

Longitudinal Associations Between Neighborhood Social Cohesion and Sleep Disturbance Among Older Adults: The Mediating Role of Depressive Symptoms

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Abstract

Sleep disturbance is highly prevalent in later life and often co-occurs with depressive symptoms. However, the social and psychological factors that contribute to its development remain poorly understood. This longitudinal study examined whether perceived neighborhood social cohesion was associated with subsequent sleep disturbance and whether depressive symptoms mediated this association among older adults. Data were drawn from five waves (2006, 2010, 2014, 2018, and 2022) of the psychosocial subsample of the Health and Retirement Study. The analytic sample comprised 3,360 respondents aged 50 years or older. Univariate and parallel process latent growth curve models were used to examine the developmental trajectory patterns and their associations. A latent growth curve mediation model was further utilized to test the indirect pathways at both the intercept and slope levels. At the intercept level, higher neighborhood social cohesion in 2006 was associated with lower levels of depressive symptoms and sleep disturbance in 2010. The indirect association via depressive symptoms was significant ($B = -0.311$, 95% CI $[-0.383, -0.239]$). At the slope level, greater declines in cohesion were associated with greater increases in depressive symptoms ($B = -0.351$, 95% CI $[-0.676, -0.026]$), and the indirect path on change in sleep disturbance was also significant ($B = -0.332$, 95% CI $[-0.651, -0.014]$). Depressive symptoms may represent an important pathway linking neighborhood social cohesion to sleep disturbance among older adults, highlighting the potential value of strengthening social cohesion and addressing depressive symptoms to promote sleep health.

Introduction

Sleep is an important factor influencing the physical and mental health of older adults (Didikoglu et al. 2020). However, sleep quality often deteriorates with age (Lauderdale et al. 2014; Lemola and Richter 2013). The aging process can alter sleep patterns among older adults, including shorter sleep duration, less sleep efficiency, greater difficulty initiating sleep, earlier awakening, and less restorative effects in the morning (Chen-Edinboro et al. 2015; Didikoglu et al. 2020), all of which constitute characteristics of sleep disturbance (Sateia 2014). Given that sleep disturbances are highly prevalent among older populations (Bierman et al. 2018; Lauderdale et al. 2014; Seo et al. 2025) and may lead to serious health problems, such as mental illness, cognitive impairment, and functional decline (Albert et al. 2017; Ancoli-Israel 2009; Foley et al. 2004), it is crucial to investigate modifiable determinants of sleep quality to develop social policies and interventions tailored to individual needs.

Previous research has identified factors associated with sleep disturbance, including but not limited to age, gender, race, ethnicity, weight, marital status, economic status, educational attainment of the respondent and their spouse, and chronic diseases (Eshkoor et al. 2013; Gu et al. 2010; Li et al. 2013; Liang et al. 2024; Sheehan and Iida 2021; Wu et al. 2012; Zhang et al. 2017). Many of these determinants are difficult to modify in later life. However, studies have also found that perceived neighborhood conditions are potential mechanisms linking objective neighborhood characteristics and health outcomes (Hill and Maimon 2012; Lu et al. 2022; Ross and Mirowsky 2001). Given that older adults spend a significant portion of their daily lives in their local communities, these neighborhood conditions

may exert a salient influence on their well-being and health-related behaviors, such as sleep. Perceived neighborhood environment, which captures individuals' overarching interpretation of their neighborhood, may contribute to sleep disturbance in later life (Bierman et al. 2018; Chen-Edinboro et al. 2015; Sutil et al. 2024; Watanabe et al. 2020; Zhang 2024). Among various environmental dimensions, neighborhood social cohesion (reflecting trust, mutual support, reciprocity, and social connectedness among residents) is particularly critical for older adults, as it fosters social engagement and provides essential access to informal support resources.

Although a growing body of evidence connects neighborhood social cohesion to sleep outcomes, the mechanisms underlying this association remain insufficiently understood. From the perspective of the stress process model, low social cohesion may serve as a chronic environmental stressor that undermines mental well-being. One plausible pathway involves depressive symptoms. The perceived neighborhood environment has been identified as an important risk factor for depression (Lu et al. 2022; Ruiz et al. 2018). A meta-analysis indicated that depression levels among older adults were significantly associated with sleep quality (Becker et al. 2017). However, most relevant studies relied on cross-sectional data (Sutil et al. 2024; Watanabe et al. 2020; Zhang 2024) and did not examine the associations of social cohesion, depressive symptoms, and sleep disturbance simultaneously. Consequently, little is known about whether changes in neighborhood social cohesion are accompanied by corresponding changes in depressive symptoms and sleep disturbance over time.

Therefore, using five waves of longitudinal data from the Health and Retirement Study (HRS), this study investigated the developmental associations among neighborhood social cohesion, depressive symptoms, and sleep disturbance trajectories among older adults. Specifically, we examined whether depressive symptoms serve as a psychological pathway linking neighborhood social cohesion to changes in sleep disturbance. By adopting a longitudinal developmental framework, this study contributes to a more comprehensive understanding of how social environments and psychological processes jointly shape sleep health in later life.

Theoretical framework and literature review

Theoretical framework

The stress process model serves as the primary theoretical framework in this research to examine how neighborhood environmental stressors impact mental health and shape sleep disturbance trajectories among older adults (Pearlin et al. 1981). Pearlin et al. (1981) identified three core components within this model, which include stressors, mediators, and the manifestation of stress. Drawing on the stress process model together with the person-environment (P-E) fit model, we conceptualize a sequential pathway in which neighborhood social cohesion represents a distal social-environmental stressor, depressive symptoms represent an intermediate psychological response, and sleep disturbance represents a more proximal manifestation of stress. From the perspective of the stress process model, stress originates from adverse social conditions, triggers psychosocial responses, and manifests as

negative health outcomes through a series of interconnected processes. While the stress process model elucidates the general mechanisms linking stressors to health outcomes, the P-E fit model explains why older adults are particularly vulnerable to poor neighborhood conditions. The P-E fit model posits that the well-being of older adults depends on the congruence between their personal competence (e.g., physical functioning, physical health, cognition, and social support resources) and the demands posed by the environment (environmental press). With age-related declines in physical, cognitive, and social capacities, older adults may become increasingly reliant on their immediate communities for social connection and support, making person-environment fit particularly important for later-life well-being. When environmental demands exceed individual capacities, person-environment misfit may increase psychological distress and undermine well-being.

As previously noted, depressive symptoms may represent a key mechanism linking neighborhood environments to sleep disturbance among older adults. Low neighborhood social cohesion may foster a sense of disconnectedness and increase the risk of mental health problems (Cagney et al. 2009; Miao et al. 2019). Low levels of social cohesion can also lead to increased social isolation among older adults, limiting their access to social and psychological support resources, which may exacerbate their emotional distress. In this context, depressive symptoms may subsequently affect sleep through both psychological and biological pathways. Individuals experiencing depressive symptoms often report heightened emotional distress, excessive rumination, and difficulties in regulating negative emotions, all of which may interfere with sleep initiation and maintenance. In addition, depressive symptoms and depression may impair the quality of sleep in later life through multiple mechanisms, including hyperactivation of the hypothalamic-pituitary-adrenal axis and the habenula or polymorphisms in CLOCK genes (Medina et al. 2014). Thus, although previous research has established the links between neighborhood social cohesion and depressive symptoms and between depressive symptoms and sleep problems, these links have largely been examined separately. To our knowledge, the full sequential pathway from neighborhood social cohesion to depressive symptoms and subsequently to sleep disturbance has not been directly examined in a longitudinal trajectory framework.

The proposed pathway also suggests the need to examine trajectories rather than only cross-sectional levels. Neighborhood social cohesion, depressive symptoms, and sleep disturbance may change over time as chronic environmental exposures accumulate and person-environment misfit increases with declines in personal competence. A trajectory approach therefore captures both individuals' initial levels and their rates of change. Importantly, a nonsignificant mean slope indicates limited average change at the sample level, but does not preclude significant between-person differences in change rate or associations between the slopes of different constructs. Thus, examining both intercepts and slopes allows us to assess whether differences in the initial levels and change rates in neighborhood social cohesion are associated with corresponding differences in depressive symptoms and sleep disturbance over time.

Perceived neighborhood environment and sleep disturbance trajectory

Existing studies have shown that trajectories of sleep disturbance differ according to demographic characteristics, including age, birth cohort, gender, race and ethnicity (Chen 2023; 2024; Kaufmann et al. 2016), as well as family context (Ma et al. 2023). These findings suggest that sleep trajectories are shaped by a wide range of individual and family-level factors. However, significantly less attention has been paid to community-level social environments as potential determinants of sleep disturbance trajectories. Few studies have explored the relationship between neighborhood social cohesion and sleep outcomes among older adults. For example, drawing on data from the 2013 and 2018 waves of the U.S. National Health Interview Survey, the study found that adults aged 50 or older living in neighborhoods with low social cohesion were more likely to report sleep disturbances than those in socially cohesive neighborhoods (Alhasan et al. 2020). Similarly, Chen-Edinboro et al. (2015) found that lower social cohesion was associated with higher odds of sleep disturbance. However, existing research has primarily examined cross-sectional associations or single-time-point sleep outcomes. The extent to which neighborhood social cohesion is associated with the longitudinal development of sleep disturbance, encompassing both baseline levels and changes over time, remains under-explored.

Mediating role of depressive symptoms

Numerous studies have explored the relationship between the perceived neighborhood environment and depressive symptoms among older adults (Baranyi et al. 2020; Lu et al. 2022; Ruiz et al. 2018; Wang et al. 2018). Baranyi et al. (2020) observed significant associations between neighborhood disorder, lack of social cohesion, and depression among older adults across 15 European countries and the United States. Additionally, using a nationally representative sample, Ruiz et al. (2018) reported that individuals with low perceived neighborhood social cohesion exhibited higher levels of depressive symptoms than those with high perceived cohesion. Supporting these findings, empirical evidence indicates that both physical and social environmental factors, such as features related to outdoor spaces, transportation, housing, community support, and health services, are significantly associated with depressive symptoms among older adults in China (Lu et al. 2022; Wang et al. 2018). In summary, neighborhood-level disadvantages may contribute to psychological distress, which may subsequently lead to sleep disturbances.

A growing body of research has suggested that depression is a significant factor related to sleep disturbances (Becker et al. 2017; Gureje et al. 2011; Maglione et al. 2012; Ouyang and Sun 2019; Rodin et al. 1988). For example, a meta-analysis by Becker et al. (2017) reported a significant association between depression and subjective sleep disturbances. Similarly, Ouyang and Sun (2019) found that depression was significantly associated with short sleep duration among Chinese older adults. However, the literature presents inconsistent findings. In a study examining lifetime depression, Gureje et al. (2011) revealed no independent association between depressive mood and future sleep problems.

Notably, much of this evidence has relied on cross-sectional or single-outcome analyses rather than longitudinal sleep trajectories. One notable exception is Gebara et al. (2018), who identified distinct trajectories of insomnia symptoms among older adults receiving antidepressant treatment and found that greater baseline depressive symptom severity predicted less favorable sleep trajectories. Nevertheless, whether depressive symptoms contribute to trajectories of sleep disturbance among community-dwelling older adults remains under-explored.

The mediating role of depressive symptoms in the relationship between perceived neighborhood environment and sleep has received increasing empirical attention. For example, Zhang (2024) demonstrated that depressive symptoms partially mediated the associations between perceived neighborhood conditions and multiple sleep problems among older Chinese adults using cross-sectional data. Similarly, Kim et al. (2022), using longitudinal data from two low-income U.S. neighborhoods, found that psychological distress partially mediated the associations between neighborhood social environments and several objectively measured sleep outcomes. These studies suggest that psychological distress serves as a critical pathway linking neighborhood environments to sleep.

The present study

However, existing studies have rarely examined whether depressive symptoms serve as a longitudinal developmental mechanism linking community social environments to the trajectories of sleep disturbance. Specifically, it remains unclear whether older adults experiencing persistent lower neighborhood social experience or declining social cohesion subsequently exhibit corresponding patterns of depressive symptoms and sleep disturbance over time. Therefore, the present study employs a parallel process growth framework to examine whether the initial level and rate of change in depressive symptoms mediate the associations between the trajectories of neighborhood social cohesion and those of sleep disturbance.

Consistent with the theoretical framework and previous empirical findings, the study tests the following hypotheses regarding the intercepts and slopes of neighborhood social cohesion, depressive symptoms, and sleep disturbance among older adults:

- (1) Neighborhood social cohesion would be negatively associated with sleep disturbance at both the intercept and slope levels: older adults who perceived higher cohesion in 2006 would report less sleep disturbance in 2010, and increases in cohesion from 2006 to 2018 would be associated with decreases in sleep disturbance from 2010 to 2022.
- (2) Depressive symptoms would be positively associated with sleep disturbance at both the intercept and slope levels.
- (3) Neighborhood social cohesion would be indirectly associated with sleep disturbance through the mediating role of depressive symptoms at both the intercept and slope levels.

Method

Data

Data were drawn from the HRS, an ongoing nationally representative longitudinal panel study of U.S. adults aged 50 or older (Sonnega et al. 2014). The HRS is sponsored by the National Institute on Aging (Grant No. NIA U01AG009740) and is conducted by the University of Michigan (Health and Retirement Study 2025a; b; c). Initiated in 1992, the survey follows respondents every two years. The study employs a multistage probability sampling design to recruit respondents. Face-to-face or telephone interviews are conducted to collect a broad range of aging-related information, including sociodemographic characteristics, social participation, family characteristics, and health status.

Data on social cohesion were obtained from the HRS Psychosocial and Lifestyle Self-Administered Questionnaire, which has been administered biennially since 2006 to a randomly selected half of all HRS respondents (Smith et al. 2023). Since this questionnaire alternates between two halves of the core sample, respondents who completed it in 2006 were followed in 2010, 2014, 2018 and 2022, resulting in five waves of observations.

Therefore, the analytic sample was restricted to community-dwelling adults aged 50 years or older who were eligible to participate in the Leave-Behind Psychosocial and Lifestyle Questionnaire in 2006. At baseline, respondents were excluded if they were younger than age 50, resided in a nursing home, completed a proxy interview, or were ineligible for the Leave-Behind Questionnaire. The selection process began with 18,469 respondents in 2006. Following the exclusion of those ineligible for the Leave-Behind Questionnaire ($n = 9,788$), proxy respondents ($n = 235$), individuals under age 50 ($n = 249$), and nursing home residents ($n = 68$), 8,129 respondents remained in the baseline sample. In each subsequent wave, respondents were further excluded if they completed proxy interviews, resided in nursing homes, were deceased, or had withdrawn from the study. In subsequent waves, the sample size was reduced to 6,814 in 2010, 5,691 in 2014, 4,543 in 2018, and 3,360 in 2022. A detailed flowchart of the sample selection process is presented in Supplementary Figure S1.

Measurement

Sleep disturbance

Sleep disturbance was assessed using a modified version of the Jenkins Sleep Scale (Jenkins et al. 1988). The scale included four items regarding the frequency of difficulty falling asleep, staying asleep, waking up too early, and feeling rested (1 = most of the time, 2 = sometimes, 3 = rarely or never). Following the reverse-coding of the first three items, the total score was computed as the sum of available items; scores were excluded if more than two items were missing. The total scores ranged from 2 to 12, where higher scores reflected more severe sleep disturbance (Nguyen et al. 2024; Qi et al.

2023). The scale demonstrated acceptable internal consistency, with Cronbach's alpha values of .65 in both 2006 and 2010, .67 in 2014, .69 in 2018, and .66 in 2022.

Neighborhood social cohesion

Neighborhood social cohesion was operationalized as residents' subjective appraisals of solidarity and trust (Cagney et al. 2009; Choi 2024; Massihzadegan and Stokes 2023). Respondents rated their agreement with the following statements: "I feel that I don't belong in this area," "Most people in this area cannot be trusted," "Most people in this area are unfriendly," and "If you were in trouble, there is nobody in this area who would help you." Responses were collected on a 7-point Likert scale ranging from 1 (*most strongly disagree*) to 7 (*most strongly agree*). All items were reverse-coded to ensure that higher scores reflect greater perceived social cohesion. Neighborhood social cohesion was measured as the mean of the available item scores. Respondents with more than two missing items were excluded from the analysis. (Cronbach's α = .81 in 2006, .85 in 2010, .86 in 2014, .86 in 2018, and .86 in 2022).

Depressive symptoms

Depressive symptoms were measured by an 8-item version of the Center for Epidemiologic Studies Depression Scale (Crimmins et al. 2011; Kail and Carr 2020). Respondents were asked to report feelings experienced in the past 7 days, including depression, happiness, loneliness, sadness, enjoyment of life, perceived effort in daily activities, lack of motivation, and restless sleep. Responses were recorded as binary variables (0 = no, 1 = yes), with positive emotion items reverse-coded. The total score was calculated by summing all items (range = 0–8), where higher scores indicated greater levels of depressive symptoms (Cronbach's α = .81 in 2006 and 2010; .80 in 2014, 2018, and 2022).

Covariates

Covariates included age (in years), gender (0 = *male*, 1 = *female*), race, educational attainment, marital status, self-rated health, number of living children, income, and residential mobility. Race was initially categorized as White, Black/African American, or other, but was recoded as a binary variable (0 = *White*, 1 = *other*) for this analysis. Educational attainment was classified into four levels: (a) less than high school, (b) general educational development or high school graduate, (c) some college, and (d) college degree or above. Marital status was recoded as a binary variable (1 = *married*, 0 = *other*). Self-rated health was assessed on a 5-point scale ranging from 1 (*poor*) to 5 (*excellent*). Individual annual income, comprising total earnings, pensions, and annuities, was log-transformed prior to analysis. Residential mobility was defined as a binary variable, where 1 indicated at least one change of residence between 2006 and 2022, and 0 indicated no change.

Data analysis

Descriptive statistics were calculated using Stata 19.5, while all other analyses were performed using Mplus 8.3. Missing data were handled by multiple imputation, with 50 imputed datasets generated in Mplus under Bayesian estimation, and parameter estimates pooled according to Rubin's rules.

Measurement invariance was examined using the original non-imputed item-level data, whereas multiple imputation was used for the subsequent substantive analyses.

First, a series of univariate latent growth curve models (LGCs) were estimated to examine the developmental trajectories of neighborhood social cohesion, depressive symptoms, and sleep disturbance across the study waves (T1 = 2006, T2 = 2010, T3 = 2014, T4 = 2018, and T5 = 2022). Specifically, neighborhood social cohesion was modeled from T1 to T4, while depressive symptoms and sleep disturbance were modeled from T2 to T5. In these models, intercept and slope factors represented initial status and the magnitude of change over time, respectively. Placing cohesion one wave prior to the mediator is consistent with the temporal-ordering guideline in longitudinal mediation models (Cole and Maxwell 2003; Selig and Preacher 2009). At the intercept level, the associations compare 2006 cohesion with depressive symptoms and sleep disturbance measured in 2010, whereas the slope-level associations compare each variable's change rate over its own assessment window.

Second, parallel process models were applied to examine longitudinal associations among the trajectories of neighborhood social cohesion, depressive symptoms, and sleep disturbance. Parallel process models were estimated for each construct pair to examine intercept–intercept and slope–slope associations: first, between neighborhood social cohesion and depressive symptoms, second, between depressive symptoms and sleep disturbance; and third, between cohesion and sleep disturbance, which served as the direct-effect baseline for the mediation model. All models accounted for covariates, including age, gender, race, education, marital status, self-rated health, number of living children, income, and residential mobility.

Third, following the establishment of associations between the latent growth processes, a latent growth curve mediation model was constructed to test whether depressive symptoms mediated the link between neighborhood social cohesion and sleep disturbance trajectories. In this structural framework, the intercept and slope factors of neighborhood social cohesion were specified as predictors, while those of depressive symptoms and sleep disturbance functioned as mediators and outcomes, respectively. Indirect effects were then estimated to determine the extent to which the initial levels and change rates in depressive symptoms mediated the association between neighborhood social cohesion and sleep disturbance over time.

Model fit was assessed using the chi-square statistic, root-mean-square error of approximation (RMSEA), comparative fit index (CFI), and standardized root mean square residual (SRMR). Non-significant chi-square estimates, values of RMSEA below .08, CFI above .90, and SRMR below .08 were considered indicative of acceptable model fit (SRMR < .08; (Bentler 1990; Kline 2023). Because the chi-square statistic is known to be sensitive to sample size (Bentler & Bonett, 1980), model fit was evaluated based on a combination of fit indices rather than on the chi-square test alone (Marsh et al. 1988).

Results

Sample characteristics

Table 1 summarizes the demographic and clinical characteristics of the study sample. At baseline, the mean age of respondents was 62.09 years (SD = 7.18), with 62.4% identifying as female. In terms of educational attainment, 34.3% had completed high school, 27.5% held a college degree or higher, 25.5% had some college education, and 12.7% had less than a high school education. The cohort was predominantly White (80.3%). A majority of participants were married (70.8%), and 83.8% reported their self-reported health as "good," "very good," or "excellent." Notably, 74.4% of respondents had remained in their residence throughout the observation period. Median annual income was \$12,000 (IQR: \$0–\$38,000), and the mean number of living children was 3.02 (SD = 1.91). Over the study period, sleep disturbance scores rose slightly from 6.60 in 2010 to 6.74 in 2022. Mean depressive symptom scores increased from 1.20 in 2010 to 1.34 in 2022. Finally, neighborhood social cohesion remained stable between 2006 and 2018, with mean scores fluctuating minimally between 5.47 and 5.55.

Table 1

Descriptive Statistics of Key Study Variables (N = 3360) *Note:* Continuous variables are reported as mean (standard deviation), except for income, which is reported as median (interquartile range) because of its highly skewed distribution. Categorical variables are reported as n (%). GED=general educational development.

Variables	N (%)	Descriptive statistics	Missing (%)
Age		62.09 (7.18)	0
Gender			0
Male	1264 (37.6)		
Female	2096 (62.4)		
Race			0
White	2699 (80.3)		
Other	661 (19.7)		
Education			0
Less than high school	426 (12.7)		
High school graduate	1151 (34.3)		
GED or Some college	858 (25.5)		
College and above	924 (27.5)		
Marital status			0
Other marital status	981 (29.2)		
Married	2379 (70.8)		
Self-rated health			0
Poor	101 (3.0)		
Fair	444 (13.2)		
Good	1007 (30.0)		
Very good	1248 (37.1)		
Excellent	559 (16.6)		
Residential mobility			0.2
Never moved	2500 (74.4)		
Moved at least once	852 (25.4)		
Income		12,000 (0–38,000)	0

Variables	N (%)	Descriptive statistics	Missing (%)
Number of living children (range: 0–11)		3.02 (1.91)	0.1
Neighborhood social cohesion (range: 1–7)			
2006		5.51 (1.28)	8.6
2010		5.55 (1.29)	15.1
2014		5.47 (1.33)	13.6
2018		5.52 (1.32)	29.4
2022		5.51(1.31)	46.8
Depressive symptoms (range: 0–8)			
2006		1.28 (1.91)	0
2010		1.20 (1.84)	2.2
2014		1.19(1.82)	3.0
2018		1.17(1.80)	13.8
2022		1.34(1.89)	23.3
Sleep disturbance			
2006		6.46 (2.07)	0
2010		6.60 (2.03)	2.2
2014		6.68 (2.06)	3.0
2018		6.64 (2.06)	13.8
2022		6.74 (2.06)	23.3

[Insert Table 1 here]

To assess potential attrition-related sample selection bias, we compared participants retained in the final analytic sample ($n = 3,360$) with those who met the baseline eligibility criteria in 2006 but were not retained in subsequent waves ($n = 4,769$). Independent-samples t tests and chi-square tests were conducted for continuous and categorical baseline characteristics, respectively (Supplementary Table S1). Compared with participants who were not retained, those included in the final analytic sample were younger ($d = 1.16$, $p < .001$), had higher incomes ($d = -0.37$, $p < .001$), better self-rated health ($d = -0.55$, $p < .001$), and fewer children ($d = 0.12$, $p < .001$). They also reported slightly fewer depressive symptoms ($d = 0.19$, $p < .001$) and lower levels of sleep disturbance ($d = 0.08$, $p < .001$). No significant difference was observed in baseline neighborhood social cohesion ($d = -0.01$, $p = .534$). For categorical characteristics, the retained and non-retained groups differed significantly in gender ($\chi^2(1) = 40.93$, $p < .001$).

.001), education ($\chi^2(3) = 295.98, p < .001$), and marital status ($\chi^2(1) = 152.92, p < .001$), whereas race did not differ significantly between groups ($\chi^2(1) = 2.72, p = .099$).

We further conducted a multivariable logistic regression analysis to examine baseline characteristics associated with retention in the final analytic sample (1 = retained, 0 = not retained; Supplementary Table S2). The overall model was statistically significant (LR $\chi^2(13) = 2,496.29, p < .001$; pseudo- $R^2 = .256$). Older age was associated with lower odds of retention (OR = 0.88, 95% CI [0.87, 0.89], $p < .001$), whereas female gender (OR = 1.64, 95% CI [1.45, 1.85], $p < .001$), higher educational attainment (ORs = 1.21–1.53, $ps \leq .030$), being married (OR = 1.33, 95% CI [1.17, 1.51], $p < .001$), higher income (OR = 1.01, 95% CI [1.00, 1.03], $p = .026$), and better self-rated health (OR = 1.57, 95% CI [1.48, 1.67], $p < .001$) were associated with greater odds of retention. In contrast, baseline neighborhood social cohesion (OR = 1.02, 95% CI [0.97, 1.06], $p = .430$), depressive symptoms (OR = 0.98, 95% CI [0.95, 1.02], $p = .339$), sleep disturbance (OR = 1.02, 95% CI [0.99, 1.05], $p = .280$), number of children (OR = 1.00, 95% CI [0.97, 1.03], $p = .919$), and race (OR = 1.15, 95% CI [0.98, 1.35], $p = .079$) were not significantly associated with retention. These findings indicate that the final analytic sample differed from the baseline-eligible cohort on several demographic and health characteristics, while baseline neighborhood social cohesion, depressive symptoms, and sleep disturbance were not independently associated with retention after adjustment.

Longitudinal measurement invariance

Longitudinal measurement invariance was examined for neighborhood social cohesion, depressive symptoms, and sleep disturbance across waves, following the standard sequence of configural, metric, and scalar invariance testing (Vandenberg and Lance 2000). A change in CFI of less than .01 was considered indicative of measurement invariance (Cheung and Rensvold 2002; Putnick and Bornstein 2016). Rather than relying on ΔCFI alone, we applied the joint decision rule recommended by Chen (2007). For example, measurement invariance was rejected only when $\Delta CFI \geq .010$ and either $\Delta RMSEA \geq .015$ or $\Delta SRMR \geq .030$ for metric invariance.

Configural models fit acceptably for all three constructs (Cohesion: $\chi^2(98) = 1386.586, p < .001$, RMSEA = 0.063, CFI = 0.908, SRMR = 0.044; Depressive symptoms: $\chi^2(458) = 4229.67, p < .001$, RMSEA = 0.05, CFI = 0.918, SRMR = 0.075; Sleep disturbance: $\chi^2(79) = 1246.44, p < .001$, RMSEA = 0.066, CFI = 0.962, SRMR = 0.044). For neighborhood social cohesion, the CFI decreased by .001 from the configural to metric model and by .006 from the metric to scalar model, both below the .010 threshold. For sleep disturbance, constraining factor loadings and intercepts did not worsen the model fit, all CFI decreases were below .010. For depressive symptoms, the CFI improved by .018 from the configural to metric model and decreased by .001 from the metric to scalar model. The RMSEA decreased by .007 from the configural to metric model and by .001 from the metric to scalar model, and the SRMR increased by .002 from the configural to metric model and remained unchanged from the metric to scalar model. No constrained model met the joint rejection criteria, measurement invariance were supported for all three constructs.

Univariate growth models

The univariate models for all LGCMs demonstrated good fit to the data. For neighborhood social cohesion, the model showed good fit ($\chi^2(5) = 27.997, p < .001, RMSEA = 0.037, CFI = 0.977, SRMR = 0.036$). The slope factor was not statistically significant ($B = -0.004, p = .709$), indicating that neighborhood social cohesion remained relatively stable over time. Across the univariate model, parallel process and mediation models, the cohesion slope variance was significant (as shown in the final model, $\text{variance} = 0.036, SE = 0.012, p = .002$). This finding indicates that respondents differed significantly in the direction and magnitude of their change in perceived cohesion even though the mean trajectory showed little change; such between-person heterogeneity in the rate of change provides the basis for meaningful slope-level associations.

Furthermore, the models for both depressive symptoms and sleep disturbance demonstrated good fit (depressive symptoms: $\chi^2(5) = 22.482, p < .001, RMSEA = 0.032, CFI = 0.990, SRMR = 0.021$; sleep disturbance: $\chi^2(5) = 28.038, p < .001, RMSEA = 0.037, CFI = 0.992, SRMR = 0.026$). Both of these models exhibited significantly positive slope factors (depressive symptoms: $B = 0.034, p = .008$; sleep disturbance: $B = 0.038, p = .004$), indicating a significant increase in these symptoms over time.

Parallel process models

Results for all parallel process models are presented in Table 2. Each model was estimated while controlling for age, gender, race, education, marital status, self-rated health, number of children, income, and residential mobility, and all models demonstrated acceptable to good model fit.

Table 2
Parallel Process Model Results

Model	Intercept → Intercept		Slope → Slope	
	B (SE)	95% CI	B (SE)	95% CI
neighborhood social cohesion → Depressive symptoms	-0.412 (0.047)	[- 0.503, - 0.320]	-0.362 (0.168)	[- 0.692, - 0.033]
Depressive symptoms → Sleep disturbance	0.753 (0.033)	[0.688, 0.817]	0.944 (0.113)	[0.724, 1.165]
neighborhood social cohesion → Sleep disturbance	-0.273 (0.051)	[- 0.374, - 0.172]	-0.281 (0.200)	[- 0.672, 0.110]

Note: B = unstandardized coefficient; SE = standard error; CI = confidence interval. Models controlled for age, gender, race, education, marital status, self-rated health, number of children, income, and residential mobility. Cohesion trajectories spanned T1–T4 (2006–2018), while depressive-symptom and sleep-disturbance trajectories spanned T2–T5 (2010–2022).

Neighborhood social cohesion and depressive symptoms

This model demonstrated good fit: $\chi^2(60) = 115.300, p < .001, RMSEA = 0.016, CFI = 0.990, SRMR = 0.018$. Older adults with higher initial levels of neighborhood social cohesion tended to have lower initial levels

of depressive symptoms ($B = -0.412$, $SE = 0.047$, $p < .001$), and individuals with increasing cohesion trajectories tended to exhibit decreasing trajectories of depressive symptoms. ($B = -0.362$, $SE = 0.168$, $p = .031$).

Depressive symptoms and sleep disturbance

This model also showed acceptable fit: $\chi^2(60) = 332.561$, $p < .001$, $RMSEA = 0.037$, $CFI = 0.968$, $SRMR = 0.019$. Higher baseline levels of depressive symptoms were associated with increased initial sleep disturbance ($B = 0.753$, $SE = 0.033$, $p < .001$). Furthermore, an increase in depressive symptoms over time was coupled with a significant increase in sleep disturbance ($B = 0.944$, $SE = 0.113$, $p < .001$).

Neighborhood social cohesion and sleep disturbance

This model demonstrated good fit: $\chi^2(60) = 114.200$, $p < .001$, $RMSEA = 0.016$, $CFI = 0.991$, $SRMR = 0.019$. While higher initial neighborhood social cohesion was associated with lower initial sleep disturbance ($B = -0.273$, $SE = 0.051$, $p < .001$), individual differences in the rate of change in neighborhood social cohesion were not significantly associated with individual differences in the rate of change in sleep disturbance ($B = -0.281$, $SE = 0.200$, $p = .159$).

[Insert Table 2 here]

Latent growth curve mediation model

A latent growth curve mediation model was utilized to test whether depressive symptoms mediated the longitudinal relationship between neighborhood social cohesion and sleep disturbance. The model exhibited satisfactory fit indices ($\chi^2(121) = 424.205$, $p < .001$, $RMSEA = 0.027$, $CFI = 0.971$, and $SRMR = 0.020$). The model controlled for age, gender, race, education, marital status, self-rated health, number of children, income, and residential mobility.

As presented in Table 3, at the intercept level, the intercept of neighborhood social cohesion was negatively associated with the intercept of depressive symptoms ($B = -0.410$, $SE = 0.047$, 95% CI $[-0.502, -0.318]$), while the intercept of depressive symptoms was positively associated with the intercept of sleep disturbance ($B = 0.758$, $SE = 0.035$, 95% CI $[0.690, 0.826]$). The total association at the intercept level was significantly negative ($B = -0.272$, $SE = 0.051$, 95% CI $[-0.372, -0.172]$). The direct association was not statistically significant ($B = 0.039$, $SE = 0.049$, 95% CI $[-0.058, 0.136]$), whereas the indirect association through depressive symptoms was significant ($B = -0.311$, $SE = 0.037$, 95% CI $[-0.383, -0.239]$).

Table 3
Path Coefficients in the Latent Growth Curve Mediation Model

Path	B (SE)	95% CI
Intercept level		
neighborhood social cohesion→ Depressive symptoms	-0.410 (0.047)	[- 0.502, - 0.318]
Depressive symptoms→ Sleep disturbance	0.758 (0.035)	[0.690, 0.826]
Neighborhood social cohesion→ Sleep disturbance	0.039 (0.049)	[- 0.058, 0.136]
Indirect effect	-0.311 (0.037)	[- 0.383, - 0.239]
Total effect	-0.272 (0.051)	[- 0.372, - 0.172]
Slope level		
neighborhood social cohesion→ Depressive symptoms	-0.351 (0.166)	[- 0.676, - 0.026]
Depressive symptoms→ Sleep disturbance	0.948 (0.117)	[0.718, 1.178]
neighborhood social cohesion→ Sleep disturbance	0.057 (0.212)	[- 0.358, 0.472]
Indirect effect	-0.332 (0.163)	[- 0.651, - 0.014]
Total effect	-0.275 (0.190)	[- 0.648, 0.097]

Note: B = unstandardized coefficient; SE = standard error; CI = confidence interval. Models controlled for age, gender, race, education, marital status, self-rated health, number of children, income, and residential mobility. Cohesion trajectories spanned T1–T4 (2006–2018), while depressive-symptom and sleep-disturbance trajectories spanned T2–T5 (2010–2022).

At the slope level, the slope of neighborhood social cohesion was negatively associated with the slope of depressive symptoms ($B = -0.351$, $SE = 0.166$, 95% CI [- 0.676, - 0.026]), while the slope of depressive symptoms was positively associated with the slope of sleep disturbance ($B = 0.948$, $SE = 0.117$, 95% CI [0.718, 1.178]). The total association at the slope level was not statistically significant ($B = -0.275$, $SE = 0.190$, 95% CI [- 0.648, 0.097]). The direct association was also not statistically significant ($B = 0.057$, $SE = 0.212$, 95% CI [- 0.358, 0.472]), whereas the indirect association through depressive symptoms was significant ($B = -0.332$, $SE = 0.163$, 95% CI [- 0.651, - 0.014]). Thus, at the slope level, the effect of change in cohesion on change in sleep disturbance was transmitted indirectly through change in depressive symptoms, with no statistically significant direct or total effect. This pattern is consistent with indirect-only mediation (Zhao et al. 2010).

[Insert Table 3 here]

Sensitivity analysis

To address the potential conceptual overlap between depressive symptoms and sleep disturbance, we conducted a sensitivity analysis by removing the sleep-related item from the depression measure and re-estimating the parallel process latent growth curve mediation model. The modified model demonstrated a good fit to the data ($\chi^2(121) = 297.52$, RMSEA = 0.021, CFI = 0.982, SRMR = 0.019). The intercept–intercept and slope–slope associations between depressive symptoms and sleep disturbance remained significant (Intercept: $B = 0.654$, $SE = 0.039$, 95% CI [0.578, 0.730]; Slope: $B = 0.828$, $SE = 0.139$, 95% CI [0.555, 1.101]). Overall, the significant associations at both the intercept and slope levels remained stable following the removal of the overlapping item, confirming the robustness of the observed relationship between depression and sleep.

Discussion

This study investigated how perceived neighborhood social cohesion, depressive symptoms, and sleep disturbance co-developed over a 16-year period. Using a parallel process latent growth curve mediation model with five waves of national longitudinal data, this study yielded three findings. First, the initial level of neighborhood social cohesion trajectory was significantly associated with the initial levels of depressive symptoms and sleep disturbance trajectories. Second, change rates in neighborhood social cohesion trajectory were significantly associated with those in depressive symptom trajectory, but not those in sleep disturbance trajectory. Third, depressive symptoms showed significant indirect associations linking neighborhood social cohesion and sleep disturbance at both the intercept and slope levels, with no significant direct association at either level.

Direct associations between developmental trajectories of neighborhood social cohesion, depressive symptoms, and sleep disturbance

Our findings revealed significant associations between neighborhood social cohesion, depressive symptoms, and sleep disturbance. Specifically, while higher initial social cohesion was associated with lower initial sleep disturbance, longitudinal changes in cohesion did not significantly correlate with changes in sleep. Conversely, both initial levels and longitudinal increases in depressive symptoms were associated with higher initial levels and greater increases in sleep disturbance, respectively. These findings are consistent with previous research showing significant associations between neighborhood social cohesion and sleep outcomes among older adults (Alhasan et al. 2020; Bierman et al. 2018; Chen-Edinboro et al. 2015). The present study further refines these findings by showing that the direct association was significant at the intercept level but not at the slope level. In addition, the significant associations between depressive symptoms and sleep disturbance at both intercept and slope levels corroborate existing findings (Becker et al. 2017; Gureje et al. 2011; Maglione et al. 2012; Ouyang and Sun 2019; Rodin et al. 1988). Our findings further indicate that depressive symptoms are associated with sleep disturbance in both initial levels and in change rates. Specifically, higher initial depressive

symptoms and larger longitudinal increases in depression were correspondingly associated with higher initial sleep disturbance and greater increases in sleep disturbance.

Indirect associations between developmental trajectories of neighborhood social cohesion, depressive symptoms, and sleep disturbance

The latent growth curve mediation model further revealed significant indirect associations between neighborhood social cohesion and sleep disturbance through depressive symptoms at both the intercept and slope levels. This finding is consistent with previous research showing that neighborhood social cohesion is associated with depressive symptoms among older adults (Baranyi et al. 2020; Ruiz et al. 2018). Limited social cohesion may foster feelings of disconnectedness and reduce informal support, thereby intensifying psychological distress (Cagney et al. 2009; Miao et al. 2019). A large body of literature also demonstrated significant associations between depression and sleep problems (Becker et al. 2017; Gureje et al. 2011; Maglione et al. 2012; Ouyang and Sun 2019; Rodin et al. 1988). Collectively, our findings provide longitudinal evidence for the stress process perspective by identifying depressive symptoms as a potential mediator between neighborhood social cohesion and sleep disturbance.

Following Zhao et al. (2010), the direct association between cohesion and sleep disturbance was not significant, whereas the indirect association through depressive symptoms was significant, indicating an indirect-only mediation at both intercept and slope levels. Perceived cohesion forms part of older adults' enduring social environments and everyday social resources. These social conditions are more plausibly linked to sleep through the psychological distress they produce than through a direct route (Pearlin et al. 1981). This logic extends to change: a worsening or an improvement in the social environment would first be reflected in depressive symptoms and only later in sleep, which is why cohesion change and sleep change are linked only through depressive symptom change. The P-E fit perspective explains why this channel may be pronounced for change rates than for initial levels. When neighborhood conditions shift, their impacts depend on the fit between those conditions and older adults' evolving capacities and adaptive processes. Thus, the psychological experience of misfit is where environmental change is first registered, before it appears in sleep-related outcomes.

Taken together, these findings suggest that depressive symptoms may represent an important psychological pathway linking neighborhood social cohesion and sleep disturbance, with the nature of this pathway differing between initial status and change over time. These longitudinal associations are consistent with the proposed theoretical framework.

Policy and Intervention Implications

First, perceived neighborhood social cohesion should be incorporated into routine screening and needs assessments for older adults to help identify those at elevated risk of higher levels of baseline sleep disturbance. Although change rates in neighborhood social cohesion were not directly associated with change rates in sleep disturbance, the significant indirect effect mediated by change rates in depressive

symptoms suggests that bolstering social cohesion can improve sleep trajectories by enhancing mental well-being. Second, given that social cohesion demonstrated a protective association with the initial level of sleep disturbance, interventions should prioritize the strengthening of social cohesion. Specific strategies could include cultivating neighborhood networks, promoting participatory governance, and fostering community-based activities that encourage social participation, volunteering, and peer support among older residents. Third, given that depressive symptoms were involved in the indirect association between neighborhood social cohesion and sleep disturbance at both the intercept and slope levels, interventions targeting depression may represent an effective strategy for mitigating the adverse sleep consequences associated with low neighborhood cohesion. Community-based mental health services, routine depression screening, and timely psychological support may be particularly beneficial for older adults in socially disconnected neighborhoods. More broadly, integrating social cohesion enhancement with depression prevention and management may provide a more comprehensive approach to promoting sleep health in later life.

Limitations

First, sleep disturbances were assessed through self-report, which may affect the reliability and validity of the data compared to objective measurements. Nevertheless, these self-reported sleep-related measures have been commonly used in the literature and are designed to capture core features of insomnia as defined by the Diagnostic and Statistical Manual of Mental Disorders and International Classification of Diseases. Therefore, they still provide meaningful insights into individual sleep patterns. Future studies employing objective measures, such as actigraphy, could further validate our findings. Second, while the final model adjusted for key covariates, potential confounding from unmeasured variables, such as sleep duration, could have influenced the associations among key variables. Future research should incorporate additional covariates related to both the neighborhood environment and sleep disturbances. Third, the representativeness of the sample may have been affected by sample attrition, because respondents lost to follow-up could have differed from those who completed all waves. This potential bias may limit the generalizability of the findings. Finally, although the multi-wave longitudinal design and latent growth curve mediation model allowed us to examine associations between initial levels and longitudinal changes, the findings should not be interpreted as establishing causal or strict temporal relationships among neighborhood social cohesion, depressive symptoms, and sleep disturbance. The observed mediation effects suggest that depressive symptoms may serve as a potential psychological pathway linking the development of neighborhood social cohesion and sleep disturbance, but alternative explanations and reverse associations cannot be fully ruled out. More intensive longitudinal designs or experimental/quasi-experimental approaches are needed to further clarify these mechanisms.

Conclusions

This study investigated how perceived neighborhood social cohesion, depressive symptoms, and sleep disturbance developed in parallel among adults aged 50 and older over a 16-year period. Higher initial

cohesion was associated with lower levels of depressive symptoms and sleep disturbance, and changes in cohesion were linked to changes in depressive symptoms; depressive symptoms mediated the association from cohesion to sleep disturbance at both the intercept and slope levels. Depressive symptoms may thus act as a proximal psychological pathway through which a distal neighborhood social resource affects sleep health in later life, supporting integrated efforts to strengthen community cohesion and to screen for and manage depressive symptoms.

Declarations

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Availability of data and materials: The datasets analysed during the current study are available in the HRS repository, [<https://hrsdata.isr.umich.edu/>].

Ethics approval and consent to participate: Ethics approval was obtained from the Ethical Review Committee of the University of Michigan. The data used in this study were anonymized before use. Informed consent was obtained from all participants.

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Authors' contributions: QZ planned the study, performed statistical analysis, wrote and revised the paper. NL contributed to literature review, theoretical framework, discussion, and wrote and revised the paper. WL contributed to literature review, data analysis, and paper writing and revision. WY contributed to data analysis and writing and revising the paper. The work has not been accepted or published elsewhere in whole or in part. All of the authors have contributed significantly to the work and approved the final manuscript.

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