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From Grief to Disability: Depression–ADL Dynamics and Heterogeneous Recovery Trajectories After Widowhood

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Abstract

Background: Widowhood is a major later-life transition often accompanied by depressive symptoms and ADL decline, but the depression–ADL relationship remains directionally contested. This study aimed to identify distinct depression trajectories after widowhood, examine their predictive value for long-term ADL outcomes, and determine the directional relationship between depression and ADL.

Methods: Data were drawn from the China Health and Retirement Longitudinal Study (CHARLS, 2011–2018). To identify post-widowhood depression trajectories, we included 683 respondents widowed in 2013 or 2015. Each had at least two valid post-widowhood depression measures. Mixture-based trajectory clustering was first performed. Multinomial logistic regression then assessed baseline predictors of class membership. A cross-lagged panel model (n = 326 widowed) tested the directional depression–ADL association. Five multiply imputed datasets were analyzed, and estimates were pooled by Rubin's rules.

Results: Three distinct trajectories were identified: low-decreasing (16.5%), moderate-stable (41.0%), and moderate-increasing (42.5%). The moderate-increasing class had the worst long-term ADL outcomes (Kruskal–Wallis $p < 0.001$). Baseline chronic disease predicted membership in both the moderate-stable and moderate-increasing classes, whereas baseline ADL difficulties predicted membership only in the moderate-increasing class. The CLPM consistently indicated a unidirectional effect from depression to subsequent ADL decline (unstandardized β = 0.025–0.029; standardized β = 0.14–0.20, all p <0.05), with no significant reverse paths. **Conclusions:** Post-widowhood depression contributes to subsequent functional decline, with the greatest risk among those exhibiting persistent symptoms. Early identification and treatment of depressive symptoms may therefore represent a viable strategy for disability prevention in this population.

Keywords: Widowhood; Depression; Activities of daily living; Cross-lagged panel model; Trajectory clustering; CHARLS

Introduction

Widowhood is a major psychosocial transition in later life that often leads to a range of adverse health outcomes, including increased depressive symptoms and faster decline in physical functioning[1, 2]. Depression is a well-documented factor reducing quality of life in older adults[3]. In China, depressive symptom rates range from 14.8% to 23.6%, while the prevalence of clinically significant depression among widowed individuals reaches 17%–20%[4]. However, adaptation to spousal loss varies considerably across individuals. Some people show considerable psychological resilience, whereas others experience persistent or worsening depressive symptoms[5]. This heterogeneity calls for empirical identification of distinct depression trajectories and an evaluation of how these patterns predict long-term functional outcomes[6].

Although depression and activities of daily living (ADL) impairment often co-occur, the temporal direction of this association remains unclear[7, 8]. Two competing models have been proposed[9]. The distress-to-disability pathway suggests that depression leads to behavioral disengagement and social withdrawal, which in turn cause physical deconditioning[10]. Conversely, the disability-to-distress pathway posits that functional limitations trigger feelings of helplessness and dependency, thereby exacerbating depression[11]. Clarifying which pathway predominates is essential for determining when and how to intervene[12]. If depression is the primary driver of ADL decline, then early identification and treatment of depressive symptoms would be a key strategy for preventing disability[13].

Widowhood is also associated with reduced social participation, which may further worsen functional limitations[13, 14]. Despite the importance of this topic, the existing literature has at least three notable gaps. First, most previous studies have focused on average effects of widowhood on depression, overlooking the heterogeneous patterns of symptom change over time and their varying implications for later physical functioning[15]. Second, the directional relationship between depression and ADL remains poorly established, as most prior evidence comes from cross-sectional studies or simple regression models that cannot adequately address temporal precedence[16]. Third, few studies have combined analysis of the different recovery patterns and the causal direction into one complete analytical framework[13, 17].

To address these gaps, we used four waves of longitudinal data from the China Health and Retirement Longitudinal Study[14] (CHARLS, 2011–2018) and applied two complementary analytical approaches.

Our first aim was to identify post-widowhood depression trajectories and test whether baseline factors predicted trajectory class and long-term ADL outcomes. Our second aim was to bidirectional temporal relationship between depression and ADL using a cross-lagged panel model (CLPM), which models reciprocal influences while controlling for autoregressive effects and within-wave covariation. By first identifying trajectory classes, then examining their baseline predictors, and finally testing longitudinal pathways from depression to ADL, this study provides an integrated chain of evidence - from risk stratification to causal inference - to inform early depression screening and targeted preventive interventions after spousal bereavement. The combination of latent growth mixture modeling with cross-lagged panel analysis has been increasingly adopted in clinical and gerontological research, supporting the validity of our analytical approach.

Methods

Study Design

This study adopted a prospective longitudinal cohort design using four waves of data from the CHARLS (2011–2018)[14]. We included individuals who experienced spousal loss during the follow-up period and had at least one assessment both before and after the loss. The same standardized measures were administered at each wave. The timeline of data collection and key study phases is shown in Figure 1.

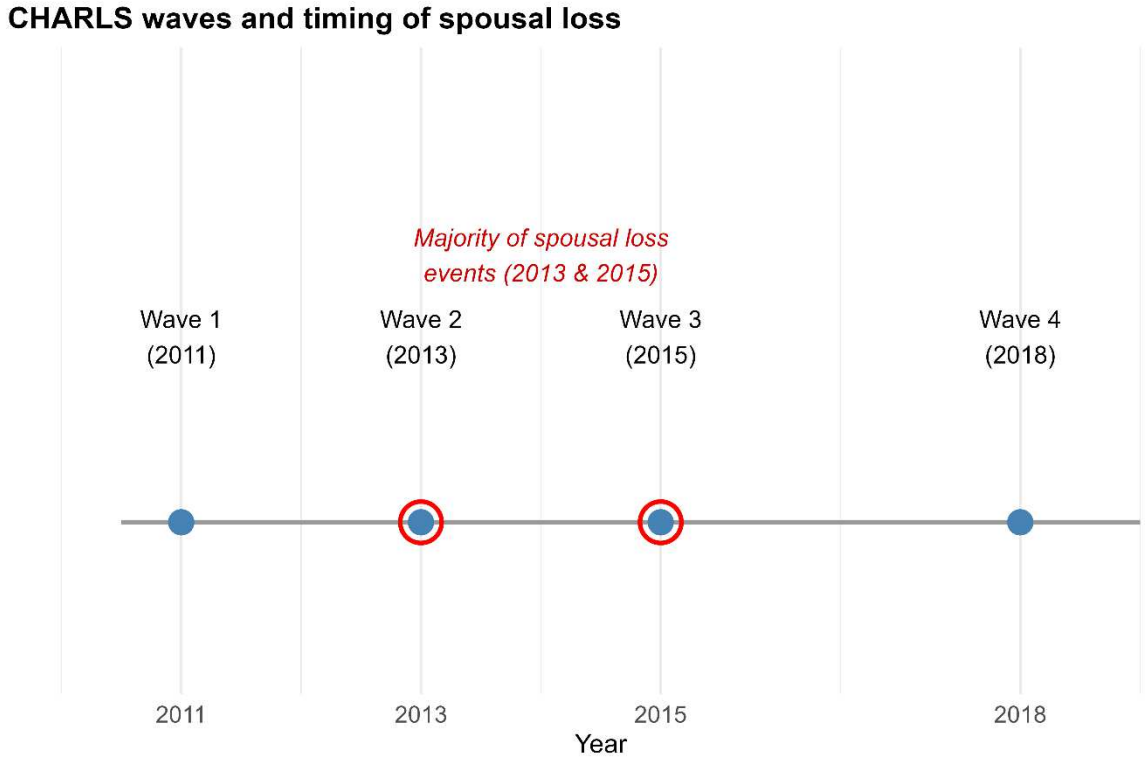


Figure 1. Timeline of CHARLS data collection and timing of spousal loss. Four waves of data were collected in 2011, 2013, 2015, and 2018. The majority of spousal loss events occurred between Wave 2 (2013) and Wave 3 (2015), as indicated by the red circles.

Participants

Of the 1,225 CHARLS participants who experienced spousal loss during follow-up, 326 had at least one pre- and post-loss survey wave and were thus included in the CLPM. For the Latent Class Growth Analysis (LCGA), we selected individuals widowed in 2013 or 2015 with at least two valid post-loss depression assessments, yielding a final sample of 683. The CLPM sample is a subset of this larger LCGA sample. Participant flow is summarized in Figure 2.

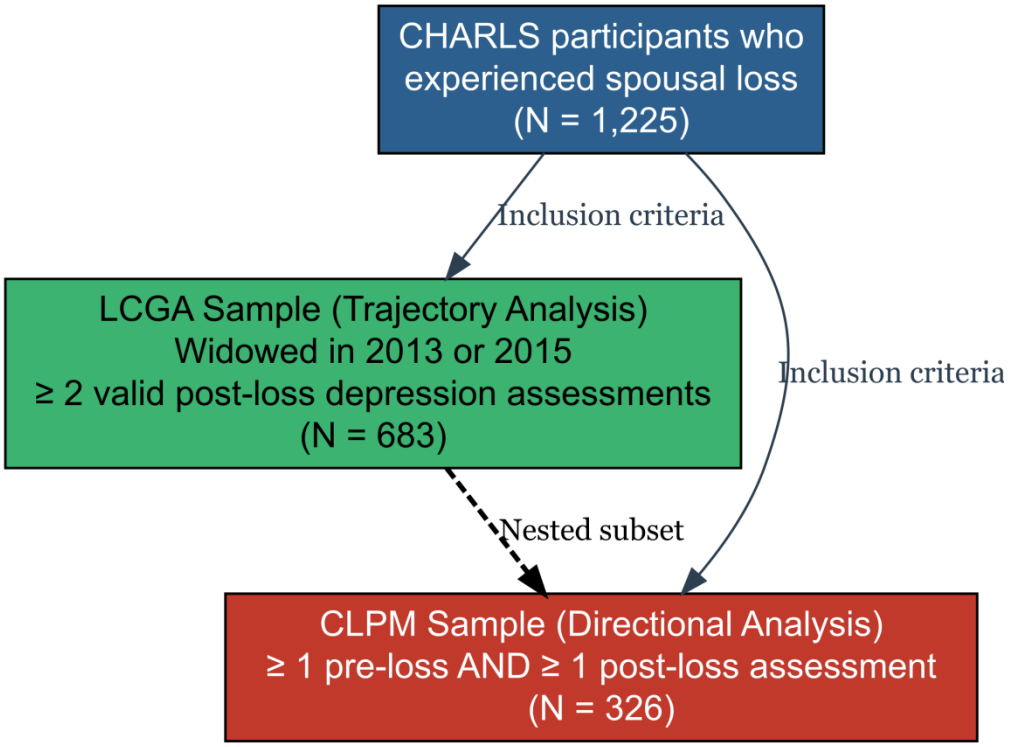


Figure 2. Participant flow diagram. A total of 1,225 participants experienced spousal loss during follow-up. Of these, 683 met the LCGA inclusion criteria (widowed in 2013 or 2015 with at least two valid post-loss depression assessments). A subset of 326 participants additionally had at least one pre-loss and one post-loss assessment and were included in the CLPM analysis. The CLPM sample is nested within the LCGA sample.

Measures

Depression

Depressive symptoms were assessed with the 10-item Center for Epidemiologic Studies Depression Scale (CES-D). Total scores range from 0 to 30, with higher scores reflecting greater symptom severity[18].

ADL

ADL function was assessed by summing the number of difficulties reported across six basic activities: dressing, bathing, eating, transferring, toileting, and continence. Total scores ranged from 0 to 6, with higher scores indicating more severe functional limitations[19].

Baseline covariates

Baseline covariates included age, gender, education, residence (urban vs. rural), number of chronic diseases, and lifestyle behaviors (drinking and smoking). Education was categorized as low (primary school or below) or high (secondary school or above).

Statistical Analysis

All analyses were conducted on five multiply imputed datasets, with estimates pooled according to Rubin's rules. Demographic characteristics were summarized as means (SD) for continuous variables and percentages for categorical variables. Pre-imputation, depression scores were missing for 8.3% of observations, whereas ADL scores were complete; missingness for all study variables is detailed in Supplementary Table S1. Diagnostic checks comparing pre- and post-imputation means and SDs (Supplementary Table S2) indicated that the imputed distributions adequately reproduced the observed data.

Objective 1: Trajectory clustering

We applied mixture-based trajectory clustering (R package flexmix) to identify distinct depressive symptom recovery patterns after widowhood, with time (years) as predictor and CES-D score as outcome. We tested solutions with 2 to 4 classes and selected the optimal number based on the Bayesian Information Criterion (BIC). Both the Vuong-Lo-Mendell-Rubin likelihood ratio test (VLMR-LRT) and the bootstrapped likelihood ratio test supported the 3-class solution over the 2-class alternative ($p < 0.001$). Classification quality was assessed using entropy and average posterior probabilities (AvePP)[20].

Robustness checks included 50 random starts, exclusion of extreme CES-D scores, bootstrap resampling, and comparison with k-means clustering. Each participant was assigned to their most likely class; final-wave ADL differences across classes were tested by Kruskal-Wallis, and baseline predictors of class membership by multinomial logistic regression. LCGA was run on the first imputed dataset; analyses on the other four imputed datasets yielded identical class solutions, confirming stability.

Objective 2: Cross lagged panel model (CLPM)

We used a CLPM to examine the temporal relationship between depression and ADL[21]. The model included autoregressive paths, cross-lagged paths, and within-wave residual correlations (Figure ??). Two specifications were compared: a simple bidirectional model and one with additional autoregressive residuals for depression. The latter was favoured by the comparison ($\Delta\chi^2 = 41.97$, $\Delta df = 3$, $p < 0.001$).

We also estimated a random-intercept CLPM (RI-CLPM) to separate between-person from within-person effects. However, the RI-CLPM produced a perfect fit (CFI = 1.00, RMSEA = 0.00) with all cross-lagged paths non-significant, suggesting insufficient within-person variance to justify this parameterization in our sample. We therefore retained the traditional CLPM with autoregressive residuals as our primary model. Fit indices for the final model were CFI = 0.912, TLI = 0.726, RMSEA = 0.127, and SRMR = 0.073. Although the RMSEA and TLI did not reach conventional cutoffs, this pattern is not uncommon in SEM with small-to-moderate samples[22]. The CFI and SRMR fell within acceptable ranges, and the consistent pattern of significant unidirectional cross-lagged paths supports the robustness of our directional findings. Both unstandardized and standardized coefficients are reported.

Sample size and missing data

We did not formally calculate the sample size for the trajectory or CLPM analyses, but our sample is similar to those used in comparable studies. Missing data were handled with full information maximum likelihood (FIML) for the CLPM and maximum likelihood for the trajectory models. Both methods use all available data, so participants with incomplete follow-up waves could still be included in the estimation.

Results

Baseline characteristics

The CLPM analysis comprised 326 widowed individuals. For the trajectory analysis, we included 683 participants who were widowed in 2013 or 2015 and had at least two post-loss depression assessments. Table 1 provides baseline demographic and health characteristics for the analytic sample (N = 326). The mean age was 64.6 years (SD = 9.31), indicating an older adult population. The sample was predominantly female (67.8%, n = 221) and largely rural residents (84.7%, n = 276). Educational attainment was low for the vast majority (93.3%, n = 304). The mean depression score was 8.98 (SD = 6.37), indicating moderate depressive symptomatology. Participants exhibited minimal functional impairment, with a mean ADL difficulty score of 0.39 (SD = 0.94), and a relatively low chronic disease burden, averaging 0.96 (SD = 1.01) comorbid conditions. In terms of lifestyle behaviors, the majority were non-drinkers (72.1%, n = 235) and non-smokers (75.8%, n = 247).

Table 1: Baseline demographic and health characteristics of the CLPM sample (N = 326).

Characteristic	Level	Overall
Total number		326
Age, mean (SD)		64.6 (9.31)
Gender, n (%)	Female	221 (67.8)
	Male	105 (32.2)
Education, n (%)	Low	304 (93.3)
	High	22 (6.7)
Urban/rural, n (%)	Rural	276 (84.7)
	Urban	50 (15.3)
Depression, mean (SD)		8.98 (6.37)
ADL difficulties, mean (SD)		0.39 (0.94)
Number of Chronic diseases, mean (SD)		0.96 (1.01)
Drinking, n (%)	No	235 (72.1)
	Yes	91 (27.9)
Smoking, n (%)	No	247 (75.8)
	Yes	79 (24.2)

Notes: SD=Standard deviation.

Overall changes in depression and ADL across waves

We first examined the overall longitudinal trends in depression and ADL scores across the study period. Across the follow-up period, depression scores followed a fluctuating pattern, rising from 9.2 (SD = 6.8)

in 2011 to 10.5 (SD = 7.3) in 2015, before declining slightly to 9.9 (SD = 7.0) in 2018. ADL disability, by contrast, showed a steady but modest increase, from 0.42 (SD = 0.97) in 2011 to 0.62 (SD = 1.29) in 2018. Despite these group-level shifts, both variables showed moderate rank-order stability between consecutive assessments. For depression, adjacent-wave autoregressive coefficients were 0.41, 0.39, and 0.46; for ADL disability, the corresponding values were 0.39, 0.37, and 0.57. Longitudinal descriptives are summarized in Table 2.

Table 2: Descriptive statistics and adjacent-wave correlations of depression and ADL.

Variable	Period	N (Mean ± SD)	Correlation (adjacent periods)
Depression	Year 2011	295 (9.16 ± 6.76)	0.41
	Year 2013	307 (8.71 ± 5.84)	0.39
	Year 2015	320 (10.50 ± 7.33)	0.46
	Year 2018	306 (9.93 ± 7.02)	—
ADL disability	Year 2011	295 (0.42 ± 0.97)	0.39
	Year 2013	307 (0.38 ± 1.01)	0.37
	Year 2015	320 (0.56 ± 1.19)	0.57
	Year 2018	306 (0.62 ± 1.29)	—

Notes: ADL = activities of daily living, SD=Standard deviation.

Trajectory classes of depression after widowhood

Mixture-based trajectory clustering identified a 3-class solution as optimal (Supplementary Table S3). Classification quality was acceptable, with entropy = 0.700 and average maximum posterior probability = 0.862. Although entropy fell below the common 0.80 benchmark, we believe this mainly reflects our larger and more heterogeneous sample (n = 683), compared with the smaller and more homogeneous samples typically used in these analyses. Both the VLMR-LRT ($p < 0.001$) and the bootstrap ARI (0.904) strongly supported the class assignments. The three trajectories are shown in Figure 3 and were labelled by their intercept and slope estimates. Class 1 was Moderate-stable (n = 280, 41.0%; intercept = 7.27, slope = 0.04); it maintained moderate depression levels with little change. Class 2 was Low-decreasing (n = 113, 16.5%; intercept = 3.06, slope = –0.08); it started low and declined slightly over time. Class 3 was Moderate-increasing (n = 290, 42.5%; intercept = 12.97, slope = 0.35); it started at a moderately elevated level and increased consistently.

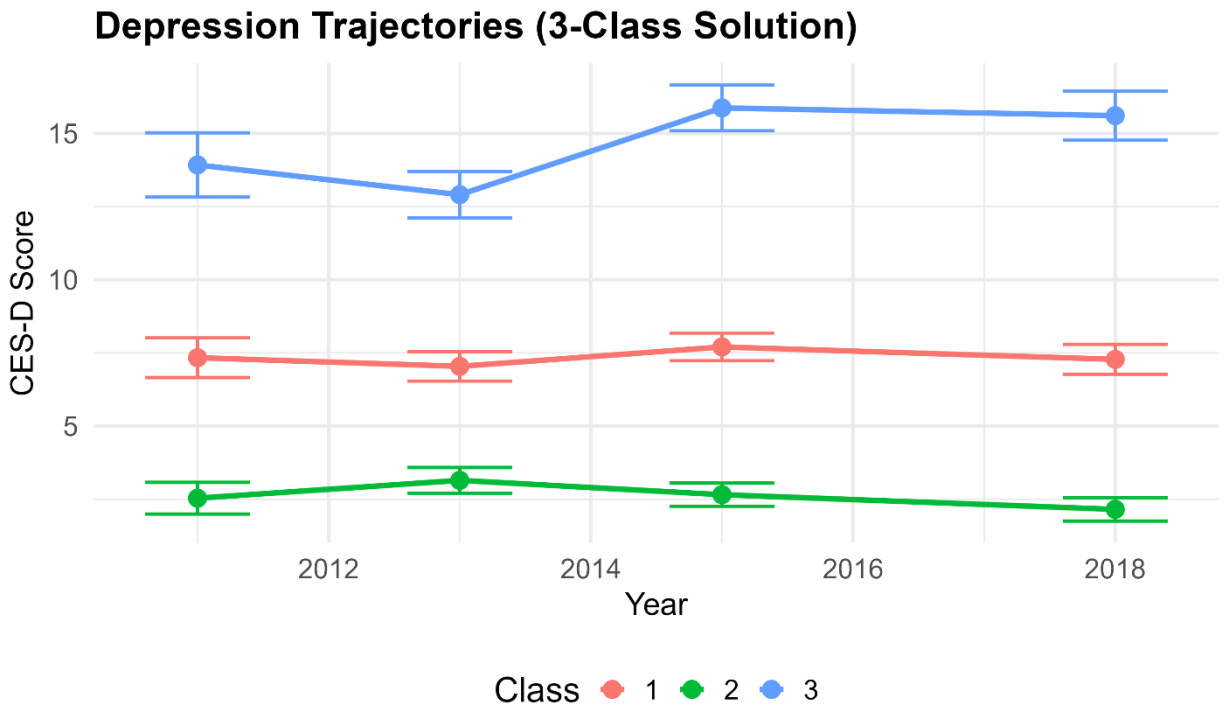


Figure 3. Three distinct trajectory classes of depressive symptoms (CES-D scores) after widowhood. Red: Class 1 (moderate-stable, n=280, 41.0%); green: Class 2 (low-decreasing, n=113,16.5%); blue: Class 3 (moderate-increasing, n=290, 42.5%). Vertical error bars denote 95% confidence intervals. The blue class consistently shows the highest CES-D scores and a steady upward slope across all time points.

Factors associated with depression trajectory membership

Having identified these three distinct trajectories, we examined which baseline characteristics predicted membership in each. Multinomial logistic regression (Table 3) identified baseline predictors of trajectory membership, using the low-decreasing class (Class 2) as the reference. A higher number of baseline chronic diseases was associated with increased odds of belonging to both the moderate-stable (Class 1; OR = 1.497, p = 0.023) and moderate-increasing (Class 3; OR = 1.711, p = 0.003) classes. Greater baseline ADL difficulties predicted membership only in the moderate-increasing class (OR = 3.409, p = 0.003), and not in the moderate-stable class (OR = 1.856, p = 0.141). Male sex was associated with lower odds of being in the moderate-increasing class (OR = 0.306, p = 0.001), but showed no significant association with the moderate-stable class.

Table 3: Multinomial logistic regression predicting depression trajectory membership (reference: Class 2 – Low-decreasing).

Characteristic	OR (95% CI)	p-value
Class 1 (Moderate-stable) vs. Class 2 (Low-decreasing)		
Age (per year)	0.989 (0.956, 1.023)	0.524
Gender (Male vs Female)	1.506 (0.795, 2.854)	0.209
Baseline chronic diseases	**0.668 (0.471, 0.947)**	**0.023***
Baseline ADL	0.539 (0.236, 1.229)	0.141
Class 3 (Moderate-increasing) vs. Class 2 (Low-decreasing)		
Age	0.994 (0.969, 1.019)	0.632
Gender (Male)	**0.460 (0.270, 0.783)**	**0.004***
Baseline chronic diseases	1.143 (0.912, 1.433)	0.246
Baseline ADL	**1.836 (1.338, 2.520)**	**0.001***

Notes: OR = Odds Ratio; CI = Confidence Interval; ADL = activities of daily living.

Differences in ADL difficulties across trajectory classes

We further examined differences in activities of daily living (ADL) difficulties across depression trajectory classes following widowhood. The distributions differed substantially: the moderate-increasing class had a wider interquartile range (0–2) and a higher proportion of individuals with multiple ADL difficulties, whereas the low-decreasing class was concentrated almost entirely at zero (IQR: 0–0). The moderate-stable class fell between these extremes (IQR: 0–1) (Supplementary Table S4). Figure 4a displays the distribution of final-wave ADL scores for each class. Although median values were identical across the three classes, the moderate-increasing class exhibited a wider interquartile range and more extreme high outliers, indicating substantially greater variability in functional outcomes at the final assessment (Kruskal–Wallis test, $p< 0.001$). Figure 4b illustrates the mean ADL difficulties over time. The moderate-increasing class showed a pronounced upward trend in ADL limitations from 2011 to 2018, with a progressively widening gap compared to the other two classes. In contrast, the low-decreasing and moderate-stable classes maintained relatively low and stable levels of ADL difficulties throughout the follow-up period. Taken together, these findings suggest that the moderate-increasing depressive trajectory is associated not only with accelerated functional decline but also with marked heterogeneity in end-stage functional outcomes, whereas the other two classes demonstrated comparatively favorable and stable functional status.

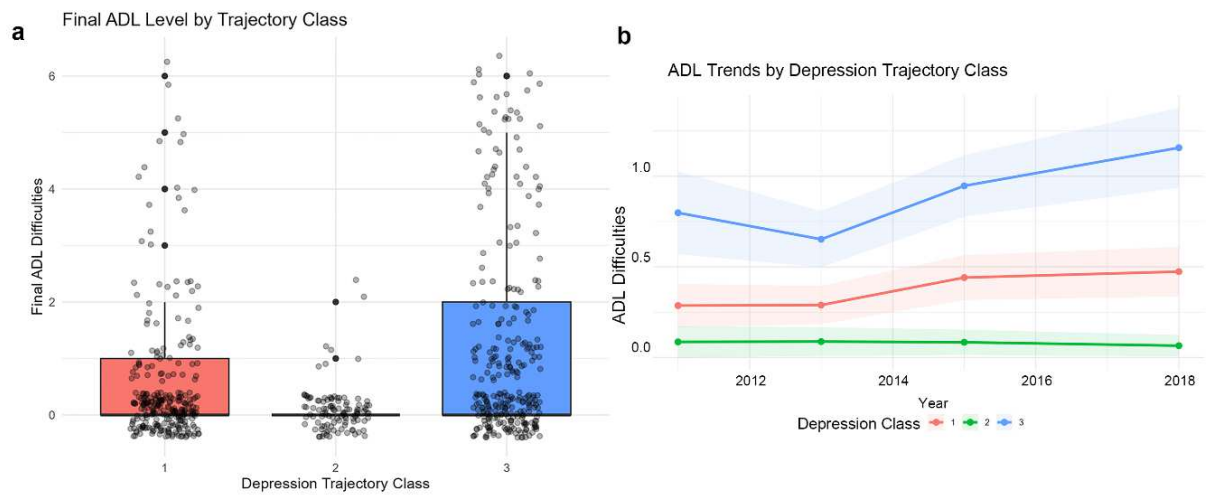


Figure 4

Figure 4. (a) Boxplots of final-wave ADL scores by depression trajectory class (whiskers: 1.5×IQR; dots: outliers). Kruskal-Wallis *p* < 0.001. (b) Mean ADL trajectories with 95% CI error bars across four waves (2011–2018). Class 1 (moderate-stable); Class 2 (low-decreasing); Class 3 (moderate-increasing,).

Directional relationship between depression and ADL (CLPM)

Although the trajectory analysis captured between-person heterogeneity in depression recovery, it cannot adjudicate temporal precedence. We therefore examined the directional relationship between depression and ADL using a CLPM (Table 4). Results indicated a consistent unidirectional effect: all three cross-lagged paths from earlier depression to later ADL were significant, while the reverse paths were not. The standardized solution appears in Figure 5. Gender-stratified analyses were not attempted because the male subsample (about 30 individuals with adequate post-widowhood data) was insufficient for reliable estimation; we return to this constraint in the Discussion.

Table 4: Cross-lagged path coefficients from the final model (Bidir_auto).

Path	Label	Unstand. β	SE	*p*	Stand. β
Autoregressive paths					
Dep2011 → Dep2013	a1	0.342	0.118	0.004	0.397
Dep2013 → Dep2015	a2	1.031	0.238	<0.001	0.837
Dep2015 → Dep2018	a3	1.128	0.212	<0.001	1.190
ADL2011 → ADL2013	b1	0.346	0.077	<0.001	0.332
ADL2013 → ADL2015	b2	0.396	0.106	<0.001	0.337
ADL2015 → ADL2018	b3	0.575	0.100	<0.001	0.531

Cross-lagged paths					
Depression→ADL					
2011 → 2013	c1	0.029	0.009	0.002	0.195
2013 → 2015	c2	0.028	0.014	0.049	0.139
2015 → 2018	c3	0.025	0.010	0.011	0.138
ADL → Drepression					
2011 → 2013	d1	0.275	0.442	0.534	0.045
2013 → 2015	d2	−0.568	0.592	0.341	−0.079
2015 → 2018	d3	−0.745	0.617	0.229	−0.130

Notes: Coefficients are pooled estimates from five multiply imputed datasets. Model includes autoregressive residuals for depression. Fit indices: CFI = 0.912, TLI = 0.726, RMSEA = 0.127, SRMR= 0.073.

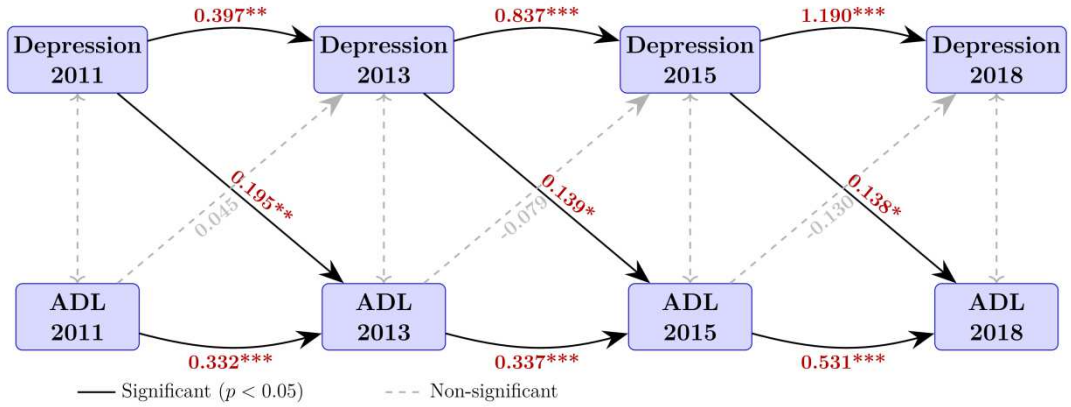


Figure 5

Figure 5. Standardized path diagram of the cross-lagged panel model (CLPM). Rectangles represent observed variables for depression and ADL at four time points (2011, 2013, 2015, 2018). Solid black arrows indicate statistically significant paths (p < 0.05). Dashed gray arrows indicate non-significant paths. Path coefficients shown in red are statistically significant; coefficients shown in gray are not. Double-headed dashed gray lines represent within-wave residual correlations. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Sensitivity analysis

We also compared the 3-class solution to a 2-class model; the VLMR-LRT favoured the 3-class model ($p < 0.001$). The classification was stable across different random starts (ARI = 1.00) and in bootstrap resampling (median ARI = 0.904). After excluding participants with extreme depression scores (>25), the

ARI was 0.739, indicating moderate stability. Overall, these sensitivity analyses suggest that the 3-class solution is robust.

Discussion

This study provides an integrated examination of depression trajectories and their directional relationship with ADL decline after widowhood, using a well-defined sample with both pre- and post-loss data. Three distinct trajectories emerged: low-decreasing (16.5%), moderate-stable (41.0%), and moderate-increasing (42.5%). The moderate-increasing class showed the poorest long-term ADL outcomes. Baseline chronic disease and baseline ADL impairment independently predicted membership in the moderate-stable and moderate-increasing classes, respectively. The CLPM further confirmed a consistent unidirectional effect from depression to subsequent ADL decline, with no evidence of reverse causation.

Our findings align with the behavioral deactivation model, which posits that depression reduces self-care and physical activity, thereby accelerating functional decline[23]. However, the CLPM results extend this framework by revealing the proximal mechanism underlying the distal trajectory patterns. The wave-to-wave directional effects ($\beta = 0.14–0.20$) suggest that each depressive episode exerts a small but cumulative erosive effect on physical function. Over the 7-year follow-up, these repeated micro-insults likely accumulate, resulting in the markedly poorer ADL outcomes observed in the moderate-increasing class. Thus, while the stable classes may reflect a dynamic equilibrium between mood and function, the escalating class represents a positive feedback loop in which depression gradually erodes the functional reserve needed for recovery[24].

The differential predictive roles of chronic disease and ADL impairment further refine this picture. Baseline chronic disease predicted membership in both stable and escalating classes, suggesting it acts as a general vulnerability factor that sustains depressive symptoms over time, regardless of trajectory direction[25, 26]. In contrast, baseline ADL impairment specifically identified the escalating class, implying a threshold-specific risk mechanism: only when functional limitations reach a certain level do they precipitate a progressive, rather than stable, depressive course[10, 27]. This distinction is consistent with the disablement process model, in which functional deficits trigger a cascade of autonomy loss and reduced social participation, driving depressive symptoms upward—a cascade that may be particularly

difficult to reverse once initiated[28, 29].

The moderate entropy of the three-class solution (0.700) warrants reflection. Rather than viewing this as a statistical weakness, we interpret it as evidence that trajectory boundaries are permeable in a large, community-based sample. This suggests that depressive responses to widowhood may lie on a continuum rather than falling into strictly discrete categories[30]. Although the three classes are not entirely discrete, the bootstrap ARI of 0.904 and the highly significant VLMR-LRT ($p < 0.001$) both support that this solution reflects meaningful population heterogeneity[31, 32]. Clinically, this boundary blurriness matters: it suggests that risk is not fixed at baseline. Instead of classifying individuals once and treating them as stable group members, we should watch for subtle declines in ADL over time as early warning signs of escalation[33]. Comparable entropy values (0.65–0.75) have been reported in other LCGA studies using large, representative samples, supporting the view that moderate classification uncertainty is not uncommon in heterogeneous community populations[34, 35].

Although our integration of trajectory clustering and CLPM draws on a large sample (683 for LCGA, 326 for CLPM) with adequate power, several limitations must be noted. The CLPM sample size of 326, while adequate for the primary analyses, precluded reliable gender-stratified analyses due to the small male subsample. Future studies with larger cohorts should examine gender-specific trajectories and pathways. The ADL measure had limited variability, the absence of data on death expectedness and pre-loss caregiving is a notable omission[36, 37]. We suspect that unexpected deaths may produce more severe acute depressive reactions, whereas expected deaths (following prolonged illness) might be accompanied by pre-loss grief and caregiver burden, potentially blunting the post-loss depression spike but accelerating pre-existing functional decline[38, 39]. If so, our pooled estimates across all widowhood types may underestimate the true effect of unexpected loss on the escalating trajectory, while potentially overestimating the baseline chronic disease effect for the stable group[40]. This bias directionality warrants explicit testing in future studies. Generalizability beyond the Chinese context also remains to be established.

Future work should replicate our findings in larger and more diverse samples to establish generalizability and, where feasible, employ random-intercept CLPMs to better distinguish within- and between-person effects. Incorporating contextual factors such as death expectedness and pre-loss caregiving would further clarify how situational variables moderate post-loss trajectories. Ultimately, clinical trials targeting early

depression treatment—particularly among individuals showing a moderate-increasing pattern—are needed to determine whether intervening on mood can modify the subsequent physical decline trajectory.

Conclusions

After spousal loss, depression appears to be the primary driver of subsequent functional decline, with risk concentrated among those showing persistently elevated or worsening symptoms. The moderate-increasing trajectory identifies a particularly vulnerable subgroup. Early and sustained depression screening after widowhood may help prevent the cascade from grief to disability.

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Author contributions:

Yongkang Fang: Writing – original draft, Supervision, Methodology, Investigation. Luhan Zhang: Data curation, Software, Methodology, Formal analysis. Guo Li: Writing – review & editing, Conceptualization, Supervision, Funding acquisition. All authors reviewed the manuscript.

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Data availability statement

The data used in this study are available from the China Health and Retirement Longitudinal Study (CHARLS) database. CHARLS data are publicly available for research purposes upon registration and application at the official website (http://charls.pku.edu.cn). The authors do not have permission to redistribute the raw data. The data analysis code used in this study is available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

This study was conducted in accordance with the Declaration of Helsinki and used data from CHARLS. The CHARLS survey was approved by the Biomedical Ethics Review Committee of Peking University (IRB00001052-11015). All participants provided written informed consent at the time of data collection. For the present study, we conducted a secondary analysis of de-identified public data. No additional ethical approval or informed consent was required, as the data access was obtained through the official CHARLS application process and the analysis did not involve any interaction with human subjects.

Consent for publication

Not Applicable.

Competing interests

The authors declare no competing interests.

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