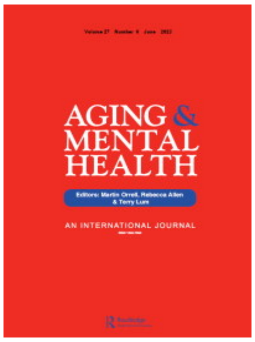

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Longitudinal associations between mental health and social environment in older adults: a multilevel growth modeling

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ABSTRACT

Objectives: This study aimed to assess longitudinal relationships between social environment indicators (social connectedness, social engagement, social contribution) and mental health indicators (depression and anxiety) among community-dwelling adults age 55 years and older.

Methods: Data were drawn from 3-waves of the national longitudinal survey of Midlife Development in the United States (MIDUS) (N = 2,020; age range = 55-94 years). We developed multilevel growth models to ascertain the relationships of interest, controlling for sociodemographic and physical health factors.

Results: Over the 20-year period of study, lower levels of emotional social support, social integration and social contribution significantly predicted depression and anxiety, whereas social network and social engagement were not significant predictors of these mental health outcomes in older adults. The models also indicated a moderation effect of the number of chronic conditions on the slopes of depression and anxiety.

Discussion: Considering our findings, interventions to enhance social contribution and social connectedness could be effective to help older adults maintain positive mental health, as well as programs that facilitate older adults' connections with their families, communities and health care providers. These interventions must also account for multiple chronic conditions since functional limitations drive declining integration in the community and participation in social activities.

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KEYWORDS
Social connectedness; social engagement; social contribution; depression; anxiety

Introduction

Social environments encompass different elements, with social connectedness, social engagement, and social contribution being important factors and criteria in promoting healthy aging and in creating age-friendly communities (Jeste et al., 2016). A rupture or fracture of their social environment puts older adults at a great risk for psychological distress and depression and anxiety due to social isolation, loneliness, and decreased access to community support often complicated by physical health conditions, medical comorbidities, and delayed care or reduced access to care (Holt-Lunstad, 2017; Kola et al., 2021; Pettigrew et al., 2014; Steptoe & Di Gessa, 2021). For example, older adults faced several challenges related to their mental health and well-being (Xie et al., 2020; 2021) due to disruptions in social environment during the COVID-19 pandemic and the resulting lack of social connections, social activities, and social engagement in their communities (Heid et al., 2021).

Cross-sectional studies found that poor social connections and social engagement were associated with symptoms of depression and anxiety and an increased risk for cognitive decline (Glass et al., 2006; Nicholson, 2012; Sarma & Byrne, 2014). Low social connectedness specifically in older men was significantly linked to increased death from suicide (Heisel et al., 2016). Moreover, low social support and social participation and reduced social contribution were found to be associated with depressed mood and poor psychological well-being (Anaby et al., 2011; Fairhall et al., 2014; Golden et al., 2009). Other studies found that a lack of social connections was significantly associated with onset of depression, increased depression and maladaptive health behaviors, and early mortality in older US adults (Cornwell & Waite, 2009; Holt-Lunstad, 2018; Saeri et al., 2018; Yiengprugsawan et al., 2018).

Most of the studies published in the past two decades on the relationships between social environment elements (social connectedness, social engagement, social contribution) and mental health outcomes (depressive and anxiety symptoms) tended to be cross-sectional (Anaby et al., 2009, 2011; Antonucci et al., 1997; Garrido et al., 2009; Golden et al., 2009; Ha & Carr, 2005; Nelson, 1993; Sarma & Byrne, 2014), making it difficult to investigate the potential changes over time. Longitudinal analyses are needed to further assess the temporal associations of social environment and mental health in older adults.

The present study

Using an adapted conceptual model from Berkman et al. (2000) model on social networks and health outcomes, in the present study we aimed to examine the relationships between social environment and mental health over time, in particular, the

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effects of the potential changes of social environment on mental health outcomes. Berkman et al. (2000) proposed a cascading causal model by which social relationships influence health. The model was based on a perspective where social networks are embedded in larger social and cultural contexts and conditioned by factors such as cultural and socioeconomic factors, politics, and social change. The model stipulated that network structure influences health through three different pathways: (a) behavioral (e.g., smoking, alcohol consumption, health service utilization), (b) psychological (e.g., depression, distress, well-being) and (c) physiological health (e.g., exposure to infection, cardiovascular reactivity). Using this model as a foundational structure, we proposed that *social connectedness*, *social engagement,* and *social contribution* impact the psychological and behavioral pathways, taking into consideration sociodemographic factors (age, sex, race/ethnicity, marital status, education, income and employment), and number of chronic conditions.

Social connectedness refers to the feeling of being cared about by others, feeling of being part of a community, or belongingness and having meaningful and close relationships with others (O'Rourke & Sidani, 2017), and includes social support, social networks and social integration. An important type of social support is emotional social support, which is related to the help with emotional difficulties and communication of love, caring, concern, sympathy and understanding given by others (Berkman et al., 2000). Social networks are based on the size, density, reciprocity of ties and relationships and proximity as well as frequency and duration of relationships (Berkman et al., 2000; Holt-Lunstad, 2015). Social integration is the connectedness with others within social groups, communities and networks (Berkman et al., 2000; Holt-Lunstad, 2015). *Social engagement* can come in several forms such as performance of physical and cognitive exercise, performance of meaningful roles, bonding or interpersonal attachment (Berkman et al., 2000). *Social contribution* is contribution to society through activities considered not only valuable by the individuals but also valued by their communities (Berkman et al., 2000; Holt-Lunstad, 2015).

Based on the aforementioned theoretical perspective and empirical evidence regarding social environment and mental health, the aim of our study was to examine the longitudinal relationships between social environment and mental health among community-dwelling older adults (55+ years). The current study addressed the following research questions (RQ) and hypotheses (H):

RQ 1: What are the associations of mental health outcomes (depression and anxiety) with (a) social connectedness, (b) social engagement, and (c) social contribution?

H 1.1: Low levels of social connectedness, social contribution and social engagement would predict high levels of depression (versus the null hypothesis of no association)

H 1.2: Low levels of social connectedness, social contribution and social engagement would predict high levels of anxiety (versus the null hypothesis of no association)

RQ 2: How do changes in social environment affect mental health outcomes over time?

H 2: Positive changes in social connectedness, social engagement and social contribution over time would be associated with improved depression and anxiety (versus the null hypothesis of no association)

Methods

Data

Data are drawn from the three waves (1995–1996, 2004–2006, 2011–2014) of the Midlife Development in the United States (MIDUS). MIDUS is a collaborative, interdisciplinary investigation of patterns, predictors, and consequences of midlife development in the areas of physical health, psychological well-being, and social responsibility. Participants are from a nationally representative random-digit-dial sample of noninstitutionalized, English-speaking adults, aged 25–74 years, selected from working telephone banks in the United States (Brim et al., 1999; Ryff et al., 2017a; 2017b).

In Wave 1, 7,108 adults completed a phone interview and then were invited to complete a self-administered questionnaire. In Wave 2, 4,963 participants from the initial cohort completed phone interviews. In Wave 3, 3,294 of those who participated in Wave 1 and Wave 2 completed phone interviews. All respondents were asked to provide extensive information on their physical and mental health retrospectively in the past 12 months to assess ways in which their lifestyles, including relationships and work-related demands, contributed to their current health conditions (Brim et al., 1999; Ryff et al., 2017a; 2017b). The current analysis focuses on participants who answered both telephone and mail questionnaires in all three Waves, were 55 years or older in Wave 1, and had information on all study variables in all waves. From the initial total of 3,034 participants, we obtained an analytical sample of 2,020 participants at Wave 1.

This study based on de-identified data set was exempt from the authors' institutional review board.

Measures

Dependent variables

1. *Depression* was assessed with the World Health Organization Composite International Diagnostic Interview Short Form (CIDI-SF), based on seven questions about depressive symptoms experienced in the past twelve months, such as loss of interest, feeling sad, anhedonia, (e.g. "During two weeks in the past 12 months, when you felt sad, blue or depressed, did you lose interest in most things?") resulting in a continuous variable with a score range of 0-7 with a higher score indicating higher symptom severity (Ryff et al., 2017a).
2. *Anxiety* was assessed with the World Health Organization Composite International Diagnostic Interview Short Form (CIDI-SF), using 10 items designed to cover the symptoms of worry experienced in the past twelve months (e.g. "How often, over the past 12 months, you were restless because of your worry?"). The variable was constructed as continuous with a score range of 0-10 with a higher score reflecting higher symptom severity (Ryff et al., 2017a).

Independent variables

3. *Emotional social support* was operationalized in MIDUS as the support received from family and friends ("How much do your family members care about you?", "How much do they understand the way you feel about things?", How much can you rely on them for help if you have a serious problem?") measured with 4-items each. Participants

were asked to rate each of the items on a 4-point Likert scale leading to a score range of 1-4 (Ryff et al., 2017a). Higher scores signify higher level of emotional support.

4. *Social networks* were assessed by the frequency of contact with family members and friends in a day, week or months, resulting in a continuous variable (range 1-8) with lower scores showing higher frequency of contact with family and friends (Ryff et al., 2017a).
5. *Social integration* was operationalized as feeling part of a community, belongingness, feeling supported and sharing commonalities with community (e.g., "I feel close to other people in my community"; "My community is a source of comfort") (Ryff et al., 2017a). The variable was continuous with higher score reflecting higher social integration (range 3-21).
6. *Social engagement* was measured with three items quantifying the frequency of attending meetings and social groups in a typical month, including but not limited to union, sports, or recreational activities, outside the workplace (Ryff et al., 2017a). The variable was continuous with a range of scores 0-70 with higher scores indicating higher social engagement.
7. *Social contribution* was operationalized in MIDUS as individuals' feeling that they have something valuable to give to society and think their daily activities are valued by their community (e.g., "I have something valuable to give to the world") (Ryff et al., 2017a). This resulted in a continuous variable with a range of scores from 3 to 21, with higher scores reflecting higher social contribution.

Sociodemographic factors

These included chronological age at the survey dates; sex (male = 0, female = 1); marital status (separated, divorced, and widowed = 0 and married = 1); race (Non-Hispanic White = 0, Non-Hispanic Black = 1, American Indian/Alaska Native = 2, Asian/Pacific islander = 3, Other = 4); education level (some grade school to some high school = 0, GED/high school graduate = 1, some college/graduate college (2-y)/vocational = 2, Bachelor's to doctorate/prof. degree = 3); annual household income (continuous variable, centered at the median \$39,000, or <\$10,000 = 0; \$10,000-\$39,999 = 1; \$40,000-\$65,999 = 2; \$70,000-\$99,999 = 3; ≥\$100,000 or more = 4); employment status (currently retired = 0, not retired = 1); and the number of chronic conditions diagnosed within the past 12 months (none = 0, 1 chronic condition = 1, 2+ chronic conditions = 2).

Time

For the present study, a time variable was created to indicate the 3 waves (Wave 1 = 0, Wave 2 = 1, and Wave 3 = 2). The time of measurement in years from the first wave to the second wave varied from 8 to 11 years and ranged between 11 and 19 years from the first wave to the third wave, with an average of 10 years between the waves.

These variables are illustrated in Supplementary Table 1.

Data analysis

We carried out a longitudinal data analysis, using R Software Version 1.1.383, with growth curves using hierarchical linear modeling to quantify within- and between individual changes in mental health over time and to estimate the extent to which the variations in mental health trajectories were shaped by social environment indicators. Our multilevel growth modeling was based on two stages.

The first modeling stage of the analysis was composed of a level-1 model or within-person model, which concerns the within-individual change during the time period under study, and of a level-2 model or between-persons model, which is focused on the interindividual differences and what predicts these differences (Singer & Willett, 2003). The first modeling phase served to describe each individual participant's trend over time and predictors of between-individual differences in initial levels of the response variable and moderators of trends over time, which is useful to understand interindividual variability in longitudinal data, thus providing information regarding the relationships between repeated measures and time-invariant and time-varying predictors (Singer & Willett, 2003; Ullman, 2006). Prior to fitting models that include the predictors, we started with the unconditional means model or null model, which quantifies the crude variation of the outcome regardless of time and the unconditional growth model, which quantifies and partitions variation in the outcome across both individuals and time.

In the second stage of the analysis, we entered the time-invariant covariates (sex, race, education level) first and then added time-varying covariates (age, marital status, income, employment, number of chronic conditions) into the composite model, made of level-1 and level-2 models. We then evaluated the main effects of the social environment indicators on individuals' mental health outcomes (depression, anxiety) after controlling for the covariates or predisposing factors. A stepwise approach was used to build the final model in order to maintain a balance between the model complexity and parsimony (Hoffman, 2015). Predictors that did not improve the model fit were therefore removed from the final model. Interaction terms were also included between time and covariates to assess possible moderating effects on the trend over time. Non-significant interactions were removed from the final model.

To reduce selective attrition bias, bias resulting from certain types of participants dropping out from wave to wave, and deal with missing values, we used the full information maximum likelihood (FIML) estimation to obtain maximum likelihood (ML) estimates, which is the preferred method of imputing incomplete data in longitudinal studies as it considers all available data. FIML estimation was done using a structural equation modeling (SEM) approach, which works by estimating a likelihood function for each individual case based on the study variables so that all the available data are used. Results obtained from this approach were similar to the multilevel modeling FIML estimation findings. FIML estimation has become the main approach to handle missing data in multilevel modeling and most of the programs use FIML estimation by default (Grimm et al., 2017; Singer & Willett, 2003).

For our analysis, we also used MIDUS post-stratification weights (age, gender, race, education), which were based on the Current Population Survey to adjust for differences with the population parameters and improve the national representativeness of the sample (Radler & Ryff, 2010; Ryff et al., 2017b). However, the estimates from the weighted analyses did not significantly differ from these of the unweighted analyses. Thus, the weights in our analyses did not significantly impact our models.

Post-Hoc power analysis of focal effects

We carried out a post-hoc power analysis based on selected results from our multilevel models using the power module in Stata-17 (Stata Corp. LLC, College Station, TX). This module provides generalized power analyses under various situations, including for regression slopes (i.e., the fixed effects of substantive interest in this study). All results are based on two-sided alternative hypotheses at the 0.05 level of significance. Inputs to the power routine included point estimates as hypothesized effect sizes associated with H_a, the parameter value under H_0 (set to 0), conservative hypothetical sample sizes smaller than 2,020 (i.e., we considered the number of individuals entering each wave of the study rather than the total measurements over three waves, $n = 3{,}034$), level-1 residual standard deviations, as well as standard deviations of the focal predictors and standard deviations of their linear combinations with time for cross-level interactions. With over 2,000 individuals measured at each occasion, this study was well powered. Post-hoc power analysis showed that focal effects attained power > 0.8 at the 0.05 level for level-2 sample sizes less than half of what were used in our analysis (see Supplementary file 1).

Table 1. Participants characteristics.

	Wave 1 *N* = 2020	Wave 2 *N* = 1384	Wave 3 *N* = 787
Mean age (yrs, SD)	63.10 (5.655)	71.48 (5.527)	79.15 (4.980)
Age Group (yrs, %)			
55-64	61.4	8.4	–
65-74	38.4	60.9	19.8
75-84	0.2	30.8	64.0
85-94	–	–	15.8
95+	–	–	–
Marital status (%)			
Married	67.3	65.00	54.3
Separated/Divorced/ Widowed	32.7	35.10	45.7
Race/Ethnicity (%)			
Non-Hispanic White	85.1	93.8	94.7
Non-Hispanic Black	4.0	3.9	3.0
Hispanic	NA	NA	NA
Asian/Pacific islander	0.2	0.2	0.3
American Indian/ Alaska Native	0.5	0.6	0.5
Other	10.1	1.4	1.6
Education Level (%)			
Some grade school-12th grade	15.0	11.2	10.0
High School/GED	32.2	31.7	29.6
Some college/ Associate	27.7	28.0	27.3
Graduate college-Doctorate	24.8	29.1	33.1
Income (%)			
Less than $10,000	10.2	15.9	14.0
$10,000-$39,999	31.8	43.6	36.3
$40,000-$69,999	22.1	22.3	22.4
$70,000-$99,999	9.3	9.2	13.5
$100,000 or more	14.8	9.0	13.7
Employment (%)			
Retired	46.5	74.4	32.5
Not Retired	53.5	25.6	67.5
Number of Chronic Condition (%)			
No chronic conditions	14.4	12.6	16.9
1 chronic condition	16.6	15.8	10.6
2+ chronic conditions	61.5	71.6	72.5
Depression (%) [1]			
0-2	91.6	92.6	92.5
3-7	8.4	7.4	7.5
Anxiety (%) [2]			
0-1	98.4	99.3	99.4
2-5	1.2	0.4	0.5
6-10	0.4	0.4	0.1

Note. [1]Based on Nelson et al. (1998) study, a score of three or more on the CIDI-SF is indicative of a diagnosis of depression. [2] Scores' intervals based on Kessler et al. (1998).

Results

Across subsequent data collection points, the sample size was reduced to 1,384 at Wave 2 (68.5% retention) and 787 at Wave 3 (56.9% retention). Descriptive statistics for the participants included in the analytic sample are summarized in Table 1.

The participants who provided longitudinal data in all waves tended to be White with higher levels of education and to report, on average, better physical health (F(2, 2018)= 19.100, *p*<.001) and mental health (F(2, 2018)= 5.147, *p*=.023) at Wave 1 and better mental health (F(2, 2018)= 4.342, *p*=.037) at Wave 2, with effect sizes varying between 0.14 and 0.32, than participants with missing values on the variables of interest. According to Cohen (1988), a small effect size is represented by values lower than 0.2, medium effect with values of 0.5, and a larger effect with values greater than 0.8 (Cohen, 1988). These findings are consistent with prior research on the effects of demographic and health variables on longitudinal retention (Radler & Ryff, 2010).

Multilevel growth modeling of mental health and social environment

From the unconditional means models (See Model A, Supplementary Tables 2 and 3), the intercepts or overall mean scores across all three measurement occasions for depression (β_{00}=0.4302, $p < 0.001$) and anxiety (β_{00}= 0.0539, $p < 0.001$) were statistically significantly different from 0, from time 0 to time 1 to time 2. The significance of the random effect variance estimates suggested individual variability in initial conditions of depression and anxiety. The intraclass correlation coefficients (ICC) indicated that about 7.1% of the total variance in anxiety, and 27.6% of the total variance in depression were attributable to the differences between community-dwelling older adults. This also suggested that including predictors in our model that differentiate older adults might be helpful in predicting this variation. In addition, the models yielded lower Akaike Information Criterion (AIC) and log likelihood values than the simple regression models, with significant likelihood ratio tests (LRTs), indicating that the unconditional means models provided a better fit than single-level regression models.

The unconditional growth models (see Model B, Supplementary Tables 2 and 3) for depression and anxiety test for a linear trend in measurements and assess between-individual variation in change over time. The increase in the ICC indicates that slope variation accounts for some portion of the total between-participant variation in initial level and change over time. Furthermore, adding a random slope significantly improved the model fits for depression, as evidenced by significant LRTs.

Results for depression

From the unconditional growth model (Model B, Supplementary Table 2), older adults had an initial mean depression score of 0.444 with a rate of change of −0.0231 ($p = 0.381$). The variance in mean initial status (σ^2_0=0.8093, 95% CI [0.544, 1.204]) showed that older adults significantly varied on their initial depression scores, and the variance in the rate of change (σ^2_1=0.1357, 95%

CI [0.060, 0.306]) indicated that older adults' depression growth rates did significantly vary. The estimated correlation −0.579, 95% CI [-0.745, −0.346] was negative, showing that older adults with lower depression scores tended to have faster growth rates.

Adding time invariant and time varying predictors (Model C-J, Supplementary Table 2) to the model improved the model fit in predicting older adults' depression growth rates. The coefficients below pertain to full growth model for depression.

Full Growth Model for Depression:

$$\begin{aligned}\mathbf{Depression_{ij}} = & \mathbf{0.486 + 0.329 * time\_n_{ij} + 0.137 * sex\_a_i} \\ & \mathbf{- 0.056 * educ\_level_i - 0.023 * c\_age_i} \\ & \mathbf{- 0.174 * marital\_status_i - 0.045 * income_i} \\ & \mathbf{+ 0.223 * nber\_chronic\_condition_i} \\ & \mathbf{- 0.107 * time\_n_{ij} x nber\_chronic\_condition_i} \\ & \mathbf{+ U_{0i} + time * U_{1i} + e_{ij}}\end{aligned}$$

A significant fixed effect of linear time (per 10 years on average) (0.329, $p < 0.001$) was found for depression. The trajectory of depression is displayed in Figure 1 showing an increase in depression growth rates. Altogether, biological sex, age, education level, marital status, income and number of chronic conditions significantly predicted depression over time, with an adjusted R^2 of 0.332 ($r = 0.576$), which shows a moderate effect as per Cohen's guidelines (Cohen, 1988). The interaction of time and number of chronic conditions was significant (-0.107, $p = 0.007$), which indicates that number of chronic conditions reduces the upward trajectory of depression by 0.107. This means that change over time in depression is lower for older adults with multiple chronic conditions (MCC) (see Figure 2).

Table 2 shows the results of the multilevel growth models predicting depression. The random intercepts were all significant and changed in the models from 1.119 to 0.345, $p < 0.001$. The estimates for the population average slopes fluctuated between 0.297 and 0.329, $p < 0.001$.

Social connectedness

The models evaluated independently the effects of emotional social support, social networks, and social integration on initial status and rates of change in depression, controlling for sex, education level, age, marital status, income and number of chronic conditions. Significant main effect was found for emotional social support (-0.208, $p < 0.001$), which indicates that emotional social support negatively predicted depression. The interaction of time by emotional support was not significant (-0.022, $p = 0.715$), suggesting that emotional social support did not moderate change in depression over time.

The main effects of social network were not statistically significant (0.030, $p = 0.1105$); however, significant main effects were found for social integration (-0.034, $p < 0.001$), showing that social integration negatively predicted depression. The interaction of time by social integration was not significant (0.002, $p = 0.756$), meaning that social integration did not moderate change in depression over time.

Social engagement

This model estimated the effects of social engagement (frequency of attending meetings and social groups) on initial status and rates of change in depression, controlling for sex, education level, age, marital status, income and number of chronic conditions, which were not statistically significant (-0.003, $p = 0.556$).

Social contribution

This model evaluates the effects of social contribution on initial status and rates of change in depression, controlling for sex, education level, age, marital status, income and number of chronic conditions. The main effects of social contribution were statistically significant (-0.028; $p < 0.001$), indicating that social contribution negatively predicted depression. Interaction of time by social contribution was not significant (0.004, $p = 0.584$), showing that social contribution did not moderate change in depression over time.

Results for anxiety

In Supplementary Table 3 Model B, older adults had initially a mean anxiety of 0.074 with a significant rate of change of −0.029 showing a decrease in the anxiety over the waves. The variance in mean initial status (σ^2_0=0.198, 95% CI [0.176, 0.223]) showed that older adults significantly vary on their initial anxiety scores and the variance in the rate change (σ^2_1=0.064, 95% CI [0.053, 0.076]) demonstrated a significant variation in older adults'

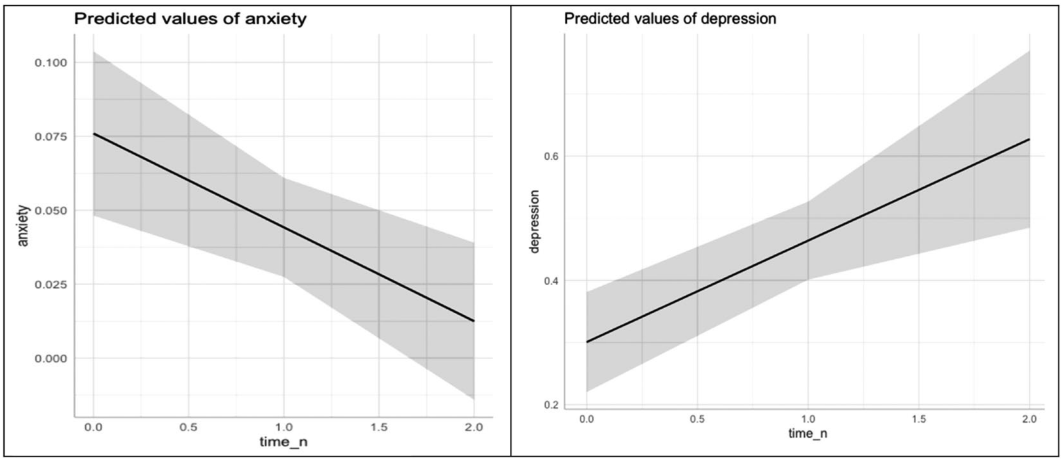

Figure 1. Trajectories of depression and anxiety for older adults.
Note: time_n represents MIDUS waves.

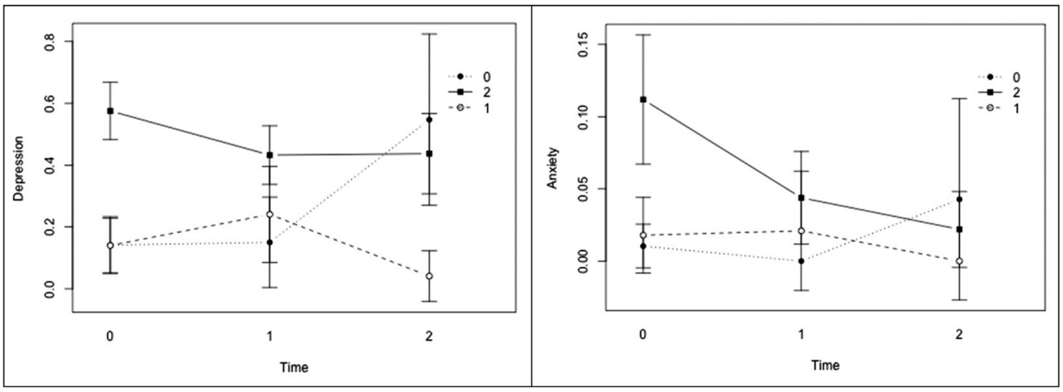

Figure 2. Interactions of time with number of chronic conditions for depression and anxiety.
Note. 0 = no chronic condition; 1 = 1 chronic condition; 2 = 2+ chronic conditions.

Table 2. Multilevel models for change of depression and social environment over time (n = 2020).

		Final Growth Model	Model-Emotional Social Support	Model- Social Network	Model- Social Integration	Model- Social Engagement	Model- Social Contribution
Fixed Effects							
Initial status (π_0)	Intercept	0.4856***	1.1194***	0.3452**	0.8978***	0.4426***	0.7107***
	Sex	0.1367**	0.1832***	0.1458**	0.1605**	0.1247*	0.1582**
	Education Level	(-)0.0564*	(-)0.0677**	(-)0.0698*	(-)0.0571*	(-)0.0635**	ns
	Age	(-)0.0231***	(-)0.0202***	(-)0.0211***	(-)0.0180***	(-)0.0206***	(-)0.0214***
	Marital Status	(-)0.1740**	(-)0.1982***	(-)0.2106**	(-)0.1877***	(-)0.2083***	(-)0.2085***
	Chronic Conditions	0.2226***	0.2164***	0.2191***	0.2102***	0.2164***	0.2214***
	Income	(-)0.0452*	ns	ns	ns	ns	ns
	Social support		(-)0.2080***				
	Social network			0.0300			
	Social integration				(-)0.0333***		
	Social engagement					(-)0.003	
	Social contribution						(-)0.0256***
Rate of Change (π_1)							
	Slope	0.3291***	0.3237***	0.3285***	0.2982***	0.2967***	0.3165***
	Chronic Conditions	(-)0.1073**	(-)0.1166**	(-)0.1146**	(-)0.1201**	(-)0.1041**	(-)0.1248**
	Social support		ns				
	Social integration				ns		
	Social contribution						ns
Variance components							
	Level-1 within-person (residual)	1.3001*	1.2801*	1.2721*	1.2571*	1.2609*	1.2627*
	Level-2 between-person (random)	0.6245*	0.685*	0.6873*	0.7112*	0.6938*	0.7158*
	In rate of change	0.1155*	0.1772*	0.1805*	0.1709*	0.1295*	0.1607*
Fit Statistics							
	ICC	32.45	34.86	35.08	36.13	35.49	36.18
	AIC	11977.46	12772.98	12765.77	12553.48	12190.41	12609.82
	BIC	12057.47	12853.79	12846.59	12634.14	12270.72	12684.31
	logLik	(-)5975.73	(-)6373.49	(-)6369.89	(-)6263.74	(-)6082.21	(-)6292.91

Note. These models predict depression for older adults as a function of social environment indicators, maintaining constant age, sex, education level, marital status, income and number of chronic conditions. ICC = Intraclass correlation coefficient; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; logLik = log likelihood value; ns = not significant.
*$p < .05$.
**$p < .01$.
***$p < .001$.

growth rates. The addition of time invariant and time varying predictors (Model C-I, Supplementary Table 3) improved the model fit in predicting anxiety growth rates, to finally obtain a full growth model for anxiety.

Full Growth Model for Anxiety:

$$\mathbf{Anxiety_{ij} = -0.00086 + 0.0124 * time\_n_{ij} + 0.0502 * nber\_chronic\_condition_i - 0.0288 * time\_n_{ij} x nber\_chronic\_condition_i + U_{0i} + time * U_{1i} + e_{ij}}$$

A significant fixed effect of linear time (per 10 years on average) (-0.032, $p < 0.001$) was found for anxiety. Figure 1 displays the trajectory of anxiety, with a noticeable decline in anxiety growth rates. The number of chronic conditions significantly predicted depression over time, with an adjusted R^2 of 0.431 ($r = 0.657$), which shows a moderate effect as per Cohen's guidelines (Cohen, 1988). The interaction of time and number of chronic conditions was significant (-0.029, $p = 0.039$), which indicates that the slope of anxiety was higher for older individuals with MCC compared to their counterparts with one or no chronic conditions (see Figure 2).

Table 3 shows the results of the multilevel growth models predicting anxiety. The population average intercepts were significant for the most part and varied in the models from −0.00086 to 0.246, $p < 0.001$ and the estimates for the population average slopes were not statistically significant.

Social connectedness

The models assessed separately the effects of emotional social support, social networks, and social integration on initial status and rates of change in anxiety, controlling for the number of chronic conditions. Significant main effect was found for emotional social support (-0.072, $p < 0.001$), which indicates that emotional social support negatively predicted anxiety. The interaction of time by emotional support was not significant (-0.028, $p = 0.202$), suggesting that the effect of emotional social support on anxiety did not change over time.

The main effects of social network were not statistically significant (0.003, $p = 0.696$); however, significant main effects were found for social integration (-0.013, $p < 0.001$), showing that social integration negatively predicted anxiety. The interaction of time by social integration was significant (0.006, $p = 0.019$), meaning that higher social integration reduces the downward trajectory of anxiety by 0.006. The change over time in anxiety is higher for older adults with lower levels of social integration.

Social engagement

This model estimated the effects of social engagement on initial status and rates of change in anxiety while maintaining number of chronic conditions constant. No significant main effects were found.

Social contribution

This model examines the effects of social contribution on initial status and rates of change in anxiety, controlling for the number of chronic conditions. The main effects of social contribution were statistically significant (-0.013; $p < 0.001$), indicating that social contribution negatively predicted anxiety. Interaction of time by social contribution was significant (0.006, $p = 0.044$), showing that higher social contribution dampened the downward trajectory of anxiety by 0.044.

To visualize the findings of the multilevel growth modeling, the simplified relationships between social environment components and mental health outcomes were shown in Supplementary Figure 1.

Discussion

This study used 3 waves of data from the national longitudinal survey of MIDUS to examine the relationships between social environments and mental health outcomes over a 20-year period among community-dwelling older adults. Using a conceptual framework adapted from Berkman et al. (2000) model on social networks and health outcomes, our present study sought to assess the trajectories of social environment components (social connectedness, social engagement, social contribution) and its long-term impact on depression and anxiety. Overall, findings indicated the significance of high levels of social environment for maintaining high levels of positive mental health.

To parse the marginal effect of each component of social environment on mental health outcomes, we estimated multilevel growth models showing that there were significant within- and between variabilities in older adults' depression and anxiety. The findings provided a partial support to our research questions, regarding predictions of depression and anxiety by social

Table 3. Multilevel models for change of anxiety and social environment over time ($n = 2020$).

		Final Growth Model	Model-Emotional Social Support	Model- Social Network	Model- Social Integration	Model- Social Engagement	Model- Social Contribution
Fixed Effects							
Initial status (π_0)	Intercept	(-)0.0008 (ns)	0.2463**	(-)0.0093 (ns)	0.2036***	0.0054 (ns)	0.2029***
	Chronic Conditions	0.0503**	0.0497**	0.0510**	0.0439**	0.0475**	0.0441**
	Social support		(-)0.0719**				
	Social network			0.0026 (ns)			
	Social integration				(-)0.0129***		
	Social engagement					(-)0.0007 (ns)	
	Social contribution						(-)0.0131***
Rate of Change (π_1)							
	Slope	0.0124 (ns)	(-)0.0812 (ns)	0.0130	(-)0.0831 (ns)	(-)0.0004(ns)	(-)0.0734 (ns)
	Chronic Conditions	(-)0.0288*	(-)0.0292*	(-)0.0293*	(-)0.0269 (ns)	(-)0.0221 (ns)	(-)0.0270 (ns)
	Social support		0.0278 (ns)				
	Social integration				0.0061**		
	Social contribution						0.0056*
Variance Components							
	Level-1 within-person (residual)	0.1677*	0.1708*	0.1704*	0.1553*	0.1523*	0.1549*
	Level-2 between-person (random)	0.2252*	0.2246*	0.2273*	0.2332*	0.2440*	0.2339*
	In rate of change	0.0778*	0.0779*	0.0790*	0.0844*	0.0869*	0.0849*
Fit Statistics							
	ICC	57.32	56.8	57.16	60.02	61.57	60.15
	AIC	5715	5686	5692	670.4	5301	5415
	BIC	5765	5748	5748	707.6	5356	5476
	logLik	(-)2849.7	(-)2833.1	(-)2837.0	(-)329.2	(-)2641.6	(-)2697.0

Note. These models predict anxiety for older adults as a function of social environment indicators, maintaining constant number of chronic conditions. ICC = intraclass correlation coefficient; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; logLik = log likelihood value; ns = not significant.
*$p < .05$.
**$p < .01$.
***$p < .001$.

connectedness, social contribution and social engagement, in terms of within and between individual changes over time.

Emotional social support, social integration and social contribution had statistically significant effects on the initial status of depression and anxiety and their rates of change over time in community dwelling older adults, controlling for sociodemographic and physical health factors. Social support, social integration and social contribution significantly negatively predicted depression and anxiety. Hence, for any positive changes in older adults' emotional social support, social integration and social contribution over time, there was a significant reduction in their depression and anxiety symptoms across the waves. In addition, while the temporal effects of emotional social support, social integration and social contribution on depression remained unchanged across the waves for depression, the temporal effects of social integration and social contribution on anxiety changed significantly over the 20-year period of study.

Social network and social engagement did not have statistically significant effects on the initial status and the rates of change of depression and anxiety over the 20-year period of study. This result is in line with previous studies providing evidence that a sense of belonging (social integration) was significantly associated with number of depressive symptoms (Norstrand et al., 2012); social support and quality of social relations were consistently and strongly associated with depression (Schwarzbach et al., 2014). Contrary to our findings that social network did not statistically affect depression and anxiety over time, previous studies revealed that low levels of social network were significantly associated with high levels of depression and anxiety over a 2-year period (Domènech-Abella et al., 2019; Saris et al., 2017). However, Cacioppo et al. (2010) found that lower levels of social network were not associated with higher depression scores over 5 years, which supports our results. Social involvement with community groups, connections in the community and social network were found to be related to better emotional well-being, specifically among older adults with chronic conditions (Reeves et al., 2014).

Social engagement was found not to be a significant predictor of depression and anxiety. Our findings are in line with studies related to social engagement suggesting no associations between social engagement (participation in the form of volunteering and joining community groups) and mental health (Kiely et al., 2021). Civic engagement is another term used in the literature for social engagement and reflects a general level of engagement in organizations. Our results are further consistent with previous studies that did not identify a link between social engagement and changes in mental health over time (Berry & Welsh, 2010; Ehsan & De Silva, 2015). Other studies have not found an association between social engagement and changes in psychological health over time (Giordano & Lindström, 2011) or depression (O'Connor et al., 2011). However, one study by Landstedt et al. (2016) found that a low level of social engagement during adolescence predicted depression in early adulthood for men but this association did not extend into mid-life and late-life and was not evident for women. Although social engagement is well established in the literature as vital to health in ageing (Burn et al., 2016) and might be important across the life course, our findings did not show any longitudinal effects of social engagement on mental health.

The findings of the multilevel growth modeling in our study also indicated that social environment and mental health changes were influenced by several sociodemographic and physical health factors. Biological sex, age, education level, marital status, income and number of chronic conditions significantly predicted depression over time with a moderate effect size. However, none of these factors significantly predicted anxiety over time, likely due to the fact that the anxiety score at time 0 was low and it did not change in later years (i.e., decreases in anxiety scores in later years were not statistically significant). Boehlen et al. (2020) found in their study that generalized anxiety disorder severity at baseline was for both older men and women the strongest predictor of anxiety over the years. Our finding is also supported by a previous study of the epidemiology of anxiety, which indicated that despite the fact that anxiety is a chronic condition and individuals may suffer from this disorder for years, anxiety reaches a peak in middle age and decreases with older age (Bandelow & Michaelis, 2015). However, as depression increased significantly over the 20-year period with older adults with lower depression scores experiencing faster growth rates, older adults reported worse mental health over time.

Another finding is the moderation effect of the number of chronic conditions on the slope of depression and anxiety. The slopes of depression and anxiety were higher for older individuals with MCC compared to their counterparts with one or no chronic condition. This indicates that MCC could be detrimental to older adults' mental health and shows the substantial impact that disease burden could have on all aspects of health, specifically mental health. Previous studies provided evidence that individuals with MCC experienced decreased social engagement and social participation related to reduced social networks and functional limitations (Rook & Charles, 2017). This is an important aspect to underscore as about 70% of older adults (65+ years) have MCC (Boersma et al., 2020; Wilson-Genderson et al., 2017).

Limitations and Future Directions

Strengths and limitations

Our study is one of the few studies that investigated how changes in social environment are related to mental health changes within and between individuals, while incorporating multiple indicators of social environment, both subjective and objective indicators.

A point of strength of our study is the longitudinal design used, allowing us to disentangle the temporal associations of social environment and depression and anxiety in community-dwelling older adults using a large sample of older adults. Furthermore, the assessment of changes occurred in a span of approximately 10 years in between waves for a total of 20-year time period. This longer time period allowed us to track more extensive changes that take place following detrimental shifts in individuals' life. Shaw et al. (2007) mentioned that individuals are more likely to undergo health deterioration within longer time periods, resulting in more extensive changes in their social environment.

Another strength of the study is that the findings are based on latent factors that take into account several dimensions of social environment and mental health. Using a composite measure allows for a more general overview of the phenomenon while taking into account its various dimensions. It is important to remember that mental health and social environment are both complex and multidimensional constructs. The variability in individuals' social relationships and connections in their quality, function and structure, may differ in their associations with mental health.

Our study also has the following limitations: First, our sample consisted of mainly non-Hispanic white older adults (more than 90% of the participants), with a high level of education and an average income level greater than $40,000. This lack of diversity limits our ability to generalize these findings across more racially/ethnically and socioeconomically diverse populations. Given the fact that social environment may be perceived to be different across cultural groups, examining the implications of social environment components in older adults with more racially/ethnically diverse samples is essential. Since MIDUS participants were not representative of the general population, of replicating the present study by using multiple and more diverse samples will be necessary.

Second, the present study did not use sex-stratified models to examine the relationships between social environment and mental health. Although sex was a predictor for depression but not anxiety, women and men tend to report qualitatively different experiences of social connectedness (Kiely et al., 2021) by extension of their social environment. Future research should address sex differences when exploring the relationship between social environment and mental health.

Third, while the present study examined associations assuming the directionality from social environment to mental health outcomes, it may be possible that these associations could be bidirectional and reciprocal. A recent study by Kiely et al. (2021) reported a reciprocal association between mental health and informal social connectedness (contact with family, friends and neighbors) in older age group (50 years and older). Schwartz and Litwin (2019) findings also indicated a reciprocal relationship between mental health and social networks. Thus, future research needs also to address the opposite directions of such potentially reciprocal relationships.

Fourth, our results are based on a specific set of variables which may be sensitive to how the survey questions were constructed and how the scales were developed. For instance, MIDUS captures social engagement in relation to the frequency of attending meetings and social groups (union, sports…) in a typical month. It does not provide data in relation to the type of engagement nor the tasks, roles or positions hold within the different associations or organizations. Future research may expand upon our study using different data sets and different measurements.

Finally, all study variables were self-reported and thus may be a source of information bias.

Contribution to References

The study adds to the existing literature through providing evidence of the long-term impacts of social environment indicators on mental health, with social connectedness and social contribution being strong predictors, even after controlling for sociodemographic factors. The study also underlines the moderation effect of the number of chronic conditions on mental health outcomes, showing the significant role played by MCC in mental health of older adults. Finally, the study highlights the non-significant long-term impact of social engagement on mental health, although social engagement is well established in the literature as vital to health in ageing.

Future Directions

An important direction of future research that would build upon the contributions of the present study and aim to expand its findings is to explore approaches to enhancing social contribution and social connectedness (emotional social support, social networks, and social integration) in order to improve mental health while examining potential mediators for the longitudinal associations such as physical activity and sleep. For instance, lack of social and emotional support significantly predict sleep deprivation, which in turn might affect older adults' mental health (Williams et al., 2016).

Considering the findings of the within-person variability of older adults' depression and anxiety, interventions to enhance social environment components may be effective in helping older adults maintain positive mental health. Because of the COVID-19 pandemic, older adults have experienced sudden and drastic changes in their social environment due to implemented public health measures (social distancing, stay-at-home order…), which exacerbated their social isolation and loneliness. Digital interventions could be practical and convenient means to enhance older adults' connections with their families, communities and health care providers. These programs should be mindful of well-known disparities in technology use, broadband access, and technology literacy among different groups of older adults (Ang & Chen, 2019; Xie et al., 2021). Hybrid interventions (digital and in-person) might be the most efficient way to promote social support and social integration as in-person social activities remained crucial in ameliorating depression in older adults (Ang & Chen, 2019; Xie et al., 2020).

Interventions aimed at enhancing social environment for older adults must also identify and address multiple chronic health conditions since functional limitations reduce social integration and social contribution and poor mental health might potentially drive declining integration in the community and participation in social activities.

Implications for aging research

The findings of our study highlight the importance and contribution of social connectedness and social contribution in older adults' mental health to inform clinical practice and planning of preventative programs/services. They also contribute to the promotion and design of preventative programs to improve social connectedness and social contribution resources in order to reduce social isolation and loneliness in older adults and promote maintenance of high physical and mental health. We recommend that policy and services designed to promote social connectedness among older adults should consider hybrid approaches (use of digital and in-person social activities) to promote mental health in older adults. In terms of clinical practice, it would be essential to promote a care approach including assessment of older adults' levels of social support, social connections and social networks in primary care settings.

Conclusion

Our study accentuates that not all components of social environment are equally beneficial and their relationships with mental health may be different. Investigating the trajectories of different social environment components or indicators and their long-term effects on depression and anxiety points to the importance of developing interventions that could assist older adults as they face the challenges of aging.

Enhancing relationships and social connections in later life is promising for optimizing developmental aspects of older adults' mental health. Continuing to advance research on the diverse processes and contexts through which the various components of social environment influence individuals' mental health outcomes will help to better fulfill the promise of these relatively overlooked relationships in clinical practice as a potential resource for our aging population.

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