early adulthood, leveling off at its lowest point in midlife, and then climbing again around age 70 as role exits such as retirement and widowhood, declines in function, and a decreased sense of control pose challenges for mental health (Clarke &

^{*} Corresponding author. Social Environment and Health Program, Institute for Social Research, 426 Thompson St., Ann Arbor, MI, 48104, USA.

E-mail address: sinkewic@umich.edu (M. Sinkewicz).

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Wheaton, 2005; Kessler et al., 1993; Miech & Shanahan, 2000; Mirowsky, 1996; Mirowsky & Ross, 2001). Earlier work also suggests that the social determinants of mental health, including social status and role occupancy represented by factors such as gender, racial/ethnic group membership, and education, as well as their consequences for economic status and health, explain, to a large extent, the age-graded patterning of depressive symptoms over mid to late adulthood (Clarke, Marshall, House, & Lantz, 2011; Mirowsky & Ross, 2001). For instance, a consistent finding in the literature is that women report more depressive symptomatology at every life stage than men (Mirowsky, 1996). This appears in both clinical and non-clinical studies, across cultures and depression instrumentation (Kessler, McGonagle, Swartz, Blazer, & Nelson, 1993; Nolen-Hoeksema, 1990; Van de Velde, Bracke, Levecque, & Meuleman, 2010; Weissman, Leaf, Holzer, Myers, & Tischler, 1984).

An extensive epidemiological literature reaches back over one hundred years to estimate the association of low socioeconomic position with the increased prevalence of psychiatric disorders. From Edward Jarvis's (1855) classic epidemiological study to a notable body of more recent empirical evidence (e.g. Dohrenwend et al., 1992), this finding has been remarkably robust across conceptual models and methodological changes in the measurement of psychopathology and socioeconomic status. More recently, the psychological literature has drawn attention to the dynamic rather than static nature of the consequences of both positive and negative life course transitions. Simandan (2018, 2020), for example, argues for recognizing that social class and social mobility ebb and flow as they are performed time and again through social actions and interactions across the life course. Gugushvili and colleagues' (Gugushvili, Zhao & Bukodi, 2019) empirical study offers further nuance, suggesting that upward and downward mobility is associated with lower and higher depressive symptoms, respectively, but only among men. Further, Paskov and Richards' (2021) sociological study highlights the importance of accounting for inequality in social status for understanding depression. There is also evidence of a strong period effect where mental health over the life course has been improving over historical time, in part due to increases in education (Clarke et al., 2011).

However, apart from considering gender differences, most longitudinal studies have assessed life course changes in depressive symptomatology in terms of a single average population trajectory for an entire study population. Averaging is useful when a population is homogeneous; however, a single population trajectory could mask critical differences if a heterogeneous population follows several different pathways. For example, in addition to the aggregate U-shape trajectory described above, some depression trajectories may follow a steadily decreasing pattern, or a constant pattern of depressive symptomatology over time, while others may be characterized by the absence of depressive symptoms over the life course.

Whereas existing research has used growth curve models to examine variation around a single population trajectory (e.g., Clarke et al., 2011; Sutin et al., 2013; Yang, 2007), the current study extends this literature by using growth mixture models to investigate the possibility of *multiple* sub-population trajectories of depressive symptoms for distinct groups of adults with different risk profiles (Langenbucher et al., 2004; Lubke & Muthén, 2004; Muthén, 2004; Muthén & Muthén, 2000; Petras et al., 2004). We use a second-order growth mixture model (SOGMM) to empirically model changes in the salience of different depressive symptoms over 25 years using a longitudinal confirmatory factor measurement model embedded within the growth structure. Ferrer, Baluerka, and Widaman (2008) have shown that growth parameters are misspecified when using composite measures of observed variables that inherently assume measurement invariance (i.e., measured equivalently across time). By explicitly modeling the invariance of the factor structure of depressive symptoms over time, we minimize misspecification in estimating the growth structure of depression over adulthood. Moreover, because our growth curve models are estimated with the latent depressive symptom factors that are free from

measurement error, we gain greater precision in estimating these trajectories and the factors shaping them over time (Ferrer et al., 2008).

Further, the current study uses data from a large nationally representative cohort of American adults followed over 25 years to investigate heterogeneity in trajectories of depressive symptomatology over adulthood. We expect that (1) depressive symptoms will be invariant across five waves of data over a 25 year period; (2) the average population trajectory of depressive symptoms will be non-linear; (3) there will be multiple trajectories of depressive symptomatology across the life course corresponding to different sub-populations; and (4) socio-demographic factors (gender, racial/ethnic group membership, socioeconomic position and birth cohort) will be associated with membership in specific sub-population trajectories.

2. Methods

2.1. Data

Data come from the Americans' Changing Lives (ACL) survey (House et al., 1994; House, Kessler, & Herzog, 1990; House, Lantz, & Herd, 2005), a cohort longitudinal study based on a stratified, multistage area probability sample of non-institutionalized adults age 25 and over, living in the coterminous United States, and followed over a 25 year period. African Americans and adults age 60 and older were over sampled. The first wave of the survey was conducted in 1986 with 3617 adults (68% response rate for individuals and 70% for households). Surviving respondents were re-interviewed in 1989 (N = 2,867, 83% of survivors), in 1994 (N = 2562 including 164 proxy respondents, 83% of survivors), in 2001/2002 (N = 1787 including 95 proxies, 74% of survivors), and again in 2011/2012 (N = 1427 including 108 proxies, 81% of survivors). Of the 3617 total respondents, 1071 (30%) completed all 5 waves, while 1361 (38%) completed all possible waves prior to their death. Of those who dropped out (N = 654, 18%), 264 (7%) completed only the first wave, 128 (3%) the first and second wave, 159 (5%) the first through third wave, and 103 (3%) all but the 5th wave. The remaining 531 (15%) had intermittent patterns of response. Sampling weights for non-response as well as a post-stratification adjustment to the 1986 Census estimates of the U.S. population age 25 years and older, make the ACL sample representative of the age, gender, and race distribution of the U.S. population living in the United States in 1986, and, except for differences due to immigration and out-migration, representative of this cohort of Americans as they age over the 25 year period.

2.2. Measures

At each of the 5 waves of data collection depressive symptoms were assessed with a short form (11 items) of the Center for Epidemiologic Studies Depression Scale (CES-D) that has been shown to maintain the same four-factor solution as, and is highly correlated with, the longer 20 item scale (Radloff, 1977) with good internal consistency reliability (Kohout, Berkman, Evans, & Cornoni-Huntley, 1993). Three items measure depressive affect (felt depressed, sad, lonely), four items tap somatic symptoms (everything was an effort, sleep was restless, didn't feel like eating, could not get going), two items capture positive affect (enjoy life, feel happy), and two items measure interpersonal interaction (people unfriendly, people dislike me). For each item respondents were asked to indicate how often they experienced each symptom during the past week using a three category set of response options (hardly ever, some of the time, and most of the time), coded from 0 to 2 at each wave.

We assessed differences in trajectories of depressive symptoms across four socio-demographic variables: gender, race/ethnicity, education, and household income. These are time invariant variables (assessed at the baseline survey) that proxy power and social capital. **Gender** is a binary variable coded 1 for female and 0 for male. **Racial/ethnic group** is a dummy variable coded 1 for non-white (Black, Hispanic, Asian and Native American) and 0 for white. **Education** was modeled with two

dummy variables contrasting less than high school (0–11 years of completed education) and high school diploma and some college or vocational training (12–15 years of education), with college degree or higher (16 or more years of education). Our measure of household *income* is based on 1986 dollars, which was the year the first wave of ACL data was collected. It is represented by two dummy variables contrasting those with a combined household income less than \$10,000 per year and \$10,000 to \$29,999 per year, to those with an income of \$30,000 or higher. Due to item non-response on the income questions we used imputed income values provided in the ACL data that were generated using the sequential regression imputation method in IVEware (Raghunathan, Solenberger, & Van Hoewyk, 2002). Finally, we accounted for four different *birth cohorts* in the ACL sample using three dummy variables for each 15-year birth cohort: the first children of the 20th Century (born before 1917), the children of the 1920s (born 1917–1931), the children of the Depression and WWII (born 1932–1946), and the Baby Boomers (birth year 1947–1961) with the latter group as the reference category.

2.3. Statistical analyses

We conducted a second-order growth mixture model (SOGMM) with an accelerated longitudinal design. In an accelerated longitudinal design, multiple cohorts observed at overlapping ages are measured longitudinally over a period of time (Bell, 1953; McArdle & Hamagami, 2001). Under the assumptions of convergence of aging-related trends across age cohorts, the accelerated longitudinal design can provide information about aging over a span broader than implied by the length of the study. Growth mixture modeling is an extension of conventional growth modeling that relaxes the assumption of a single population trajectory. By using latent trajectory mixtures (or *classes*, categorical latent variables), the growth mixture model allows individual trajectories to vary around qualitatively distinct growth curve means and variances. Our model is a second-order growth curve model, which means that we are modeling change in a latent variable (depressive symptoms), where depressive symptoms are defined by a longitudinal factor analysis measurement model. Our purpose is to structure the covariation among the latent depression constructs through

second-order growth factors (intercept and slopes) within latent trajectory classes (Fig. 1).

1. *Factor structure.* The first step in the analyses tested the factor structure of the ordered categorical depression items at each of the 5 waves.
2. *Factorial invariance.* Following the identification of the optimal factor structure, we tested the factorial invariance of the confirmatory factor model over time. We tested for both weak factorial invariance (constraining the factor loadings to be invariant across time) and strong factorial invariance (additionally constraining item intercepts to be invariant across time). Goodness of fit was evaluated with the Chi-square difference test, root mean square error of approximation (RMSEA) (Browne, Cudeck, Bollen, & Long, 1993), the comparative fit index (CFI) (Bentler, 1990), and the Tucker-Lewis Index (TLI) (Tucker & Lewis, 1973). A simulation study conducted by Hu and Bentler (1999) suggested that an RMSEA smaller than 0.06 and a CFI and TLI larger than 0.95 indicate relatively good model-data fit.
3. *Growth curve model.* The structural part of the growth model was then incorporated with the longitudinal factor model by relating the first order latent variables to the second order latent growth factors (intercept, slope, quadratic slope). To identify this model and scale the latent growth factors we fixed the factor loadings of the first items and fixed the first item intercepts to zero following Ferrer et al. (2008). In addition, we specified items as continuous variables at this stage of the analysis, which was necessary for model convergence. The time metric for the growth curve model is age (in years) and within the accelerated longitudinal design creates a synthetic cohort spanning ages 25 through 100. In order to facilitate parameter interpretation, we centered age at the initial point of data collection (setting age 25 to 0) and tested the fit of models allowing for both linear and quadratic growth. Covariances among unique factors for depressive symptoms were included for adjacent time points to accommodate the autocorrelation among depressive symptoms not otherwise captured by the variance and covariance of intercept and slope factors.

Of particular interest is the latent trajectory class variable, which

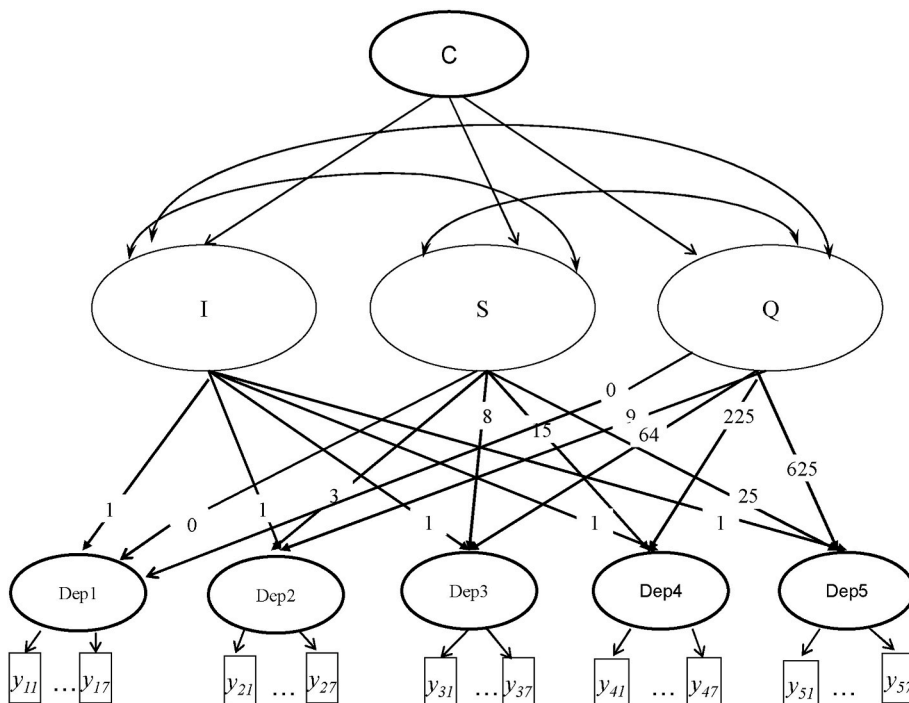


Fig. 1. Path Diagram of second-order growth mixture model of depressive symptoms over adulthood
 Fig. 1 Path diagram of a second-order growth mixture model. Observed variables are represented by squares. Latent variables are represented by circles. The growth parameters are represented by I = intercept, S = slope and Q = quadratic and factor loadings are indicating. Growth parameters are regressed on classes = C. Although not depicted in this figure, the intercepts of the manifest variables are estimated. Unique variances and factor loadings are invariant across time but are not depicted in the figure. Covariates depicting class membership are also not included in the figure but are estimated in the model.

represents the unobserved subpopulations of growth. This model feature allows for the empirical identification of population sub-groups with separate and potentially qualitatively distinct growth curves. While substantively-based theory is used as the primary means to determine the best number of latent classes, good fitting models are characterized by (i) increasingly smaller values for the Bayesian Information Criterion (BIC) (Raftery, 1995) and Akaike Information Criterion (AIC) (Pan, 2001); and (ii) distinct posterior probabilities for individual class membership (Langenbucher et al., 2004; Lubke & Muthén, 2004; Muthén, 2004; Petras et al., 2004).

4. *Regression on social determinants.* Class membership was regressed on sociodemographic characteristics to examine differences in the characteristics among respondents in different latent classes of depressive trajectories.

All models were estimated in Mplus Version 8.3 using full information maximum likelihood (FIML) with robust standard errors. Multiple random starts were used to minimize local optima in the likelihood. Respondent-level weights were used to adjust for unequal selection probabilities in the ACL study as well as differential non-response over the 25 years of the survey (older adults and those with health problems were more likely to drop out of the study, while women, White adults, and those from a higher socioeconomic position were more likely to continue participating in the survey over time). Following the missing at random assumption, by including these variables in our model with maximum likelihood estimation, we assume that the depressive symptom score for a subject who drops out at a given wave is the same for a subject who remains at that wave, if they have the same covariates (Feng, Silverstein, Giarrusso, McArdle, & Bengtson, 2006).

3. Results

Table 1 describes the characteristics of the sample at baseline (in 1986), weighted to account for the sampling design, non-response, and post-stratification to population by age, gender, and race/ethnicity. The majority of respondents were white (N = 2205, weighted percent 79.2) while 1412 respondents (weighted percent 20.8) were non-white (Black (N = 1156), Hispanic (N = 74), or other race (N = 182). Just over half of respondents had a high school diploma, and roughly half were female. On average (across all five waves) mean depressive symptom scores

Table 1
Weighted percent and means for study sample characteristics, N = 3617 Americans' Changing Lives Study (1986).

Variable	Weighted Mean (SD) or Percent
Age (in years) (range 25–96)	53.6 (17.6)
Birth Cohort (%)	
1947–1961	42.0
1932–1946	24.8
1917–1931	20.9
1916 or earlier	12.3
Depressive symptoms (range 0–2)	0.5 (0.4)
Gender (%)	
Male	47.1
Female	52.9
Race (%)	
Non-white	20.8
White	79.2
Education (%)	
Less than High School	25.6
High School Diploma	54.7
College Degree	19.7
Annual Household Income (%)	
<\$10,000	19.2
\$10,000 - \$29,999	40.5
\$30,000 or higher	40.3

SD = standard deviation.

Table 2
Confirmatory factor analysis (standardized factor loadings) for 7-item depressive affect factor by survey wave: Americans' changing lives study (1986–2011).

CES-D Items*	Wave 1 (1986)	Wave 2 (1989)	Wave 3 (1994)	Wave 4 (2001)	Wave 5 (2011)
Feel Depressed	.83	.85	.85	.85	.86
Everything an Effort	.63	.64	.63	.69	.74
Trouble Sleeping	.57	.55	.59	.57	.61
Feel Lonely	.75	.72	.74	.71	.80
Trouble Eating	.60	.58	.61	.61	.68
Feel Sad	.84	.84	.85	.8	.86
Can't Get Going	.66	.67	.61	.64	.77
Fit Indices					
CFI	.98	.97	.99	.98	.99
TLI	.97	.96	.98	.97	.99
RMSEA	.07	.08	.05	.07	.06

* Items are modeled as ordered categorical; all loadings are significant at $p < .05$.

CES-D = Center for Epidemiological Studies Depression Scale.

CFI = Comparative Fit Index.

TLI = Tucker-Lewis Index.

RMSEA = Root Mean Square Error of Approximation.

were relatively low. However, there was evidence of variability in socioeconomic status, which may contribute to variations in depressive symptomatology over the adult life course.

1. *Factor structure.* Similar to the published factor structure of the CES-D (Radloff, 1977) an exploratory factor analysis (EFA) of the depressive items suggested that the 11 items loaded on three distinct factors with a single factor capturing the seven negative affect and somatic symptoms items, and the two positive affect items and the two interpersonal items loading on two other separate factors. This three factor model resulted in the best fit (RMSEA < 0.05) at each of the five waves of ACL data (results not shown). We therefore chose to focus on the single factor capturing general depressive affect (represented by seven items) and ran separate confirmatory factor analyses (CFA) to verify the fit of the model across all five waves. Table 2 presents the factor loadings and fit statistics for the CFA across the five waves of ACL. The results support the factor structure of the depressive latent variable at each wave. Of additional interest is the change in factor loadings across waves where the depressive affect items evolve into a more loneliness and physical disability-based construct over the 25 years between baseline and fifth follow-up interviews.
2. *Factor invariance.* The next step in our modeling process tests measurement invariance in this depressive affect factor over time. Table 3 reports the results for a systematic progression of models testing first weak (metric) and then strong (scalar) factorial invariance of depressive affect over the five waves of the ACL study. Results suggest there is support for strong factorial invariance of the measurement of depressive affect over all five waves. This is supported when specifying the items as categorical (as measured) or continuous (as used in the subsequent models) (Table 3).
3. *Growth curve model.* After confirming the invariance of the measurement model over time, the next sequence of models incorporates this longitudinal measurement model within a larger latent variable model by relating the first order latent variables to latent growth factors and a latent class variable. Table 4 reports on the results of a systematic progression of mixture models, incrementally increasing the number of classes. The first column presents the results for the single class model, specifying a quadratic (non-linear) form to the model with the frequency of depressive symptoms highest in the early period of adulthood, declining significantly over the mid-life

Table 3
Model Fit Statistics for Test of Measurement Invariance in 7-item CESD over time: Americans' Changing Lives Study (1986–2011).

Items Modeled as:	Configural Invariance ^a		Metric Invariance ^b		Scalar Invariance ^c	
	Categorical	Continuous	Categorical	Continuous	Categorical	Continuous
χ^2 / df^d	–	–	1.9	2.1	6.5	9.3
CFI	.95	.88	.96	.88	.96	.87
TLI	.95	.87	.96	.87	.96	.87
RMSEA	.03	.04	.03	.04	.03	.04

CFI = Comparative Fit Index TLI = Tucker-Lewis Index RMSEA = Root Mean Square Error of Approximation.

^a Same indicators of the latent construct are specified at each occasion.

^b Weak factorial invariance = Constraining factor loadings for items to be equal over time.

^c Strong Factorial invariance = Additionally constraining item intercepts to be equal across time.

^d For models with categorical items the chi-square difference test (DIFFTEST option in Mplus) is used to compare nested models.

Table 4
Second order growth mixture model for depressive symptoms over adulthood: Americans' changing lives study 1986–2011.

	Single Class	Two Class Solution	
		Class 1 (60.2%)	Class 2 (39.8%)
Fixed Effects			
Intercept	1.10***	.82***	1.35***
Slope (age)	-.22***	-.50***	.15**
Age ²	.04***	.09***	-.02
Variance Components			
Intercept	.96***	.55***	.93***
Slope (age)	.08***	.07***	.10***
Age ²	Set to 0	Set to 0	
Model Fit			
-2LogL	-72319.7	-71715.5	
AIC	145059.3	143562.9	
BIC	145106.4	143971.6	

*p < .05 **p < .01 ***p < .001 (two-tailed tests).

AIC = Akaike Information Criterion BIC = Bayesian Information Criterion.

Table 5
Logistic regression for latent class membership of depressive symptoms over adulthood: Americans' changing lives study 1986–2011

	Latent Class 2 ^a (Persistently Depressed)	
	Coefficient	OR (95% CI)
Female ^b	.59*	1.81 (1.47, 2.24)
Non-white Race/Ethnicity ^c	.38*	1.46 (1.17, 1.83)
Less than High School ^d	1.35*	3.86 (2.58, 5.77)
High School ^d	.47*	1.60 (1.13, 2.25)
Income less than \$10,000 ^e	1.36*	3.89 (2.83, 5.35)
Income \$10K-\$30K ^e	.50*	1.64 (1.26, 2.14)
Birth Cohort 1916 or earlier ^f	-.21	0.81 (0.51, 1.33)
Birth Cohort 1917–1931 ^f	-.19	0.83 (0.53, 1.29)
Birth Cohort 1932–1946 ^f	.47**	1.60 (1.66, 2.20)

OR = adjusted odds ratio CI = confidence interval * p < .01.

^a Latent Class 1 (U-shaped depression) is the reference class.

^b Reference group is Male

^c Reference group is White.

^d Reference group is College degree or higher

^e Reference group is annual income >\$30K.

^f Reference group is birth cohort 1947–1961.

period, and rising again in later life. The second and third columns of Table 4 report the results for the two-class solution. The change in the BIC and AIC suggest that a two class solution is preferable to a single class model. Membership in each class showed good classification quality with individuals most likely to belong to their predicted class (posterior probability is markedly higher (>0.90) than for the other class). Adding a third and fourth class (models not shown) did not result in any improvement in model fit and the posterior probabilities did not differentiate class membership well.

Fig. 2 shows the estimated growth curves for depressive symptoms according to the 2 class solution. The two curves represent two distinct mental health trajectories over adulthood: Class 1 (with 60% of the sample) represents the majority of the sample, which we term the “U-shaped depression class”, following the population average trajectory. By contrast, individuals in Class 2 (40% of the sample) have persistently high scores on the depressive symptoms index over adulthood, (which we term the “persistently depressed class”), with somewhat more rapid gains in the frequency of symptoms over early adulthood and a slight deceleration over the mid-to-late life period (not statistically significant).

4. Regression on social determinants. The next step in the modeling process adds the covariates to the model, regressing class membership on gender, race/ethnicity, education, income, and birth cohort. Table 5 reports the results from the logistic regression for class membership (adjusted odds ratios and 95% confidence intervals) using the latent “U-shaped depression” class as the reference group. Compared to individuals in the reference class, individuals in the persistently depressed class were more likely to be female, and from a non-white racial/ethnic group, after controlling for other covariates.

However, the largest associations were related to socioeconomic position. Compared to individuals in the reference class, individuals in the persistently depressed class were more likely to have less education, and to have lower incomes. Individuals with less than a high school diploma were almost 4 times as likely as those with a college degree to

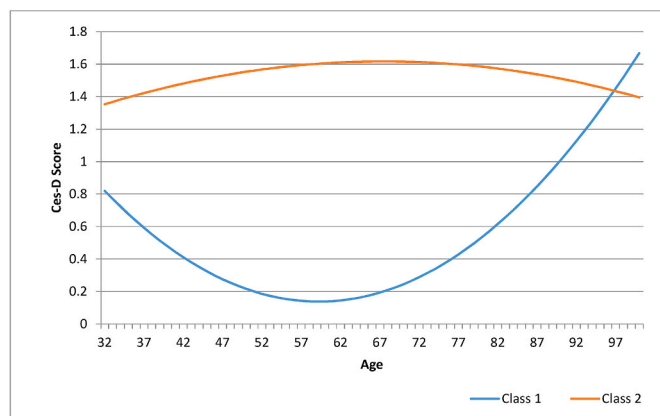


Fig. 2. Predicted CES-D Scores from Two Class Second Order Growth Mixture Model: Americans' Changing Lives Study (1986–2011)

Note: CES-D = Center for Epidemiologic Depression Scale (7 items). Class 1 = Normative U-Shape depressive symptoms class (60% of the sample). Class 2 = Persistently depressed class (40% of the sample). Predicted CES-D scores are illustrated beginning at the midpoint of each 15 year birth cohort in the accelerated longitudinal design.

be in the persistently depressed class (adjusted odds ratio = 3.9, 95% confidence interval = 2.6, 5.8, [Table 5](#)). Lower levels of household income were also strongly related to membership in the persistently depressed class. Compared to those with incomes over \$30,000, the risk of being in the persistently depressed group was almost four-fold higher among those with a combined household income of less than \$10,000 per annum (1986 dollars) (adjusted odds ratio = 3.9, 95% confidence interval = 2.8, 5.4, [Table 5](#)).

There were also significant cohort differences in the odds of class membership. Respondents born in the Depression through Second World War period (pre-Boomers) had 60% higher odds of membership in the persistently depressed class compared to those born in the post-war (Baby-Boomer) generation suggesting lasting effects of historical period events on mental health over adulthood.

4. Discussion

This study makes both substantive and methodological contributions to research on depression, providing a nuanced picture of the variation and course of depressive symptomatology over adulthood. The persistently depressed trajectory and its predictors revealed in the current analyses are often missed when only the population average is used. In addition, the use of the SOGMM with an accelerated longitudinal design is, to our knowledge, the first time this technique has been used with a research design of this kind. The SOGMM with an accelerated longitudinal design builds upon previous work ([Ferrer et al., 2008](#); [Grimm & Ram, 2009](#); [Muthén, 2004](#); [Muthén & Shedden, 1999](#)) and adds to the broader literature on growth mixture modeling as a method to understand different population trajectory *classes* of change over time.

This study generated several important findings. First, the seven-item version of the CES-D demonstrated strong factorial invariance across five waves of data, which indicates that general depressive affect has meant the same thing for this cohort of aging Americans since 1986 and thus meaningful comparisons can be made at the factor level. At the same time, it is notable from a policy perspective that the CES-D items tapping loneliness and physical limitations (everything is an effort/trouble eating/can't get going) have increasingly higher factor loadings compared to the depressive/sadness traits as the cohort ages over the 25 year span of the study. These results are parallel to the age stratification perspective in social gerontology that was influential in directing attention to the effects of social structure and structured social inequality with aging ([Riley, 1987](#)). Compared to social roles occupied over early adulthood and midlife, later life social roles were seen as relatively devoid of content ([Rosow, 1976](#)). The term "structural lag" ([Riley, Foner, & Waring, 1988](#); [Riley, Kahn & Foner, 1994](#)) specifically drew attention to the potential misfit between the social institutions that regulate aging and the productivity needs of new cohorts of older adults. Our results lend support to this theory, highlighting the mental health consequences of a "role-less role" for older persons ([Riley et al., 1988](#)). Our findings can inform research and programmatic initiatives on aging in place and the need to focus community investments to meet the evolving needs of older populations to contribute to society as they age. The potential benefits include improving quality of life, purpose in life, reducing depressive symptoms with age, and reducing public and private economic burdens associated with people who are aging - a growing sector of the population.

This study also found that the functional form of the population average depressive symptomatology trajectory across the life course is consistent with previous work ([Clarke et al., 2011](#); [Sutin et al., 2013](#); [Yang, 2007](#)). It has a nonlinear form which is highest in early adulthood, declines significantly over the midlife period and rises again in later life. However, beyond the population average, the mixture model analyses identified a second trajectory class (40% of the sample) that was characterized by persistently high depressive symptomatology across the life course. The findings concerning this second trajectory are important. Members of this class are disproportionately at risk for potentially

avoidable psychiatric hospitalizations and emergency department visits, housing instability, and involvement with the criminal legal system. For example, it is well documented that people with serious and persistent mental illness are vastly overrepresented among the poor and unhoused, as well as in jails and prisons ([Bronson & Berzofsky, 2017](#); [Steadman, Osher, Robbins, Case, & Samuels, 2009](#)). This situation imposes high costs on individuals, families, and society. The current findings underline the need to take a public health approach by investing in community-based mental health and social services, rather than continuing the criminalization of mental illness and the expansion of mental health treatment capacity in the criminal legal system (e.g. [Chrastil, 2021](#)).

The current analyses provide insights into relations between depression trajectory group membership and the social determinants of health: gender, non-white racial/ethnic group, educational attainment, income, and birth cohort. The results show that membership in the persistently high depressive symptomatology class was associated with identification as female, after controlling for other covariates. This finding is consistent with a large body of research that shows that the burden of depression falls disproportionately on girls and women. In one study, the global 12-month prevalence of major depressive disorder was 5.8% in females and 3.5% in males ([Ferrari et al., 2013](#)), contributing to the general view that gender differences in depression represent a key health disparity. At the same time, other research shows that Black fathers experience alarmingly high rates of depression ([Sinkewicz & Lee, 2011](#)), suggesting that this topic needs further examination. The current study lays the groundwork for a more extensive investigation of gender stratified analyses in longitudinal population based surveys of depressive symptoms. In addition to further specifying differences in the trajectories of depressive symptoms between men and women, such research will inform the issue of conceptual equivalence and the reliability and validity of diagnostic instruments across gender groups.

The current study also found that membership in the persistently high depressive symptomatology class was associated with the non-white racial/ethnic group, after controlling for other covariates. Although our analyses use an admittedly crude measure of race-ethnicity (white/nonwhite) that reflected the US population in 1986, the results align with the [U.S. Office of the Surgeon General's Report \(2001\)](#) on race-ethnic disparities in mental health, as well as several national studies such as [Williams et al. \(2007\)](#) who examined major depressive disorder across African Americans, Caribbean Blacks and non-Hispanic Whites. By contrast, other researchers find lower prevalence of mental disorders, particularly depression, among Blacks and other race ethnic minorities as compared to Whites, casting doubt on the utility of the stress paradigm to explain mental health disparities (e.g. [Breslau, Kendler, Su, Gaxiola-Aguilar, & Kessler, 2005](#)). However, Jackson and colleagues (2012) theorized that Blacks respond to high social stress with unhealthy but stress-relieving behaviors that compromise physical health but may lower risk for mental disorder. The current study contributes to this debate by providing new empirical evidence, from a life course perspective, about the relative disadvantage of non-white racial/ethnic groups in the risk for persistent depression over adulthood.

Finally, the strongest social determinants of depressive trajectory in our analyses concerned socioeconomic position (SEP). Respondents with less than a high school education or lower incomes were almost four times as likely to fall into the persistently high depressive symptomatology category, even after controlling for other significant predictors such as gender and race-ethnicity. This study adds new evidence from a life course perspective to over a century of psychiatric epidemiological research (e.g. [Dohrenwend et al., 1992](#); [Jarvis, 1855](#)) concerning the inverse relation between SEP and psychopathology. Although specifying and testing the dynamic mechanisms that underlie the social determinants of depression require different methods than those used in this study, the current findings support prior research (e.g. [Allen, Balfour, Bell, & Marmot, 2014](#); [McManus, Meltzer, Brugha, Bebbington, &](#)

Jenkins, 2007) and underline the potential benefits of addressing upstream determinants such as quality public education and living wage reforms.

The strengths of this study include a quarter century of prospective follow up on a nationally representative sample and their depressive symptoms over time. In addition, the use of a second order growth mixture model allowed for the identification of distinct subpopulations of trajectories in this sample, while simultaneously modeling the confirmatory factor structure of the observed depressive symptomology items. By including a prediction of class membership, this study also sheds insight into those at highest risk for persistent mental illness throughout adulthood. This study also has limitations. There are other potentially important time-varying predictors of membership in different depressive trajectories. For example, chronic illnesses that increase in later life are associated with higher depressive symptomatology. Because of model complexity, our analyses were limited to time-invariant risk factors. Future research should explore the role of time-varying factors. Our use of weights, which adjust for both non-response bias and sample attrition bias due to mortality, cannot fully eliminate selection effects. About 38% of ACL respondents died over the 25-year period of the study. Thus, older respondents are select survivors. Their reported levels of depressive symptoms likely differ from those who died at younger ages. Also, due to data limitations, we were not able to examine the effect of depression treatments, such as antidepressant use or psychotherapy, on depressive trajectories. Additionally, a better understanding of the role of social causation and social selection in the relation between SEP and depression will help in tailoring policy and practice implications.

Despite these limitations, the identification of multiple sub-population trajectories of depressive symptoms across groups with discrete risk profiles in a nationally representative sample of adults can inform health and social policy. The Surgeon General's Mental Health Supplement Report (2001) states that addressing health disparities involves identifying population variation in the prevalence and course of mental disorders - a vital first step toward mitigating disproportionate disability burdens due to loss of health and productivity across sub populations. A clearer picture of persistent trajectories of depression over the life course will help inform specialized mental health services, social supports, and the distribution of resources to improve outcomes for the most vulnerable groups of people. Additionally, the goal of achieving long-term cost savings by focusing on chronic illness ("The Patient Protection and Affordable Care Act", 2010) depends on improved knowledge of variation in illness trajectories and their correlates in order to appropriately screen and treat mental illness in a heterogeneous population.

Lastly, this research extends the groundwork and supports additional areas of inquiry about the etiology and course of depression. In response to the Healthy People 2010 mandate to reduce health disparities (National Center for Health Statistics, 2012), researchers continue to develop theories and use population level data to test hypotheses regarding variation in the prevalence of mental disorders (Jackson, Knight, & Rafferty, 2010; Schwartz & Meyer, 2010). Cohen, Murphy, and Prather (2019) provide a useful review of outstanding theoretical and empirical challenges. The key issues include conceptual definitions, cumulative effects, and differences in impacts across the life course. Abbott (2001) proposes to address some of these deficits with sequence analysis, which constructs population-level inquiries that retain some of the elements and value of single-case narratives. Finally, Lester Salamon's study of a New Deal policy experiment (Salamon, 1979) shows the imperative of accounting for the time dimension, so-called latent and sleeper effects, in evaluating dynamic outcomes as they change across the life course and across generations as well.

The current study aligns with the Healthy People 2030 overarching goals to eliminate health disparities and create social, physical and economic environments that promote health and well-being (Office of Disease Prevention and Health Promotion, n.d.). By moving beyond

simple differences in prevalence to a more nuanced understanding of distinct life course trajectories of depression and their predictors, this study contributes to theory development about the etiology of depression across diverse populations, and offers empirically-based implications for policy and practice to address mental health disparities and their social determinants.

Author statement

Marilyn Sinkewicz: Conceptualization, Writing-Original Draft, Writing – Review & Editing.

Ola Rostant: Conceptualization, Methodology, Writing – Original Draft.

Kara Zivin: Conceptualization.

Ryan McCammon: Conceptualization, Methodology.

Philippa Clarke: Conceptualization, Methodology, Data Curation, Software, Formal Analysis, Writing – Original Draft, Writing – Review & Editing.

Declaration of competing interest

None.

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