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Latent Subtypes of Depression in a Community Sample of Older Adults: Can Depression Clusters Predict Future Depression Trajectories?

Celia F. Hybels, PhD,

Department of Psychiatry and Behavioral Sciences, Center for the Study of Aging and Human Development, Duke University Medical Center, Box 3003, Durham NC 27710, celia.hybels@duke.edu, Phone: (919) 660-7546, FAX: (919) 668-0453

Lawrence R. Landerman, PhD, and

Department of Medicine, Center for the Study of Aging and Human Development, Duke University Medical Center

Dan G. Blazer, MD, PhD

Department of Psychiatry and Behavioral Sciences, Center for the Study of Aging and Human Development, Duke University Medical Center

Abstract

Identifying sources of heterogeneity in late life depression remains an important focus of psychiatric investigation. Community samples are particularly informative since many older adults have clinically significant depressive symptoms but fail to meet criteria for major depression and older adults generally do not seek treatment for their depressive symptoms. The primary data used for these analyses were those collected in a community-based survey of over 3000 adults age 65 or older followed for up to ten years. Depressive symptoms were measured by the Center for Epidemiologic Studies-Depression scale (CES-D). Latent class analysis was used to identify clusters of participants based on their symptom profiles at baseline. Mixed models were used to examine trajectories of CES-D scores based on cluster assignment. A model with three unique clusters best fit the data. Cluster 1 (59%) had a low probability of any symptom endorsement. Cluster 2 (31%) endorsed as a group some negative affect and somatic symptoms but their endorsement of low positive affect did not differ from Cluster 1. Participants in Cluster 3 (10%) had a higher probability of endorsement of all symptoms compared to Clusters 1 and 2. The results did not appreciably differ when symptom severity was included. Cluster assignment was a significant predictor of change in CES-D score over the ten-year follow-up period, and the effects over time differed by sex. Depressive symptom profiles predict the longitudinal course of depression in a community sample of older adults, findings that are important especially in primary care settings.

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Correspondence to: Celia F. Hybels.

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1. Introduction

As the field of psychiatry moves toward a revised nomenclature there has been considerable discussion surrounding the inherent heterogeneity within diagnoses and the move to include dimensional as well as categorical descriptors in a revised approach (Caine, 2007; Helzer *et al.*, 2006; Kraemer, 2007; Krishnan, 2007; Parker *et al.*, 2012). Depression in particular offers challenges due to its potential social, behavioral, genetic and biological etiologies (Blazer, 2003; Blazer & Hybels, 2005) as well as the documented importance of subsyndromal depression (Judd *et al.*, 1997). Identifying sources of heterogeneity in depressive symptom profiles among adults in community samples remains an important focus of psychiatric investigation. Community samples are particularly informative because a significant number of persons with depressive symptoms do not receive treatment.

Latent class analysis has been a useful tool in grouping individuals who share similar symptom profiles into homogeneous classes that may differ from other classes in their associations with demographic, health and social variables. Many of these investigations have been based on lifetime depressive symptom experiences or only included adults who were currently experiencing clinically significant depressive symptoms. Few studies have examined the longitudinal outcome of these subtypes. For example, investigators using data from the National Epidemiologic Survey of Alcohol and Related Conditions (NESARC) identified four latent classes among adults with a lifetime history of depressive symptoms: 1) a severely depressed class who endorsed most or all of the depressive symptoms; 2) a psychosomatic class who endorsed primarily symptoms such as reduced appetite and sleep disturbance, 3) a cognitive-emotional class who primarily experienced worthlessness or guilt, impaired concentration and suicidal ideation, and 4) a non-depressed class who had low probabilities of endorsing depressive symptoms (Carragher *et al.*, 2009).

Identifying unique depressive subtypes is not new. Kender *et al.* (1996) reported from a sample of female twin pairs that depression was not etiologically homogeneous but instead made up of several unique syndromes that were distinct from a clinical, longitudinal and genetic perspective. Their research identified seven classes of depressive syndromes including an atypical subtype of depression similar in severity to mild, typical depression but characterized by increased eating, hypersomnia, frequent, relatively short episodes and a proclivity to obesity. They later replicated these findings using the National Comorbidity Survey data (Sullivan *et al.*, 1998). This investigative team also validated earlier findings of distinct subtypes using data from both male-male and male-female twin pairs. The classes were generally on a gradient, with the most severe corresponding to typical major depression, the least severe similar to minor depression and atypical major depression at an intermediate level (Sullivan *et al.*, 2002). Similar findings of heterogeneity in depressive samples have also been reported from community samples of adults (Blazer *et al.*, 1988; Eaton *et al.*, 1989; Chen *et al.*, 2000; Lamers *et al.*, 2010). Lincoln *et al.* (2007) examined profiles of current depressive symptoms among African Americans and Caribbean Blacks and identified two unique classes: a high symptom and low symptom class. It is not clear whether these profiles would generalize to a more representative population.

Few studies have explored sources of heterogeneity among samples of older adults that included those without a history of depression and focused on current rather than lifetime symptoms. The prevalence of clinically significant depressive symptoms among older adults sampled from both community and clinical populations, however, can be as high as 14% (Beekman *et al.*, 1995; Blazer, 2003; Lyness *et al.*, 1999; Parmelee *et al.*, 1989; Regier *et al.*, 1988; Steffens *et al.*, 2000; Teresi *et al.*, 2001), and depressive symptoms in late life are a significant public health concern with their associated impairments in physical and cognitive functioning as well as increased mortality. In addition, the number of older adults with a

history of major depression, bringing a susceptibility to future depression episodes, is expected to increase over the next several decades (Heo *et al.*, 2008).

We recently investigated the structure of late life depression among samples of older patients initially diagnosed with major depression. We reported considerable heterogeneity among patients with this one clinical diagnosis and the existence of three to four distinct latent subtypes, depending on the depression scale used to measure depressive symptoms (Hybels *et al.*, 2011; Hybels *et al.*, 2009). We reported clinical indicators such as depression history may play less of a role differentiating unique clusters of patients than variables such as stress, social support, and functional limitations. We also identified unique depressive symptom clusters in a mixed age sample of patients diagnosed with major depression and found while there were age differences in symptom endorsement, there was not a unique symptom profile specific to late-life depression (Hybels *et al.*, 2012). While the study of latent subtypes of depression in patient samples is clinically informative, most older adults do not seek treatment for their symptoms, and if treatment is sought, it is usually outside of the health care setting, supporting the importance of studying depression symptom profiles in non-clinical populations.

The purpose of the analyses described here was to extend earlier findings from clinical samples by 1) identifying unique clusters of community-dwelling older adults based on their depressive symptom profiles, 2) determining if these clusters could be differentiated by risk factors and correlates of late life depression, 3) determining if symptom severity further distinguished the clusters, and 4) determining whether cluster membership longitudinally predicted trajectories of depressive symptoms. Risk factors included demographic variables, health and functioning variables, and social variables known to be associated with depressive symptoms in older adults (Blazer, 2003; Blazer & Hybels, 2005).

2. Material and Methods

2.1 Sample Design

The primary data used were those collected for the Duke site of the Established Populations for Epidemiologic Studies of the Elderly (EPESE), a multi-site longitudinal study of community-dwelling older adults age 65 or older followed for up to ten years. The study design has been documented elsewhere (Blazer *et al.*, 1991; Cornoni-Huntley *et al.*, 1990). Briefly, the sample was a multi-stage area probability sample representative of a five-county area in central North Carolina. Blacks were oversampled and comprised 54% of the baseline sample. A total of 4,000 in-person interviews were completed with participants at baseline. An additional 162 interviews were completed by proxy respondents, resulting in an overall baseline response rate of 80%. Follow-up interviews were conducted at three, six, and ten years post baseline. Approximately 50% of the sample was deceased at ten years, but attrition for reasons other than death was minimal. Depression scores were not available for persons who participated by proxy, approximately 8% at three years, 11% at six years, and 15% at ten years. Persons with missing data on any of the depression items or covariates at baseline were excluded. Complete data were available for 3345 participants at baseline (3401 had complete symptom data), 2526 participants at three years, 1847 participants at six years and 1206 participants at ten years. All participants provided written consent, and the study protocol was reviewed and approved annually by the Duke University Institutional Review Board.

2.2 Measures

Depressive symptoms were measured using the Center for Epidemiologic Studies-Depression scale (CES-D) (Radloff, 1977). The Duke EPESE used a modified version

containing all 20 items but with participants indicating (N=0/Y=1) whether they had experienced each symptom the previous week rather than 0–3 as done in the original version. Positive affect items were reverse coded so higher scores indicated symptom presence (Blazer *et al.*, 1991; Hybels *et al.*, 2009).

Sociodemographic variables included age as a continuous variable, sex, race (Black vs. White/Other with less than 1% Other), <12 years of education vs. 12+, and married vs. not married.

Health and functioning variables included a dichotomous variable indicating mild to moderate cognitive impairment vs. no impairment based on the Short Portable Mental Status Questionnaire (SPMSQ) (Pfeiffer, 1975). Chronic conditions were measured using a summary measure of the presence and impact of heart problems, hypertension, diabetes, stroke, and cancer (Fillenbaum *et al.*, 1998), with those in the upper third classified as having more conditions. Self-rated health was measured as excellent/good vs. fair/poor. Limitations in basic activities of daily living (ADLs) was measured as needing help with five activities defined by Katz *et al.* (1970): bathing, dressing, eating, getting from bed to a chair and toileting. Instrumental limitations (IADLs) were measured using five items from the Older Americans Resources and Services (OARS) survey (Fillenbaum, 1988), and included driving/traveling alone, shopping alone, preparing meals, doing housework, and handling money. Mobility was measured using three items from Rosow and Breslau (1966) – doing heavy work, ability to walk up and down stairs and ability to walk half a mile.

Social variables included subjective social support measured by asking participants how much they could count on or talk about their deepest problems with family or friends, with higher levels indicating more support (Hybels *et al.*, 2001). The number of negative life events experienced within the previous year was measured as 2+ vs. <2.

Time was modeled as 0, 3, 6 and 10 years past baseline.

2.3 Supplemental Data – the Yale EPESE

Data from the Yale EPESE were used to replicate the analyses from the Duke site to identify subtypes based on measures that incorporated symptom severity. The study population for the Yale EPESE was a stratified cluster sample drawn from the population of New Haven, Connecticut. A total of 2,811 adults age 65 or older were interviewed at baseline, a response rate of 82%. The sample design of the Yale EPESE is described elsewhere (Coroni-Huntley *et al.*, 1986). Age-eligible non-institutionalized participants were sampled from three strata – public housing for the elderly, private housing specifically for the elderly and other community residences not specifically for the elderly selected from a sampling frame of utility listings. The study protocol was the same as that of the Duke EPESE, while research interviews were similar but not identical.

Depressive symptoms were measured using the original version of the CES-D, but were coded 1–4 in the Yale data instead of 0–3. Self-perceived health was coded as excellent/good vs. fair/poor/bad. The Mental Status Questionnaire (MSQ) was used to measure cognitive status (Kahn *et al.*, 1960). This instrument was similar to the SPMSQ, with a possible range of scores from 0 to 10, representing the number of errors. We adjusted the number of errors for education and race, and cut-points were determined as in the Duke EPESE. The number of health conditions reported (range 0 to 7) was used to code the number of chronic conditions. There was not a measure of IADL limitations in the Yale EPESE, but ADL and mobility limitations were measured as was done at Duke. We used perception of a confidante (Yes=1, No=0) to measure social support. The number of

negative life events experienced over the past year (range 0–8) was coded as done at Duke, 2 or more events vs. <2.

2.4 Data Analysis

We used latent class cluster analysis to identify unique classes of older adults based on their responses to the indicator variables, in this case the CES-D items at the time of the baseline survey. The dependent variable was a k -category latent variable where each latent subgroup (k) represented a unique cluster of participants. Individuals were assigned to clusters based on their posterior membership probabilities and assigned to the cluster where the probability was the highest (Vermunt & Magidson, 2002; Vermunt & Magidson, 2005). We first estimated models using the CES-D items from the Duke EPESE. To determine if symptom severity affected the pattern of observed clusters, we replicated the analyses using the CES-D items from the Yale EPESE, first coding the symptoms (0–1) as done at the Duke site and then in their original (0–3) format. We then examined in both samples whether the sample characteristics were differentially distributed across the clusters. We next estimated within the Duke EPESE a repeated measures mixed model using cluster assignment (cluster number) as a predictor of CES-D score over time (up to four measures over ten years) controlling for selected covariates (age, sex, race, marital status, health conditions, cognitive status and mobility status) at their baseline value to see if the unique classes of participants had different trajectories. Our first model was uncontrolled. In Model 2 we allowed the covariates to affect the intercept and in Model 3 we allowed the covariates to affect the intercept and slope. In Model 4, we estimated through higher order terms whether the effect of cluster membership on the slope differed across the level of each covariate. These three-way interactions with time*cluster*each of the covariates were tested as a group and nonsignificant terms were removed using backward elimination. Two-way interactions with cluster and with time were also tested as groups following the same protocol, controlling for significant three-way terms in this final model.

To determine the optimal number of clusters, we estimated five consecutive models for each site with 1–5 clusters each. To compare the fit among the models we used the Bayesian Information Criteria (BIC) statistic that takes the number of parameters into account, the log-likelihood ratio tests of the significance of an additional cluster and changes in the classification error. Because class assignment is based on membership probability, a participant may have a high probability of being in one class but a lower probability of being in another class, resulting in potential classification error. In our final models, we examined the inclusion of bivariate residuals to adjust for highly correlated parameters.

The latent class cluster models were estimated using Latent Gold software (Vermunt & Magidson, 2005; Vermunt & Magidson, 2005). The mixed models and the descriptive analyses were estimated using SAS software, Version 9.3 (SAS Institute, 2011). As the research intent was to identify heterogeneity within a sample of older adults rather than make population estimates, the latent cluster models were estimated without using the survey design weights. The proportion of participants in each depression class therefore is not representative of the community populations from which the samples were selected.

3. Results

Table 1 presents the characteristics of the analysis samples at the time of the baseline survey. The Duke EPESE sample had a mean age of over 70 and was predominantly female and Black. The majority had less than 12 years of education. The sample was generally healthy and had few functional limitations. As expected, few of those who provided responses to the CES-D had any cognitive limitations. The sample overall had good social support and few had experienced negative stressors over the past year. The majority of the

participants had few depressive symptoms. The mean CES-D score was 3.1 (3.4) and ranged from 0 to 18, while the median CES-D score was 2.

A higher percentage of participants in the Yale EPESE were White and had completed 12 or more years of education, while a lower percentage was female compared to participants in the Duke EPESE. Those in the New Haven sample appeared to have more limitations in ADL tasks and to have recently experienced negative stressful events.

As shown in Table 2, a three-cluster model best fit the Duke EPESE data where the twenty CES-D symptoms were coded 0 (not present) or 1 (present the previous week). The addition of a cluster was significant at each stage. The classification error increased with the addition of the fourth cluster, confirming the choice of a three-cluster model. Our final model included two bivariate residuals to reduce local dependencies between CES-D symptoms 12 (happy) and 16 (enjoyed life) and CES-D symptoms 15 (people were unfriendly) and 19 (people disliked me). The classification error in our final model indicated a good separation among the clusters.

A total of 59% of the participants were in Cluster 1 with a profile of essentially no symptom endorsement. A total of 31% of the participants were in Cluster 2 and endorsed as a group some negative affect and somatic symptoms but their endorsement of low positive affect symptoms did not appear to differ from those in Cluster 1. Participants in Cluster 3 (10%) had more endorsement of negative affect symptom, low positive affect symptoms and somatic symptoms compared to both Clusters 1 and 2. These profiles are shown in Figure 1. The clusters for the most part differed by severity.

Within the New Haven EPESE data we found a three cluster model also best fit the data when each symptom was coded as 0–1 as in the Duke site or as in the original scale with higher scores indicating greater severity (see Table 2). We assessed model fit as done in the Duke EPESE.

Using these CES-D items coded both ways, we found the profiles were closely aligned within the Yale data for the two coding schemes and very similar to the three profiles found in the Duke data. The cluster profiles for the Yale sample using binary coding as done in the Duke EPESE are shown in Figure 2. A total of 50% were in Cluster 1, 36% in Cluster 2 and 14% in Cluster 3. The profiles for the full coding scheme in the Yale data are shown in Figure 3. A total of 47% of the participants were in Cluster 1, 42% in Cluster 2, and 11% in Cluster 3.

Because these samples were slightly different and selected from different geographic areas, we did not expect the proportions assigned to different clusters to be comparable between sites (using the full coding from the Yale site). With the exception of participant race in the Yale EPESE, we found demographic, health and social sample characteristics differentiated the clusters, with similar patterns observed across both sites as shown in Table 1. Those in Cluster 1, for example, were younger, less likely to be female, more likely to be White, have 12 or more years of education, be married, have less cognitive impairment, be in better health as measured by number of conditions and self-report, have fewer functional limitations, and less likely to have experienced negative life events the previous year compared to those in Clusters 2 and 3. As expected, those in Cluster 3 had not only the highest mean scores for each symptom but were older, more likely to be female, have fewer years of education, be unmarried, have more chronic health conditions and perceive their health as fair or poor, have more functional limitations, have low perceived social support and more stressful experiences. Within the Yale data, we also observed differences by housing stratum, with a higher proportion of those selected from public housing in Cluster 2, private housing for the elderly in Cluster 3, and regular community housing in Cluster 1.

These findings suggest those in housing specifically for the elderly may be more vulnerable to higher levels of depressive symptoms.

Using repeated measures mixed models we found cluster assignment was a significant predictor of CES-D score over time. That is, the depression trajectories differed by cluster assignment. These associations remained significant when selected covariates were controlled at their baseline level, and when the covariates were allowed to affect both the intercept and slope for each cluster. The results of the regression models are presented in Table 3. The predicted trajectories of CES-D score for each Cluster adjusted for potential confounders at the mean are shown in Figure 4. Participants in Cluster 1 essentially experienced few if any depressive symptoms over the course of the study. Participants in Cluster 2 maintained low depressive symptomatology over the ten-year follow-up period. Participants in Cluster 3 started with higher scores on average but the CES-D scores declined over time resulting in convergence by the ten-year follow-up. While significantly different and non-parallel trajectories were noted for the three clusters, these findings suggest the heterogeneity identified at the time of the baseline survey based on depression symptom scores alone was less obvious over time. We also show in Figure 4 the observed (uncontrolled) mean CES-D score for each cluster at each of the four time points. These findings suggest, for Cluster 3 that the decrease in CES-D score occurred primarily by the time of the three year follow-up.

In the final model (Model 4, results not shown) we found the effect of cluster assignment differed by level for three covariates: sex, age and SPMSQ score. These differences were most noticeable within Cluster 3. Men, those ages 75+ and those with lower SPMSQ scores had faster rates of recovery/decline in CES-D score within Cluster 3. We estimated the mixed models within Cluster 3 only, controlling for the listed covariates and found neither time*age nor time*cognitive status were significant. Time*sex was significant within Cluster 3 so we focused on this more robust finding only. The trajectories for men and women did not appear to differ for Clusters 1 and 2 as shown in Figure 5. Within Cluster 3, the CES-D scores for men declined faster than those for women. We examined the observed (uncontrolled) means for Cluster 3 by sex and found that men showed a greater decrease in CES-D score by the three-year follow-up (11.3 at baseline to 5.9) compared to women (10.8 to 7.3), and then both men and women maintained a generally stable course. That is, the mean score for men was 5.2 at both six and ten years while for women the mean scores were 6.7 and 7.0.

4. Discussion

We report several new findings from this research. Within our sample of older adults in the Duke EPESE we identified three unique clusters of participants based on their endorsement of CES-D symptoms at the time of the baseline survey. While each respondent had a low probability of endorsing any given symptom, 75% of the participants endorsed at least one of the twenty items. The clusters were differentiated by negative affect and somatic symptoms but less so by low positive affect symptoms. While our clusters differed primarily in terms of severity, we noted some symptoms such as low positive affect had a low probability of being endorsed even among the cluster with the highest probabilities of symptom endorsement. When we replicated the results in data from the Yale EPESE which incorporated severity, we also found a three-cluster model best fit the data, and the profiles for the three clusters were remarkably similar suggesting that symptom endorsement alone may differentiate older adults.

Of particular interest to clinicians and researchers is the distribution of sample characteristics across the clusters. We noted gradients in the associations with the risk

factors/correlates but also noted Cluster 2 seemed to be more similar to Cluster 3 than to Cluster 1. That is, endorsement of any symptoms in an older cohort may be associated with older age, female sex, being of White race/ethnicity, having fewer than 12 years of education, being unmarried, having mild to moderate cognitive impairment, having more health conditions, self-rating health as fair or poor, having more functional limitations, having lower levels of perceived social support and experiencing more stress.

In summary, three clear clusters were found and replicated in a second community sample. These clusters were for the most part not differentiated by symptom patterns. Within the field of psychiatry it has been assumed that older adults with more severe depression would have a symptom profile that would be qualitatively different from a profile for those with less severe depression (e.g., that more severe depression would be associated with more somatic symptoms while mild depressive symptoms would present primarily as low positive affect). These baseline analyses suggest that the symptom patterns are essentially parallel with minor differences.

Using data from the Duke EPESE we also estimated statistically rigorous regression models to determine if cluster assignment at baseline predicted the trajectory of CES-D scores over the ten year follow-up. Not only did cluster assignment have a direct effect on depression course, but we also noted these associations remained significant when selected covariates were allowed to influence the intercept and slope. While we noted some qualitative differences in symptom expression, the clusters at baseline differed primarily by severity, resulting in intercepts that reflected, in part, a low, moderate and high level of symptoms. These intercepts necessarily determined much of the course of depression. This may explain why we noted that cluster assignment appeared to have a greater effect earlier in the study period and that baseline differences became less apparent over time.

The trajectories were not parallel, however, suggesting cluster assignment affected the slope as well as the intercept. While Clusters 1 and 2 reflected a stable course of low or moderate symptom level, participants in Cluster 3 (those with a high level of depressive symptoms) saw a decrease in CES-D score over time rather than a stable high trajectory. We can only venture a guess what lies behind the decreasing scores for those in Cluster 3, reflecting perhaps recovery from depressive symptoms or statistical regression to the mean. We also noted within Cluster 3 that the likelihood of endorsing the CES-D symptoms among male participants decreased more rapidly than among female participants. To the best of our knowledge this is the first study to identify trajectories of the course of depression based on symptom profiles at baseline in a community based sample of older adults. Our findings of potential sex differences in these trajectories will be the focus of future work.

Our research is not without limitations. We measured depressive symptoms and do not know which of the participants met criteria for major or minor depression. Attrition is a potential problem for all longitudinal studies of older adults and the Duke EPESE was no exception. Participants who become cognitively impaired or developed serious health problems that precluded their participation were excluded from later assessments. A significant number of participants died over the course of the follow-up. Depression symptoms are linked to higher mortality rates (Blazer *et al.*, 2001), potentially resulting in selective survival to ten years of those participants who were most physically and emotionally healthy. Finally, participants were assigned to their respective classes based on posterior probabilities. Participants with relatively equal probabilities of belonging in two classes may have been misclassified. Our data suggest, however, that cluster separation was excellent.

Our research had a number of strengths which outweigh the potential limitations. We used data from two large representative samples of older adults to identify symptom profiles. Our

sophisticated analytic methods allowed us to use a model-based approach to identify the unique clusters of participants. In addition, we used statistically rigorous statistical techniques to model the trajectories of CES-D scores over time. In this research, participants were included even if they didn't have a history of depression or weren't currently experiencing depressive symptoms which allowed the identified subtypes to represent the participants in the two diverse samples.

Overall, these findings are particularly relevant for clinicians, especially those in busy primary care settings, who often see older adults with a range of depressive symptoms but have very little knowledge how different symptom profiles may affect depression outcomes. The natural history is the template upon which one can judge the effectiveness of both psychotherapies and pharmacotherapy. Finding that women who are more depressed initially also express more depressed symptoms over time compared to men has clear clinical usefulness, though one must take care not to over generalize and to realize that different therapies may impact women differently than men.

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Figure 1.
Profiles of depressive symptoms in the Duke EPESE.

Figure 2.
Profiles of depressive symptoms in the Yale EPESE using 0–1 coding.

Figure 3.
Profiles of depressive symptoms in the Yale EPESE using 1–4 coding.

Predicted CES–D Score by Cluster Adjusted for Potential Confounders

Figure 4.
Ten-year trajectories of CES-D score by cluster assigned at baseline in the Duke EPESSE

Predicted CES–D Score by Cluster Adjusted for Potential Confounders

Figure 5.
Ten-year trajectories of CES-D score by cluster assigned at baseline and sex in the Duke
EPESE

Table 1
Sample Characteristics by Cluster for the Duke sample (coded 0–1) and New Haven Sample (coded 0–3) (unweighted)

Characteristic	Duke (n=3401)			Yale (n=2340)		
	Total Sample	Cluster 1	Cluster 2	Cluster 3	Total Sample	Cluster 1
		n=2019 (59.4%)	n=1053 (31.0%)	n=329 (9.7%)		n=1110 (47.4%)
Mean age in years (sd)	73.1 (6.4)	72.6 (6.2)	73.9 (6.6)	74.1 (6.8)	74.3 (6.8)	73.6 (6.6)
				F(2,3398)=17.08, p<0.0001		75.5 (7.1)
No. Female (%)	2203 (64.8%)	1186 (58.7%)	762 (72.4%)	255 (77.5%)	1356 (58.0%)	585 (52.7%)
				$\chi^2[2]=82.2$, p<0.0001		594 (60.8%)
No. White (%)	1552 (45.6%)	982 (48.6%)	433 (41.1%)	137 (41.6%)	1876 (80.2%)	889 (80.1%)
				$\chi^2[2]=18.1$, p=0.0001		776 (79.4%)
No. Years of Education <12 (%)	2600 (76.5%)	1451 (71.9%)	866 (82.2%)	283 (86.0%)	1557 (67.7%)	681 (62.3%)
				$\chi^2[2]=59.9$, p<0.0001		693 (72.4%)
No. Married (%)	1342 (39.6%)	940 (46.7%)	323 (30.7%)	79 (24.0%)	902 (38.6%)	500 (45.1%)
				$\chi^2[2]=110.6$, p<0.0001		327 (33.5%)
No. with Mild to Moderate Cognitive Impairment (%)	342 (10.1%)	159 (7.9%)	123 (11.8%)	60 (18.4%)	213 (9.1%)	66 (6.0%)
				$\chi^2[2]=38.0$, p<0.0001		103 (10.6%)
No. with More Chronic Conditions (%)	1146 (33.9%)	612 (30.5%)	381 (36.4%)	153 (46.8%)		
				$\chi^2[2]=37.9$, p<0.0001		
Mean No. Health Conditions (sd)					1.20 (1.02)	1.06 (0.95)
						1.26 (1.03)
No. with Fair or Poor Self-Rated Health (%)	1524 (45.0%)	661 (32.9%)	620 (59.2%)	243 (74.8%)	935 (40.0%)	268 (24.2%)
				$\chi^2[2]=321.2$, p<0.0001		487 (50.0%)
Mean IADL Score (sd)	0.57 (1.20)	0.37 (0.98)	0.77 (1.34)	1.17 (1.57)		
				F(2,3394)=89.4, p<0.0001		
Mean ADL Score (sd)	0.19 (0.69)	0.11 (0.54)	0.26 (0.79)	0.45 (0.98)	0.33 (0.90)	0.17 (0.64)
				F(2,3359)=43.4, p<0.0001		0.38 (0.95)
Mean Mobility Score (sd)	0.84 (1.09)	0.56 (0.93)	1.15 (1.17)	1.54 (1.14)	0.75 (1.02)	0.46 (0.84)
				F(2,3389)=198.7, p<0.0001		0.90 (1.07)
No. with Low Subjective Social Support (%)	990 (29.2%)	486 (24.1%)	367 (35.1%)	137 (41.9%)		
				$\chi^2[2]=68.0$, p<0.0001		
No. without Confidante (%)					371 (16.0%)	166 (15.0%)
						146 (15.1%)
No. with 2+ Negative Events Past Year (%)	526 (15.7%)	189 (9.4%)	222 (21.5%)	115 (35.7%)	962 (41.3%)	365 (33.0%)
				$\chi^2[2]=183.3$, p<0.0001		456 (47.1%)
Housing Stratum Public					607 (25.9%)	241 (21.7%)
						303 (31.0%)
						63 (24.9%)
						$\chi^2[6]=41.6$, p<0.0001
						59 (23.5%)
						$\chi^2[2]=12.0$, p=0.0025
						141 (56.2%)
						$\chi^2[2]=67.8$, p<0.0001
						$\chi^2[6]=41.6$, p<0.0001

Characteristic	Duke (n=3401)			Yale (n=2340)				
	Total Sample	Cluster 1 n=2019 (59.4%)	Cluster 2 n=1053 (31.0%)	Cluster 3 n=329 (9.7%)	Total Sample	Cluster 1 n=1110 (47.4%)	Cluster 2 n=977 (41.8%)	Cluster 3 n=253 (10.8%)
Private					726 (31.0%)	326 (29.4%)	301 (30.8%)	99 (39.1%)
Community					984 (42.1%)	530 (47.8%)	364 (37.3%)	90 (35.6%)
Community (Bulk Meters)					23 (1.0%)	13 (1.2%)	9 (0.9%)	1 (0.4%)

Analysis of Model Selection

Table 2

Model	BIC	Number of Parameters	L ²	df	Bootstrap p-value	Classification Error	-2LL Diff	df	Bootstrap p-value
Duke EPESE <i>Coded 0-1</i>									
1-Cluster	55292.316	20	18432.770	3381	<0.0001	0.0000			
2-Cluster	48632.994	41	11602.679	3360	<0.0001	0.0350	6830.0906	21	<0.0001
3-Cluster	47914.653	62	10713.570	3339	0.0200	0.0997	889.1091	21	<0.0001
4-Cluster	47815.665	83	10443.814	3318	0.0600	0.1844	269.7560	21	<0.0001
5-Cluster	47788.589	104	10245.969	3297	<0.0001	0.2008	197.8447	21	<0.0001
Final Model ^a	47598.657	64	10381.310	3337		0.0991			
3-Cluster									
Yale EPESE <i>Coded 0-1</i>									
1-Cluster	50342.512	20	20713.955	2320	<0.0001	0.0000			
2-Cluster	43948.766	41	14157.293	2299	<0.0001	0.0350	6556.6621	21	<0.0001
3-Cluster	43111.525	62	13157.136	2278	0.1160	0.0855	1000.1565	21	<0.0001
4-Cluster	42960.783	83	12843.478	2257	0.2900	0.1469	313.6580	21	<0.0001
5-Cluster	42929.722	104	12649.501	2236	0.3180	0.1659	193.9770	21	<0.0001
Final Model ^b	42686.021	65	12708.358	2275		0.0876			
3-Cluster									
Yale EPESE <i>Coded 0-3</i>									
1-Cluster	70394.059	60	39561.864	2280	<0.0001	0.0000			
2-Cluster	64365.848	81	33370.736	2259	<0.0001	0.0361	6191.1272	21	<0.0001
3-Cluster	63156.896	102	31998.868	2238	0.0440	0.0698	1371.8682	21	<0.0001
4-Cluster	62906.159	123	31585.216	2217	0.2160	0.1302	413.6525	21	<0.0001
5-Cluster	62828.385	144	31344.525	2196	0.2160	0.1599	240.6905	21	<0.0001
Final Model ^c	62874.341	104	31700.798	2236		0.0720			
3-Cluster									

Note: Some models with four or more clusters unstable; L2 = likelihood-ratio statistic; df=degrees of freedom; -2LLDiff = log likelihood ratio χ^2 comparing nested models;

^aFinal model includes 2 bivariate residuals included as direct effects;

^bFinal model includes 3 bivariate residuals included as direct effects;

^cFinal model includes 2 bivariate residuals included as direct effects;

Table 3

Results of repeated measures mixed models predicting CES-D score over time.

	Cluster	Model 1				Model 2				Model 3			
		Parameter Estimate	Standard Error	t	p-value	Parameter Estimate	Standard Error	t	p-value	Parameter Estimate	Standard Error	t	p-value
Intercept		0.9370	0.0309	30.35	<0.0001	0.6591	0.2910	2.26	0.0236	0.6749	0.2984	2.26	0.0238
Time		0.1447	0.0103	14.09	<0.0001	0.1476	0.0103	14.40	<0.0001	0.1399	0.1197	1.17	0.2424
Cluster	3	9.8648	0.0825	119.55	<0.0001	9.5655	0.0850	112.59	<0.0001	9.5876	0.0852	112.58	<0.0001
	2	3.6816	0.0527	69.83	<0.0001	3.5058	0.0540	64.89	<0.0001	3.5195	0.0541	65.00	<0.0001
	1	0											
Time*Cluster/	3	-0.7105	0.0309	-22.97	<0.0001	-0.7071	0.0308	-22.93	<0.0001	-0.7407	0.0319	-23.23	<0.0001
	2	-0.2222	0.0186	-11.92	<0.0001	-0.2199	0.0186	-11.84	<0.0001	-0.2400	0.0192	-12.51	<0.0001
	1	0											
Age at Baseline						-0.0021	0.0039	-0.53	0.5950	-0.0014	0.0040	-0.36	0.7165
Female						0.0578	0.0533	1.08	0.2783	0.0223	0.0549	0.41	0.6846
Married						0.0800	0.0538	1.49	0.1374	0.0739	0.0555	1.33	0.1829
White						-0.0801	0.0471	-1.70	0.0890	-0.0839	0.0485	-1.73	0.0837
<12 Years of Education						0.3136	0.0557	5.63	<0.0001	0.2757	0.0574	4.80	<0.0001
More Health Conditions						0.1648	0.0492	3.35	0.0008	0.1482	0.0506	2.93	0.0034
Mobility Limitations						0.1995	0.0236	8.46	<0.0001	0.1910	0.0242	7.88	<0.0001
Mild/Moderate Cognitive Impairment						0.1393	0.0786	1.77	0.0765	0.1586	0.0802	1.98	0.0481
Time*Age										-0.0011	0.0016	-0.68	0.4945
Time*Female										0.0524	0.0195	2.68	0.0073
Time*Married										0.0086	0.0189	0.45	0.6493
Time*White										0.0081	0.0170	0.48	0.6332
Time*Education										0.0520	0.0193	2.70	0.0070
Time*Health Conditions										0.0271	0.0185	1.47	0.1429
Time*Mobility										0.0157	0.0095	1.65	0.0999

Cluster	Model 1			Model 2			Model 3					
	Parameter Estimate	Standard Error	t	p-value	Parameter Estimate	Standard Error	t	p-value	Parameter Estimate	Standard Error	t	p-value
Time*Cognitive Impairment									-0.0479	0.0388	-1.23	0.2173

F tests examine overall significance, including effects within interaction terms : Model 1 - F=294.62 p<0.0001; Model 2 - F=293.12 p<0.0001; Model 3 - F=295.37 p<0.0001