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BRIEF REPORT

Socioeconomic Resources Predict Trajectories of Depression and Resilience Following Disability

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Objective: Adjustment to chronic disability is a topic of considerable focus in the rehabilitation sciences and constitutes an important public health problem given the adverse outcomes associated with maladjustment. While existing literature has established an association between disability onset and elevated rates of depression, resilience and alternative patterns of adjustment have received substantially less empirical inquiry. The current study sought to model heterogeneity in mental health responding to disability onset in later life while exploring the impact of socioeconomic resources on these latent patterns of adaptation. ***Method:*** Latent growth mixture modeling was utilized to identify trajectories of depressive symptoms surrounding physical disability onset in a population sample of older adults. Individuals with verified disability onset ($n = 3{,}204$) were followed across four measurement points representing a 6-year period. ***Results:*** Four trajectories of depressive symptoms were identified: resilience (56.5%), emerging depression (17.2%), remitting depression (13.4%), and chronic depression (12.9%). Socioeconomic resources were then analyzed as predictors of trajectory membership. Prior education and financial assets at the time of disability onset robustly predicted class membership in the resilient class compared to all other classes. ***Conclusion:*** The course of adjustment in response to disability onset is heterogeneous. Our results confirm the presence of multiple pathways of adjustment surrounding late-life disability, with the most common outcome being near-zero depressive symptoms for the duration of the study. Socioeconomic resources strongly predicted membership in the resilient class compared with all other classes, indicating that such resources may play a protective role during the stress of physical disability onset.

Impact and Implications

The current analysis helps to establish that the course of adjustment to disability onset in later life is heterogeneous, with the most common trajectory being resilience, followed by alternative patterns of adjustment that indicate more significant depressive burden. Socioeconomic variables strongly predicted membership in the resilient class compared to other classes, suggesting that such resources may buffer against the psychological stress of functional decline. Current findings suggest that older adults with lower socioeconomic status are most at risk for elevated depressive symptoms following disability onset. Socioeconomic factors may thus be important predictors of adjustment difficulty, which has important policy implications for the guidance and targeted distribution of treatment resources.

Keywords: adjustment, depression, latent growth mixture modeling, Heath and retirement study, socioeconomic resources

Introduction

The onset of a physical disability is an undeniably challenging and difficult life event. Empirical evidence has linked physical disability with a high prevalence of depression as well as a range of other mental health outcomes (Ormel et al., 1994). The association between physical disability and depression has been detected across the life span (Aneshensel, Frerichs, & Huba, 1984; Brenes et al., 2008) but is especially prominent in later adulthood as risk

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for functional impairment increases (Regan, Kearney, Savva, Cronin, & Kenny, 2013). Some estimates of clinically significant depression in samples of physically disabled older adults are above 35% (e.g., Ormel, Rijsdijk, Sullivan, van Sonderen, & Kempen, 2002; Turner & McLean, 1989; Turner & Noh, 1988). Despite these elevations, it is clear that not all who become disabled will develop depression or other psychopathologies. This raises crucial questions about the longitudinal course of adjustment to physical disability in later life and whether there are alternative "latent" patterns of adaptation. Furthermore, if the course of adjustment to disability is indeed heterogeneous, are there important determinants of these differential pathways?

To address these questions, the current study identified trajectories of depressive symptoms using latent growth mixture modeling (LGMM) in a population sample of older adults with verified physical disability onset. We utilized true prospective data that covered a 6-year period, beginning 2 years before disability onset and continuing 4 years after. Given evidence suggesting socioeconomic factors play a protective role in the disability onset stress-adaptation process (Kavanagh et al., 2015; Mandemakers & Monden, 2010; Smith, Langa, Kabeto, & Ubel, 2005), we targeted two socioeconomic variables as predictors of trajectory membership.

Method

Data

The current study used data from the Health and Retirement Study (HRS; http://hrsonline.isr.umich.edu), a nationally representative research initiative funded by the National Institute on Aging. Data were analyzed in accordance with approval from the NYU Medical Center Internal Review Board. The HRS was designed to explore socioeconomic, physical, and mental health factors relevant to aging and retirement in the United States, and participant data were gathered every 2 years (see Sonnega et al., 2014, for HRS sampling methods). Ten biennially sampled waves were used for the current analysis (1994–2012), extracted from the HRS RAND data files Version N (Chien et al., 2014). We centered data around the wave of disability onset using a floating-baseline methodology (Galatzer-Levy & Bonanno, 2014; Galatzer-Levy, Bonanno, & Mancini, 2010), aligning participants from different HRS cohorts to the same four measurement points: T1 (baseline), T2 (disability onset), T3 (2 years after), and T4 (4 years after).

Participants and Procedure

Physical disability onset was defined as the change from no impairment in activities of daily living (ADLs) to difficulty in at least one domain. HRS respondents were asked whether they currently experience difficulty in any of five ADL domains: walking across a room, getting dressed, bathing, eating, and getting out of bed. All respondents included in the current sample reported no difficulties with ADLs in the year of baseline measurement (T1, ADL = 0), followed by a subsequent two waves of ADL impairment (T2–T3, ADL ≥1). Thus, all individuals in the current sample transitioned from no impairment (T1) to chronic disability, defined as two consecutive waves of functional disability (T2–T3). To facilitate model convergence, the sample was restricted to participants with at least two available depression measurements across the four waves. The final sample comprised 3,204 participants, predominantly female (65%) and Caucasian (77.4%), with a mean age at time of disability onset of 72.6 years (SD = 11.68). Sample demographics are summarized in Table 1.

Depression was assessed using a brief eight-item version of the Center for Epidemiological Studies–Depression scale (CES-D; Radloff, 1977). The eight-item CES-D has been validated for use with older populations, with adequate reliability (α = .84; Karim, Weisz, Bibi, & ur Rehman, 2015). The HRS suggests a cutoff score of 4 for clinically significant depression (Steffick, 2000).

Data Analysis

Trajectories of depressive symptoms were identified using LGMM (Mplus 8.1; Muthén & Muthén, 2017). Successive models of increasing complexity were tested, comparing k versus k – 1 model-fit statistics. We allowed the variance of the slope and the intercept to be freely estimated but fixed the quadratic parameter. Final unconditional model selection was guided by fit statistics, interpretability, and theoretical coherence (Bonanno, 2004; Muthén, 2004). We explored a range of demographic and situational covariates (age, gender, education, wealth, marital status, race, ethnicity) for possible inclusion in the conditional model based on their theoretical relevance to the question of disability adjustment in later life. Three variables were entered successfully into the conditional model and influenced class membership in a multinomial logistic regression: age, participant education (coded 0 = high school or less, 1 = some college or more), and wealth (total household financial savings at the time of disability onset, including the value of home ownership and other property, minus debt). We normalized the financial variable by first shifting the distribution to remove negative asset values (i.e., adding a constant to each score) and then conducting a natural logarithmic transformation.

Results

Unconditional Model

We tested one- to five-class unconditional solutions and observed continued improvement in model fit through four classes

Table 1
Sample Demographics (n = 3,204)

Variable	Value
Gender, n (%)	
Male	1,117 (34.9)
Female	2,087 (65.1)
Race/ethnicity, n (%)	
White	2,478 (77.4)
Non-White	726 (22.6)
Age, M (SD), y	72.6 (11.68)
Marital status, n (%)	
Married	1,693 (52.8)
Unmarried	1,502 (46.9)
Education, n (%)	
High school or below	2,308 (72.0)
College or above	896 (28.0)

(see Table 2). Although the five-class solution also resulted in improved fit, it was theoretically and practically less interpretable. The proportion of resilience was identical in both the four- and five-class solutions (56%), but the five-class solution split the emerging trajectory into two smaller trajectories, adding little new useful information to the model. For this reason, the four-class model was selected as the optimal solution (see Figure 1).

The largest class was *resilient* (56.5%), exhibiting consistent low levels of depressive symptoms across 6 years (low intercept, $b = 1.05$, $SE = 0.05$, $p < .001$; a flat but significant linear slope, $b = 0.62$, $SE = 0.06$, $p < .001$; and a significant negative quadratic parameter, $b = -0.13$, $SE = 0.02$, $p < .001$). An *emerging-depression* group was characterized by low initial depression that increased after disability onset (low intercept, $b = 1.94$, $SE = 0.11$, $p < .001$; a significant increasing linear slope, $b = 3.49$, $SE = 0.21$, $p < .001$; and a significant negative quadratic parameter, $b = -0.90$, $SE = 0.07$, $p < .001$). A *remitting-depression* trajectory (13.4%) demonstrated high initial depression followed by decreases over subsequent waves (high intercept, $b = 4.72$, $SE = 0.18$, $p < .001$; significant decreasing linear slope, $b = -1.77$, $SE = 0.29$, $p < .001$; and a significant quadratic parameter, $b = 0.37$, $SE = 0.08$, $p < .001$). Finally, a *chronic depression* class (12.9%) demonstrated high levels of depressive symptoms across the 6-year study (high intercept, $b = 6.30$, $SE = 0.14$, $p < .001$; a flat nonsignificant linear slope, $b = -0.27$, $SE = 0.15$, $p = .08$; and a nonsignificant quadratic parameter, $b = 0.03$, $SE = 0.06$, $p = .64$).

Conditional Model

The addition of age, education, and wealth covariates to create a conditional model did not significantly alter the shape of the trajectories and resulted in only minor alterations of proportional trajectory membership (entropy = 0.78, was comparable). One participant was excluded from covariate analyses due to missing data (final sample $n = 3{,}103$).

We examined predictors of class membership in a multinomial logistic regression (see Table 3). Compared to the resilient class, all other classes had significantly lower financial assets, less education, and younger age. Compared with the chronic group, the emerging and remitting depression groups had significantly greater assets and older age, and the emerging group had significantly greater education. The emerging and remitting depression groups did not significantly differentiate on socioeconomic predictors or age.

Discussion

A growing number of studies have mapped the physical process of functional decline, modeling trajectories of ADL impairment (e.g., Gill, Gahbauer, Han, & Allore, 2010; Liang, Xu, Bennett, Ye, & Quiñones, 2010; Nusselder, Looman, & Mackenbach, 2006; Wolf, Freedman, Ondrich, Seplaki, & Spillman, 2015), and at least one study has modeled psychological functioning using hierarchical linear modeling (HLM; Lucas, 2007). In the current study, we used LGMM to identify four trajectories, confirming the course of disability adjustment is heterogeneous. The majority of our sample (56.5%) demonstrated resilience: low depressive symptoms pre- and postdisability onset. We also identified a chronic depression group (12.9%), characterized by high predisability depression that remained elevated throughout the study; a remitting-depression trajectory (13.4%), characterized by high predisability depression that decreased over time; and an emerging-depression trajectory (17.2%), characterized by low predisability depression levels that increased sharply in response to the event and remained elevated for a 2-year period.

Although a majority of our sample evidenced resilience, two of the identified classes—the chronic and emerging depression classes—depicted clinically significant depressive elevations for a substantial period of time postdisability onset. Importantly, however, a significant segment of our sample was depressed in the wave *prior to* disability onset (both the chronic and the remitting-depression trajectory). This fact highlights the utility of true prospective data, which helps to demarcate preexisting clinically significant depressive symptoms from depression in response to the event. Only one trajectory—the emerging-depression class—depicted a clinically significant depressive reaction that was temporally related to disability onset. This is consistent with prior research that highlights disability onset as a stressful life event (Turner & Beiser, 1990; Turner & Noh, 1988). Individuals with clinically significant depression in response to acute health events have been shown to be at increased risk for distal adverse health outcomes (e.g., myocardial infarction and attendant risks for early mortality; Galatzer-Levy & Bonanno, 2014), highlighting the need for further exploration of the emerging-depression profile.

Table 2
Fit Indices for Two- to Five-Class Latent Growth Class Analyses of Depression

Statistic	One class	Two classes	Three classes	Four classes	Five classes
AIC	48,854.65	48,151.16	47,920.21	47,672.22	47,541.98
BIC	48,915.37	48,236.17	48,029.51	47,805.80	47,699.86
SSBIC	48,883.60	48,191.69	47,972.32	47,735.90	47,617.25
Entropy	—	.83	.78	.78	.77
VLM LRT (p value)	—	711.49 (.0000)	238.95 (.0000)	256.00 (.0000)	138.23 (.001)
LMR LRT (p value)	—	690.11 (.0000)	231.77 (.0000)	248.31 (.0000)	134.08 (.001)
BLRT (p value)	—	711.49 (.0000)	238.95 (.0000)	256.00 (.0000)	138.23 (.0000)

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion; SSBIC = sample size adjusted Bayesian information criterion; LMR LRT = Lo-Mendell-Rubin likelihood ratio test; VLM LRT = Vuong-Lo-Mendell-Rubin likelihood ratio test; BLRT = bootstrap likelihood ratio test.

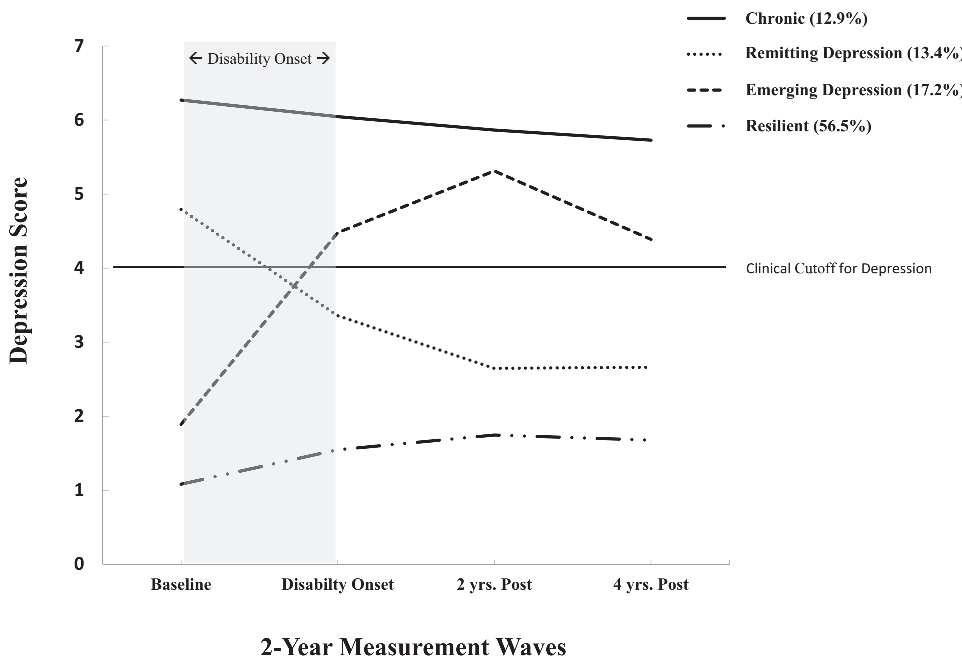

Figure 1. Final four-class model of depression trajectories across four time points (n = 3,204). Vertical gray bar represents window of disability onset.

Socioeconomic variables were consistent predictors of resilience. Compared with all other classes, resilient individuals were more likely to have greater wealth, suggesting that financial assets play a protective role with respect to disability onset. This effect has been demonstrated in previous research on disability. Smith et al. (2005) showed that increased financial assets buffered against the stress of new disability onset in a sample of HRS respondents: Net assets 2 years prior prospectively predicted smaller decrements in subjective well-being at the time of disability onset. Likewise, in an Australian sample of newly disabled individuals, Kavanagh et al. (2015) showed that declines in mental health were the largest for individuals in the bottom tertile of the wealth distribution. In the current analysis, participant's level of education also strongly predicted membership in the resilient class, again extending prior studies (e.g., Mandemakers & Monden, 2010). Although education and wealth covary in important ways, our data suggest that these are *unique and independent* predictors of disability adjustment. Together, our findings and previous research support resource-model theories of stress resistance (e.g., Hobfoll, 2001, 2002), which propose that access to resources (e.g., social, material) can mitigate the deleterious impact of stressful life events.

Limitations

There were several limitations in our study worth noting. The biennial spacing of the HRS sampling waves prevents the capture of short-term fluctuations in both ADL impairment and depressive

Table 3
Multinomial Logistic Regression Predicting Class Membership (n = 3,203)

	Resilience vs. emerging depression		Remitting depression		Chronic depression	
Reference class	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
Wealth	−2.26***	0.62	−1.32*	0.57	−4.40***	0.83
Education	−0.51***	0.15	−0.67***	0.16	−0.95***	0.17
Age	−0.03***	0.01	−0.02**	0.01	−0.05***	0.01
	Chronic vs. emerging depression		Remitting depression		Remitting depression vs. emerging depression	
Wealth	2.14*	0.96	3.08**	1.02	−0.94	0.81
Education	0.47*	0.21	0.28	0.23	0.17	0.20
Age	0.02**	0.01	0.03***	0.01	−0.01	0.01

* $p \leq .05$. ** $p \leq .01$. *** $p \leq .001$.

symptoms. Given that the temporal onset of disability can technically occur anywhere between the first two measurement waves (see onset window, Figure 1), we were unable to precisely model acute depressive reactions contemporaneous to the onset. To minimize this limitation, we employed stringent inclusion criteria (i.e., selecting only chronic cases), to ensure that the trajectories identified would reflect broad patterns of responding to chronic disability onset over time. However, the wide spacing of the HRS may be less ideal with respect to the study of disability (Wolf & Gill, 2009), given that whole episodes and recoveries may occur within smaller measurement windows (e.g., Cronin-Stubbs et al., 2000).

Second, while depression represents a critical target variable, other important outcomes are relevant to the disability adjustment process (e.g., anxiety, general distress), and at least one study has modeled trajectories of subjective well-being using HLM (Lucas, 2007). In cases of sudden or traumatic disability, posttraumatic stress symptoms are of particular relevance. Thus, future trajectory studies might examine alternative (or multiple) disability adjustment measures. Finally, our data lack specific information about the etiology of disability. While this is typical of population-based studies that utilize panel data (e.g., Cronin-Stubbs et al., 2000; Regan et al., 2013), future studies should seek to prioritize the relationship between trajectory membership and the etiology of disability (e.g., chronic health conditions vs. normal aging vs. trauma).

Conclusion

The course of depression surrounding late-life disability onset is heterogeneous. We observed multiple pathways of depression symptoms, with the most common trajectory (56.5%) being resilience, or stable low depressive symptoms across a 6-year measurement period. We also observed that disability onset intensified mental health–related challenges for many individuals, as a segment of our sample (17.2%) endorsed clinically significant depressive elevations in response to disability onset (emergent depression). However, as with other findings that utilize true prospective data, we identified a substantial number of individuals who were depressed prior to becoming disabled (chronic depression, 12.9%; remitting depression, 13.4%), underscoring the fact that depressive elevations previously cited in the disability literature may be confounded by a lack of preevent data. Finally, we found that socioeconomic factors robustly predicted these trajectory patterns. Our findings thus dovetail with prior research demonstrating that financial and educational resources play a protective role in the stress-adaptation process for those individuals who experience functional decline. It will be important for future research to more thoroughly examine the mechanism behind this association.

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