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Research Article

Activity Patterns and Health Outcomes in Later Life: The Role of Nature of Engagement

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Abstract

Background and Objectives: The health benefit of activity participation at older ages is documented in the current literature. Many studies, however, only explored the health benefits of engaging in a few activities and did not examine mechanisms connecting activity participation to health. We investigated the pathway between activity and health by testing the mediation role of the nature of engagement (physical, cognitive, and social) on physical, mental, and cognitive health of older adults.
Research Design and Methods: We analyzed data of 6,044 older adults from the 2010 and 2012 Health and Retirement Study linked with 2011 Consumption and Activity Mail Survey. We used latent class analysis to identify the patterns of participating in 33 activities as well as patterns of nature of engagement, and examined how these patterns were associated with cognition, depressive symptoms, and self-rated health in later life.
Results: Meaningful patterns of activity (high, medium, low, passive leisure, and working) and the nature of activity engagement (full, partial, and minimal) were identified. High and working groups, compared to the passive leisure group, showed better health and cognition outcomes. The nature of engagement mediated the relationship between activity patterns and health, especially for older adults who were either full or partially engaged.
Discussion and Implications: The nature of engagement may play a more important role than the activity itself in relation to health. Identifying the heterogeneity in activity engagement in later life is critical for tailoring interventions and designing programs that can improve the health of older adults.

Keywords: Activity engagement, Cognition, Depression, Self-rated health

Introduction

Activity is central to many models of healthy aging. For examples, the successful aging (Pruchno, Wilson-Genderson, Rose, & Cartwright, 2010; Rowe & Kahn, 1997) and productive engagement frameworks (Morrow-Howell, Hinterlong, & Sherraden, 2001) suggest that staying active by remaining physically, cognitively, and socially engaged has the potential to reduce disease burden and achieve optimal health status (Kim, Chun, Heo, Lee, & Han, 2016; Mejía, Ryan, Gonzalez, & Smith, 2017; Pruchno et al., 2010). Across many disciplines, activity engagement is regarded as modifiable behavior that can be influenced through prevention, program, or policy actions (Chang, Wray, & Lin, 2014; Hao, 2008). As such, researchers have examined how different types of activity (e.g., physical activity, productive activity, and social and leisure activity) correspond to health outcomes in later life.

Research has provided evidence that activity, regardless of the type, generally leads to positive health outcomes for older adults. These outcomes include improved perceived self-rated health (Hong & Morrow-Howell, 2010; Meyer, Castro-Schilo, & Aguilar-Gaxiola, 2014; Wagner & Short, 2014) and psychological well-being, such as life satisfaction and positive affect (Baker, Cahalin, Gerst, & Burr, 2005; Chang et al., 2014; Kim et al., 2016; Matz-Costa, Besen, James, & Pitt-Catsouphes, 2014) and reduced decline in depressive symptoms (Chao, 2016; McDonnall, 2011; Meyer, Castro-Schilo, Aguilar-Gaxiola, 2014), physical functioning such as recurrent falling (Peeters et al., 2010), functional limitations (Choi, Tang, Kim, & Turk, 2016), and physical functioning like grip strength and gait speed (Shah, Lin, Yu, & McMahon, 2017), cognition such as memory (Bielak, Anstey, Christensen, & Windsor, 2012) and dementia (Llamas-Velasco, Contador, Villarejo-Galende, Lora-Pablos, & Bermejo-Pareja, 2015; Wang, Karp, Winblad, & Fratiglioni, 2002), and even mortality risks (Han, Tavares, Evans, Saczynski, & Burr, 2017; Martinez-Gomez, Guallar-Castillon, Garcia-Esquinas, Bandinelli, & Rodriguez-Artalejo, 2017; Ueshima et al., 2010; Wagner & Short, 2014).

Conceptual Framework and Hypotheses

That activity leads to better health in later life can be theoretically framed by the social model of health promotion (Fried et al., 2004). Although the model originally focused on the health benefits of volunteering, this model, which is fundamentally meditational in nature, suggests that a wider range of activities can be health-producing *through* physical, cognitive, and social pathways (Hong & Morrow-Howell, 2010; Matz-Costa, Carr, McNamara, & James, 2016). A large body of health-related literature has used such a model to understand the direct impact of activities on health in later life. However, the majority of these studies focused on the role of single type of activity, such as physical activity (Llamas-Velasco et al., 2015; Martinez-Gomez et al., 2017; Ueshima et al., 2010) or productive activity (Choi et al., 2016; Hao, 2008; Matz-Costa et al., 2014; McDonnall, 2011) in relation to health outcomes. Only a few examined how engagement in multiple types of activities relates to health outcomes (Bielak et al., 2012; Chang et al., 2014; Chao, 2016; Wang et al., 2002). There are even fewer studies that have investigated activity patterns based on the rationale that older adults can and do participate in multiple activities simultaneously. These have shown that activities can complement each other (Hao, 2008) and cluster together in meaningful ways (Burr, Mutchler, & Caro, 2007). Additionally, empirical evidence from population-based studies (Burr et al., 2007; Matz-Costa et al., 2016; Morrow-Howell et al., 2014; Shah et al., 2017) has shown that there is heterogeneity of activity engagement among older adults and that self-reported health varies by different activity clusters. Despite the fact that this direct relationship between activity patterns and health has been demonstrated, the mechanism from these activity patterns to positive health outcomes remains unknown.

It is possible that the effect of the activity patterns can be partially explained by the nature of engagement (i.e., physical, cognitive, and social engagement), which is consistent with the social model of health promotion (Fried et al., 2004). Further, just as the activities could be aggregated into clusters, it is highly possible that the nature of engagement may also cluster together in a meaningful way. Except for a few cases, this theoretical argument is not extensively examined in the current literature. Several studies have supported this argument by investigating how participation in Experience Corps (EC), a national program that brings older volunteers into public school to improve academic achievement of children at risk, faired on health outcomes (Hong & Morrow-Howell, 2010). The results showed that older EC volunteers experience fewer depressive symptoms, better cognitive function and fewer declines in health. This evidence supports the social model of health promotion in that it suggests that it is not just what an activity is (e.g., volunteering); it may be the nature of the activity—social, cognitive, and/or physical engagement—that leads to health outcomes.

A recent study (Matz-Costa et al., 2016) contributes to the development of the social model of health promotion by integrating a wider range of activities into clusters and showing indirect effects on health through physical, cognitive, social, and emotional mediators. This work represents one of the first attempts to distinguish the nature of the activity from the activity itself. This study measured the nature of engagement via summing items of capturing the physical, cognitive, and social nature of activity engagement. However, such approach may not be able to differentiate individuals into unique patterns (e.g., physically, cognitively, and socially engaged vs physically engaged only), and therefore does not allow further exploration of the nature of engagement that could be independently examined.

The present study advances current evidence by assessing the nature of engagement via clustering the items related to the physical, cognitive, and social aspects of activity rather than summing them. In this study, we used latent class analysis (LCA) to identify unique behavioral patterns in activity as well as patterns in the nature of engagement. Further, the present study expands on previous work by considering a wider set of health outcomes, beyond physical and psychological to include cognitive. Guided by the social model of health promotion and recent evidence, we hypothesized that activity patterns directly influence health in later life, and indirect effects can be observed between these patterns and the nature of engagement in relation to health outcomes for older adults. The purpose of this study is to explore how the patterns of nature of engagement connect activity patterns and health in later life when the sociodemographics are considered. To our knowledge, this is the one of the few studies that examines how nature of engagement affects the relationship between activity and health of older adults.

Design and Methods

We used data from the 2010 (baseline) and 2012 Health and Retirement Study (HRS), a biennial nationally representative data set in the United States that collects information on health and economic well-being among 20,000 older adults aged 50 and above since 1992. The HRS used multi-stage probability design with considerations of geographic stratification and clustering with oversampling for African Americans, Hispanics, and residents of Florida (Sonnega et al., 2014).

To address the sample attrition issues over time, the HRS refreshed its sample by every sixth year since 1998 to ensure the representativeness of the U.S. population, and this presence of refreshment samples may influence the sample characteristics in the following waves. The Consumption and Activity Mail Survey (CAMS), conducted every other year since 2001, is a subset of the HRS that collects type and nature of activities among older adults. In 2001, the CAMS selected approximately 5,000 random households from the 2000 HRS, and one primary respondent from each household was followed-up by every 2 years. From 2005 onward, the sample extended to the available spouses of the primary respondents. Further, the CAMS is also influenced by the refreshment samples of the HRS (i.e., 2004 and 2010). Because the CAMS is a subset of HRS, the respondents from the CAMS can be linked to the HRS using personal and household identifiers. Therefore in this study we linked the 2010 and 2012 HRS with 2011 CAMS and the sample across three time points was 6,159. We studied the attrition across time and excluded deceased respondents. The final sample of this study was 6,044.

Measures

Following previous studies (Matz-Costa et al., 2016; Meyer et al., 2014), we used cognitive function, depressive symptoms, and self-rated health as measures for health. Cognition was measured as numbers of words recalled immediately and delayed (Mejía et al., 2017; Wagner & Short, 2014), and these two measures were summed (*range*: 0–20), with a higher score indicated higher levels of cognition. It should be noted that the full cognitive measures in the HRS (i.e., telephone interview for cognitive status, TICs) were not available for this study due to the fact that the TICs were only administered among individuals aged 65 and above (Ofstedal, Fisher, & Herzog, 2005) whereas our sample was aged 50 or above. However, this subset of cognitive measure has been empirically shown as the most sensitive measure of memory function in the HRS (Wagner & Short, 2014). Depressive symptoms were assessed with the modified version of the Center for Epidemiologic Studies-Depression scale used in the HRS (Morrow-Howell et al., 2014; Steffick, 2000). Respondents reported on how they felt in eight questions related to depressive symptoms (e.g., *depressed*, *lonely*, *sad*) during the past week (1 = *yes*; 0 = *no*). We reverse coded two positive items (*happy* and *enjoyed life*) and summed these eight measures (*range*: 0–8); a higher score indicated a higher levels of depressive symptoms. Self-rated health (1 = *excellent*; 5 = *poor*), operationalized as respondents' feeling toward their health status, was used as an overall measure of health because this single-item measure has been well-established among older adults in the United States. (Hong & Morrow-Howell, 2010; Meyer et al., 2014). We reverse coded the measure so that a higher score indicated better perceived health status.

Measures of activity and nature of activity engagement were selected from the CAMS. We used 33 items that captured a wide range of activities (reading, walking, volunteering, visiting with friends, etc.) that involved varying degrees of physical, cognitive, and social engagement. Following previous established methods (Morrow-Howell et al., 2014), we studied the distribution of each activity and divided the amount of activity into three levels (none/low, medium, high). For each activity measure, if the proportion who reported no engagement in that activity was small (5% or less), the sample was trichotomized evenly into one-thirds (low, medium, and high). That is, the low category included a small proportion who did not engage at all. When there was a large group reporting no activity, that group was retained and the remaining sample was evenly dichotomized and three groups (none, medium, and high) were created. Such an approach provided computational benefit to avoid scaling problems. We also used four measures about the physical, cognitive, and social demands of their activities as whole using a four-point Likert scale (1 = *rarely* to 4 = *almost all the time*) (Matz-Costa et al., 2016). Physical and cognitive engagement was captured by two questions that asking how often did respondents use their body and mind when they were doing activities. Social engagement was measured by two questions asking how often activities were done with other people and how often the activities benefitted other people.

Covariates in this study were drawn from the RAND HRS, a clean and organized data set constructed by the RAND Corporation that provides variables that could be compared across waves in the HRS. It should be noted that, for some composite measures such as health limitations (see below), some items may be taken out of the index as these items were not measured at certain waves in the HRS. Covariates included gender (1 = *female*, 0 = *male*), education (in years), age (in years), race (*white*, *black*, *Hispanic*, and *others*), marital status (1 = *married*, 0 = *not married*), urban–rural level (1 = *rural*, 9 = *metropolitan*), number of limitations out of five activities of daily living (ADL) and five instrumental activities of daily living (IADL), and economic variables including income (in dollars), assets (in dollars), homeownership (1 = *owing a home*; 0 = *other*), and owing a car (1 = *owing a car*; 0 = *not*) (Han & Hong, 2013). Continuous variables were normally distributed with the exception of depressive symptoms and economic variables, which were logarithmically transformed (original values were presented in the descriptive and bivariate analyses).

Statistical Analyses

We used Mplus 7.4 to perform LCA in this study (Muthén & Muthén, 2012). LCA is a model-based approach which allows identifying the behavioral patterns of individuals and then classifying respondents into several meaningful subgroups based on their response to a set of observed indicators when variables were ordinal or categorical in nature (Wang & Wang, 2012). We first conducted a confirmatory factor analysis (CFA) with weighted least squares estimation to handle the ordinal nature of 33 activity measures. We used CFA because we sought to confirm the activity domains identified in previous works, where Matz-Costa and colleagues (2016) used a subset of the 2001 to 2011 CAMS activities (28 items) and Morrow-Howell and associates (2014) used the same 33 activities from the 2009 CAMS. We also expected that differences between this study and previous ones might arise from the fact that new observations were added to the HRS sample in 2010.

A nine-factor solution for 33 activity participations (see Supplementary Table 1), including personal leisure, civic/religious activity, physical exercise, interior house chores, exterior house chores, managing medical bills, employment/computer use, interpersonal exchange, and community leisure, was confirmed in this analysis and the results showed the model fit the data well. LCA was further employed to create activity patterns using the nine activity factors and to create the patterns of the nature of engagement using four engagement measures. Objective fit indices, including Bayesian Information Criterion (BIC) and the Lo–Mendell–Rubin (LMR) test and its bootstrap form, were used to select the appropriate numbers of latent class (Nylund, Asparouhov, & Muthén, 2007). As suggested by Nylund and colleagues (2007), a latent class model with the lowest BIC value indicates the model has appropriate numbers of latent class, and a significant LMR test result suggests the LCA model is improved when one more class is added into the model. Model interpretability and practical discretions, however, are also critical to deciding numbers of latent class for LCA models (Collins & Lanza, 2010). Therefore, we used both model interpretability and objective indices to determine the best model for LCA analyses for both activity and the nature of engagement.

After we obtained the unique patterns of activity and the nature of engagement, we used a two-step regression analyses procedure developed by Zhao, Lynch, and Chen (2010) to examine the mediating role of the nature of engagement between activity patterns and health outcomes. The first step in Zhao's two-step procedure is to examine the associations between the predictor and the mediator, and the associations should be significant. The second step investigates whether the associations between the mediator and the outcome are significant when the predictor was controlled in the model. Using this logic, we first conducted multinomial logistic regression to examine the relationship between activity patterns and nature of engagement, and then employed linear regression to investigate how activity patterns influence health outcomes when the mediator (i.e., nature of engagement) was included in the model. These two types of analyses were combined to examine the mediation effect using the distribution-of-product method (Tofighi & MacKinnon, 2011) provided with 95% confidence interval (CI); the existence of mediation effect is confirmed if the CI does not across zero. This multistage approach allowed us to analyze a categorical mediator in the model (Mackinnon & Cox, 2012).

Although less than 5% of the data were missing, we corrected this issue by creating 20 imputed data sets using multiple imputations with chained equations (White, Royston, & Wood, 2011). As suggested by White and colleagues (2011), the numbers of imputed data sets should at least equal to the percentage of incomplete cases, which is 5% in our sample. The empirical evidence based on the Monte Carlo simulation has shown that 20 imputed data sets produce almost the same efficiency in estimations as that of being produced in 100 imputed data sets (Graham, Olchowski, & Gilreath, 2007). The results were combined using Rubin's rule (Rubin, 1987). In this study, the 2012 health outcomes were regressed on activity patterns and the patterns of engagement in 2011, with the baseline covariates and health measures controlled. Such time-order arrangements supported a causal argument, although the study remained observational. To address the time variant issue of the covariates in influencing the relationship between activity, nature of engagement, and health, a sensitivity test comparing health outcomes regressed on the activity and the nature of engagement when covariates (baseline vs 2012) were controlled showed that the results did not differ, and therefore a possible threat of time changes could be minimal (see Supplementary Table 2). All the analyses were adjusted for complex survey design, including sampling weight, clusters, and strata, in the HRS using Stata/SE 14.2 (StataCorp, 2015).

Results

The sample characteristics at the baseline in Table 1 showed that half of the respondents were female (54%), and the majority were white (79%) and married (61.7%). On average, respondents' age was 64.3 years (SD = 10.4 years), with 13.2 years in education (SD = 2.9 years). Paired-t tests showed that self-rated health (M_{2010} = 3.20, M_{2012} = 3.16, t = 3.58, p < .001), depressive symptoms (M_{2010} = 1.43, M_{2012} = 1.46, t = −1.29), and cognition (M_{2010} = 9.92, M_{2012} = 9.67, t = 5.99, p < .001) declined over the 2-year period, although the differences were small (see Supplementary Table 3).

Identification of Latent Class in Activity and Nature of Engagement

The results of LCA analyses for activity and the nature of engagement are presented in Figure 1 and Table 2. We

Table 1. Sample Characteristics at the Baseline

Variable	Weighted M (*SD*) or Unweighted *n* (Weighted %)
Covariates (continuous)	
Age	64.35 (10.37)
Education (years)	13.22 (2.93)
Urban/rural level	4.99 (2.42)
Numbers of ADL (range: 0–5)	0.26 (0.79)
Numbers of IADL (range: 0–5)	0.22 (0.71)
Household income	75,463.6 (93,397.8)
Household assets	471,173.3 (957,287.6)
Covariates (categorical)	
Gender	
Male	2,528 (46.0%)
Female	3,516 (54.0%)
Race	
White	4,222 (79.0%)
African American	1,009 (10.2%)
Hispanic	640 (7.6%)
Other	164 (3.2%)
Marital status	
Married	3,655 (61.7%)
Not married	1,792 (27.7%)
Never married	597 (10.5%)
Owing a car	4,729 (80.6%)
Homeownership	5,124 (87.9%)
Health outcomes	
Self-rated health (range: 1–5)	3.27 (1.09)
Depressive symptoms (range: 0–8)	1.39 (1.97)
Cognition (range: 0–20)	10.25 (3.25)

Note: M = mean, *SD* = standard deviation.

selected the five-class model for activity based on empirical and pragmatic reasons because this model had the lowest BIC values (BIC = 113,807.560) and allowed us to examine the maximum variation in the activity patterns (see Table 2). We labeled and interpreted these five activity patterns using visual presentation. Across nine activity factor domains, class 4 (33.3%) had high probabilities in engaging physical exercise, exterior household chores, and the highest involvement in employment/computer use. Because of these characteristics, we labeled this group as "Working." We labeled classes 1 and 3 as "Moderate activity" (29.0%) and "High activity" (18.1%) because these groups engaged in each activity domain at a medium and a high level, respectively. Classes 2 and 5 were most similar because these two groups were engaged in each activity domain at a lower level except for managing medical conditions (for class 5) and in the employment/computer use domain (for class 2). A further investigation showed that individuals in class 2 had a higher probability of using computer rather than being employed, and therefore we

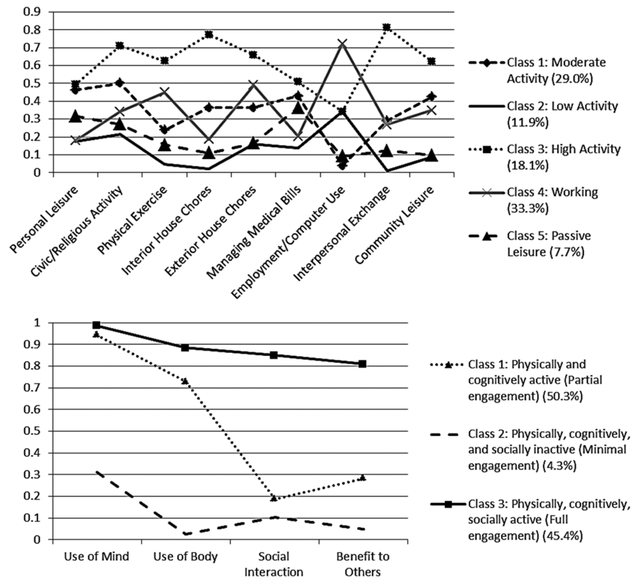

Figure 1. Latent class analysis results for activity and the nature of engagement. *Note:* The numbers on the vertical axis indicate the probability of endorsement in each activity/nature of engagement.

labeled class 2 as "Low activity (11.9%)." Class 5 (7.7%) had higher probabilities both in the domain of personal leisure and managing medical conditions, and therefore we labeled this group as "Passive leisure."

The LCA analysis of the nature of activity engagement using four indicators (i.e., *use of mind*, *use of body*, *social interaction*, and *benefit to others*) showed that the three-class model fit the data best because of the lowest BIC values (*BIC* = 24,010.599) and the significant LMR test (*LMR* test = 180.540; Bootstrap *LMR* test = 184.691) (see Table 2). As shown in the figure, across physical, cognitive, and social engagement, the proportion was similar for class 1 (50.3%) and class 3 (45.4%). Class 1 was labeled as "Physically and cognitively active (Partial engagement)" because this group had a higher probability only in use of their mind and body. Class 3 was labeled as "Physically, cognitively, and socially active (Full engagement)" because this group had the highest probability in engagement in each type. Class 2, although the proportion was small (4.3%), was practically justified because, by in large, most individuals would at least have some levels of engagement either physically, cognitively, or socially, but apparently some individuals are quite disengaged. This group had the lowest intensity in each dimension of engagement, and therefore we labeled this group as "Physically, cognitively, and socially inactive (Minimal engagement)."

Regression and Mediation Analyses

The ANCOVA results (see Supplementary Tables 4 and 5) suggest that both the "Passive leisure" group (from activity) and "Minimal engagement" group (from nature of engagement) are the most vulnerable groups in regards to health

Table 2. Latent Class Analysis Results for Activity Participations and Nature of Engagement

Class	χ^2 (*df*)	BIC	LMR Test	Bootstrap LMR Test
Activity pattern				
2 Class	22,490.595***(19,590)	114,713.612	2,974.944***	2992.927***
3 Class	21,167.616***(19,574)	114,047.566	826.230***	831.475***
4 Class	20,612.736***(19,555)	113,837.146	373.591***	375.850***
5 Class	20,381.813***(19,533)	113,807.560	193.844	195.016
6 Class	20,014.060***(19,514)	113,818.268	153.791	154.721
Nature of engagement				
2 Class	198.161*** (6)	24,151.800	1,359.141***	1,390.939***
3 Class	3.582 (1)	24,010.599	180.540***	184.691***
4 Class	N/A	24,051.064	2.957	3.025

Note: BIC: Bayesian Information Criterion; *df*: degrees of freedom; LMR Test: Lo–Mendell–Rubin Likelihood Ratio Test; N/A: model does not show the value due to insufficient degrees of freedom.
***$p \le .001$.

outcomes, and therefore we use these two groups as reference in the regression models. As shown in Table 3, the multinomial logistic regression results of activity patterns on the nature of engagement showed that compared to Passive Leisure group, older adults in the Moderate activity class were more likely to be either partial (b = 0.53, SE = 0.20) or full engaged (b = 1.04, SE = 0.27). Similarly, older adults in High activity (b = 2.06, SE = 0.43) and in Working groups (b = 1.11, SE = 0.34), compared to the Passive leisure group, were more likely to be partially engaged. Further, these two groups of older adults also showed a stronger tendency to be fully engaged (high activity: b = 3.16, SE = 0.46; Working: b = 2.14, SE = 0.35) because these coefficients were larger than that of in the partial engagement model. Our results also showed that older adults in the Low activity, compared to the Passive leisure group, were more likely to be fully engaged (b = 0.63, SE = 0.30), but such an effect was not observed in the partial engagement.

The linear regression results of activity patterns on health outcomes when the mediator (i.e., nature of engagement) was included in the model suggested that, compared to Minimal engagement, older adults who were either full engaged or partial engaged had better health outcomes, including higher self-rated health (Partial engagement: b = 0.15; SE = 0.06; Full engagement: b = 0.22; SE = 0.06) and cognition (Partial engagement: b = 0.56; SE = 0.25; Full engagement: b = 0.59; SE = 0.27) and lower depressive symptoms (Partial engagement: b = −0.06; SE = 0.04; Full engagement: b = −0.09; SE = 0.04). Results suggest that, compared to Minimal engagement, older adults with fuller engagement have the best health outcomes compared to those with partial engagement. Using self-rated health as an example, compared to older adults with minimal engagement, older adults with partial engagement were 0.15 points higher in self-rated health, but it is 0.22 point higher for older adults with full engagement. Further, activity patterns, such as High activity, Working, and Moderate activity group, had an independent and positive effect on self-rated health (High activity: b = 0.18; SE = 0.05; Working: b = 0.23; SE = 0.05) and cognition (High activity: b = 0.48; SE = 0.19; Working: b = 0.57; SE = 0.19; Moderate activity: b = 0.46; SE = 0.16), but this direct influence was not observed on depressive symptoms.

Table 4 shows that the nature of engagement, either partial or full engagement, mediated the relationship between activity patterns and health outcomes. Specifically, the Moderate activity, High activity, and Working groups, at either partial or full engagement, showed higher self-rated health and better cognition. For example, in Table 4, the CI values of the relationship connecting Moderate activity, partial engagement, and self-rated health does not include zero (CI = 0.01, 0.18), indicating that partial engagement mediated the relationship between Moderate activity and self-rated health. There is no difference between Low activity and Passive leisure in depressive symptoms and cognition, no matter what the nature of engagement. However, for low activity with full engagement, there are higher levels of self-rated health compared to the Passive leisure group. For depressive symptoms, the results suggested that the Moderate activity, High activity, and Working group had lower level of depressive symptoms (compared to the Passive leisure) only when they had full engagement in the activity.

Discussions and Implications

This study demonstrates that clustering is a feasible and informative approach to capturing the heterogeneity both for activities and the physical, cognitive, and social demands of an activity pattern (Burr et al., 2007; Morrow-Howell et al., 2014). We further employed this clustered approach on a refreshed national representative older sample to explore the behavioral patterns of the nature of engagement, advancing previous work (i.e., Matz-Costa et al., 2016) by presenting a clear picture about the role of nature of engagement in connecting activity patterns and health in later life. Our results showed that five unique activity patterns, including High activity, Moderate activity, Low activity, Passive leisure, and Working. For the

Table 3. Regression Results of Activity Patterns, Nature of Engagement, and Health Outcome

	Partial vs minimal engagement		Full vs minimal engagement		Self-rated health		Depressive symptoms		Cognition	
Variable	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Activity pattern (*ref* = passive leisure)										
Moderate activity	0.53*	0.20	1.04***	0.27	0.10	0.05	−0.02	0.04	0.46**	0.16
Low activity	0.16	0.24	0.63*	0.30	0.11	0.06	−0.02	0.04	0.34	0.21
High activity	2.06***	0.43	3.16***	0.46	0.18**	0.05	−0.04	0.04	0.48*	0.19
Working	1.11**	0.34	2.14***	0.35	0.23**	0.05	−0.06	0.04	0.57**	0.19
Nature of engagement (*ref* = minimal engagement)										
Partial engagement					0.15*	0.06	−0.06	0.04	0.56*	0.25
Full engagement					0.22**	0.06	−0.09*	0.04	0.59*	0.27
Control variables (baseline)										
Age	0.01	0.01	0.01	0.01	−0.003*	0.001	−0.002	0.001	−0.07***	0.01
Gender (*ref* = male)	0.35*	0.16	0.53**	0.17	0.03	0.02	0.03	0.02	0.63***	0.09
Education (years)	0.06	0.03	0.09*	0.03	0.02***	0.004	−0.01**	0.00	0.13***	0.02
Race (*ref* = White)										
African American	0.06	0.21	0.28	0.20	0.02	0.04	−0.03	0.03	−0.33*	0.13
Hispanic	−0.10	0.53	−0.03	0.56	−0.02	0.05	−0.04	0.04	0.01	0.16
Other	0.35	0.65	0.10	0.63	0.13	0.06	−0.01	0.05	0.22	0.28
Marriage (*ref* = married)										
Not married	−0.30	0.24	−0.49	0.26	−0.02	0.03	0.04	0.02	0.01	0.10
Never married	0.24	0.31	0.08	0.31	−0.04	0.04	0.03	0.03	0.01	0.17
Household income	0.00	0.05	0.07	0.05	0.00	0.01	−0.01	0.01	0.09*	0.04
Household assets	0.05	0.18	−0.05	0.18	0.08***	0.02	0.001	0.02	0.09	0.07
Home ownership	0.02	0.17	0.08	0.20	0.003	0.05	−0.05*	0.02	0.30*	0.13
Owing a car	−0.40	0.25	−0.07	0.27	−0.06	0.04	−0.01	0.03	0.20	0.15
Numbers of ADL	−0.06	0.10	−0.07	0.11	−0.04	0.02	0.04	0.01	0.01	0.07
Numbers of IADL	−0.31*	0.10	−0.36*	0.13	−0.01	0.03	0.03	0.01	−0.33**	0.10
Urban–rural level	−0.04	0.03	−0.04	0.03	−0.01	0.00	0.001	0.003	−0.01	0.02
Self-rated health (2010)	0.21	0.10	0.37**	0.11	0.60***	0.02	−0.08***	0.01	0.09	0.05
Depressive symptoms (2010)	−0.14	0.13	−0.38**	0.13	−0.12***	0.02	0.51***	0.02	−0.15*	0.07
Cognition (2010)	0.06	0.03	0.07*	0.03	0.001	0.004	0.003	0.003	0.39***	0.02

Note: Results were based on 20 multiple imputation data sets.
$^{*}p \le .05$; $^{**}p \le .01$; $^{***}p \le .001$.

nature of engagement, we found three clusters: Minimal, Partial, and Full engagement. We further found that activity patterns were associated with nature of engagement, and the nature of engagement was associated with all three health outcomes. Further, our hypotheses of the direct associations between activity patterns and health outcomes and the mediating role of the nature of engagement are supported.

Table 4. Mediation Effect of the Nature of Engagement

Mediator	Self-rated health 95% CI	Depressive symptoms 95% CI	Cognition 95% CI
Moderate vs passive leisure			
Partial	(0.01, 0.18)	−0.09, 0.01	(0.02, 0.71)
Full	(0.08, 0.42)	(−0.20, −0.01)	(0.06, 1.35)
Low vs passive leisure			
Partial	−0.05, 0.11	−0.05, 0.02	−0.19, 0.43
Full	(0.01, 0.31)	−0.15, 0.001	−0.01, 0.97
High vs passive leisure			
Partial	(0.06, 0.62)	−0.31, 0.04	(0.13, 2.40)
Full	(0.30, 1.15)	(−0.56, −0.04)	(0.19, 3.74)
Working vs passive leisure			
Partial	(0.03, 0.36)	−0.18, 0.02	(0.06, 1.40)
Full	(0.20, 0.79)	(−0.39, −0.02)	(0.13, 2.57)

Note: The values in the parenthesis indicate the existence of mediation effect because the *CI* does not across 0; *CI* = confidence interval.

Our study replicates and builds on previous works but some differences in findings regarding activity patterns are noteworthy. All these studies showed that older adults' activity patterns could be grouped based on their intensity of engaging in activities, including low, moderate, and high activity engagement groups. Further, the working group is consistently identified. However, our LCA analysis produced one class of older adults—Passive leisure—which is different from the previous works, as Morrow-Howell and associates (2014) found a "Physical active" class and Matz-Costa and colleagues (2016) identified a "Traditional leisure" group. These results suggest that activity patterns in later life have substantial similarity, but some heterogeneity remains. These differences in activity patterns highlight that the identification of activity patterns could be influenced by the measures included in the analysis, sample characteristics, and changes in activity engagement over time. For example, although our study and Morrow-Howell et al. (2014) used the same sets of activity measures, the studies used different waves of data as well as somewhat different samples (given the refreshing of the HRS sample). Matz-Costa et al. (2016) used a smaller set of activity items than the other two studies. These differences possibly explain why activity patterns differ between studies, and these findings spur the need for future research on how activity and the nature of engagement may change over time, and implications for these changes on later life health (see Chao, 2016).

Consistent with previous literature, the findings suggest that the nature of engagement plays an important mediating role between activity and health. That is, the extent of physical, cognitive, and social engagement associated with activity influences health outcomes more than the activity itself (Fried et al., 2004; Hong & Morrow-Howell, 2010). Clearly, the type of activity relates closely to the nature of engagement, but these mediation analyses demonstrate that the nature of engagement is a major pathway to health outcomes. The findings also reveal that health varies by nature of engagement, with minimal engagement showing the least favorable health outcomes in later life. In most cases, either partial or full engagement leads to better health and cognitive function for older people, but health benefits are more evident in the presence of full engagement. Older adults across most activity patterns may experience better health outcomes if the activities involve physical, cognitive, and social aspects. In particular, we found that the nature of engagement is critical to depressive symptoms; and the association between activity patterns and depressive symptoms is only via the nature of engagement. This mediating result corresponds with previous evidence (Matz-Costa et al., 2016).

It is instructive to note that in the case of the Working and High activity group (compared to Passive leisure), there remains a direct effect of activity patterns on self-rated health and cognition. This suggests that there is something beyond physical, cognitive, and social engagement that leads to better health. In terms of health benefits of working, previous studies suggest that work in later life may offer older adults opportunities for on-going income, stimulation and challenges, social integration, and increased sense of belonging and security (Choi et al., 2016; Hao, 2008; McDonnall, 2011). Similarly, in addition to physical, social, and cognitive engagement, the High activity group may experience a stronger sense of purpose or identity.

Our results have implications for program design, theory development, and research methods. Historically, there have many programs to engage older adults in various activities, like volunteering, life-long learning, and activities at senior centers or adult day health. However, our mediation results suggest that it is *not just these activities themselves* but the extent to which individuals are socially, physically, or cognitively engaged as they perform these activities. Our findings show that even for the Low activity group, better health outcomes can be attained if individuals are able to exercise their physical and cognitive capacities and make social connections. We argue that programs should be designed not just to achieve activity per se but to achieve quality engagement across physical, cognitive, and social domains. Although this study was completed on a community sample, we believe that these findings can be extended to older adults in long-term care settings where activities can be designed more purposively to achieve fuller engagement. Another program implication involves identifying older adults at risk. Our findings suggest that the Passive leisure group and older adults with minimal engagement are vulnerable to lower self-rated health, poorer cognition, and higher depressive symptoms. Therefore, health promotion programs should seek strategies to identify these individuals and maximize their capacity for fuller engagement.

In terms of theory development, this work supports that fundamental idea of the social model of health promotion, in that physical, cognitive, and social pathways link activity to health outcomes. We suggest that other pathways capturing the nature of engagement may be important to add to the model, including such psychological concepts of sense of purpose or meaning. Methodically, we argue that using a clustering approach advances our understandings of the relationship between activity and health. Some scholars suggest the importance of examining specific activities and health effects among older adults (Han et al., 2017). Although such an approach may be the most useful for a specific research question, we advocate that using an index, scale, or clustering approach allows us to take a "whole-person" view because older adults usually engage in different activities simultaneously.

There are several limitations in this study. First, both activity and nature of engagement were self-reported and could be influenced by the recall bias. Second, although the time-ordered arrangement of the data strengthens a causal argument, causality cannot be inferred. Further, the window of observation of this study only includes three time points over 2 years, and longer observational periods will be instructive. Third, although environmental measure, like neighborhood context, influence activity engagement as well as health (Meyer et al., 2014), these measures were not available across our full sample. Fourth, although we have included multiple measures to capture activities and engagement of individuals, not all measures were available, and most of these items were measured at a gross level (i.e., engaging at a specific activity) without the expression of the important contextual information (e.g., purpose for doing such an activity). A more comprehensive list for both activities and the nature of engagement could be further useful in capturing a nuanced meaning of activity engagement in later life (Matz-Costa et al., 2014). Lastly, although this study hypothesizes that health in later life is influenced by activity and by nature of engagement based on a theoretical framework, a possible reverse causation must not be ignored. For example, the deterioration in health may influence activity participations and the nature of engagement, which may not only influence the construction of the patterns for both activity and the nature of engagement, but affect subsequent health status. Past work has indicated that certain sociodemographic and health statuses are related to activity patterns (Morrow-Howell et al., 2014); and clearly future study needs to address the dynamics between health, activity, and the nature of engagement. The strength of this study is that it is one of the few studies that consider how nature of engagement may mediate the relationship between activity and health using a population-based probability sample and sophisticated analytical approach. Further, this study advances our knowledge on how activity and nature of engagement influence different health outcomes in later life.

In sum, this study builds on the work of Matz-Costa et al. (2016). These two studies use different approaches, yet the findings converge and support the fundamental idea that nature of engagement matters more than the activity itself and that fuller physical, cognitive, and social engagement produces better outcome. Further, taken together, the studies together extend the range of health outcomes to which this finding can be applied. Our study highlights the vulnerability of low activity groups and those older adults whose activities are minimally engaging. Implications for program development include designing activity interventions with more attention to quality engagement across physical, cognitive, and social domains as well as improved outreach to the vulnerable low activity, minimally engaged group of older adults.

Supplementary Material

Supplementary data are available at *The Gerontologist* online.

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Conflict of Interest

None reported.

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