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Consolidated Measures of Activity among Older Adults: Results of a Three Data Set Comparison

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ABSTRACT

This study explores the potential to consolidate a broad range of activity items to create more manageable measures that could be used in statistical modeling of multi-activity engagement. We utilized three datasets in the United States: Panel Study of Income Dynamics, Health and Retirement Study, and Midlife in the United States. After identifying activity items, exploratory and confirmatory factor analysis were used to empirically explore composite activity measures. Findings suggest that discrete activity items can be consolidated into activity domains; however, activity domains differ across datasets depending on availability of activity items. Implications for research and practice are further discussed.

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Activity in later life; older adults; HRS; MIDUS; PSID

Introduction

Within the last decade, there has been an increased focus internationally on active ageing as societal norms and expectations of older adults change and shift. In the United States, recent research into activity in later life has centered mainly on either productive roles older adults engage in such as volunteering, later-life employment, and caregiving or on traditional physical and leisure activities. The study of late life roles has been important in developing new knowledge about how roles influence global health and wellness outcomes as well as other life choices. For example, Matz-Costa, Besen, James and Pitt-Casouphes (2014) found that the intensity of engagement in volunteer, caregiving, and paid work roles is a moderator of positive psychological well-being, with those engaged at higher levels gaining greater benefits. Researchers have shown that volunteering is often a pathway to engagement in new or other activities (Morrow-Howell, Lee, McCrary, & McBride, 2014), can facilitate transition within roles such as

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from full to part-time employment (Carr & Kail, 2013), and can secure social bonds with friends that reduce the likelihood of relocating from one's local area of residence (Shen & Perry, 2014). Thus volunteering might be viewed as a mediating variable in models of activity transition. The interest on what influences productive engagement reflects a growing emphasis on positive views of ageing within the field of gerontology (Johnson & Mutchler, 2014).

The study of physical and leisure activity has a long history in the field of gerontology and has demonstrated the positive outcomes of engagement in both. Most recently, investigations have yielded significant insight into the importance of understanding the relevance of environmental context variables as well as psychosocial factors and socioeconomic traits in facilitating activity engagement. An example of this is found in the area of neighborhood walking by older adults. A study by Carlson et al. (2012) found that rather than ecological characteristics alone such as quality of sidewalks and neighborhood aesthetics, it was the interaction of walkability and social support that significantly predicted moderate or vigorous physical activity outdoors among older adults and the interaction of walkability and self-efficacy that predicted walking for leisure. Further inquiry into self-efficacy and neighborhood walking among older adults by Gallagher, Clark, and Greteback (2014) demonstrated gender differences in types of self-efficacy that mattered. Men noted neighborhood barriers, such as crime and quality of sidewalks; and women expressed more concern about their physical ability to negotiate neighborhood walks. Examining context variables in greater detail, King and Clark (2015) in the first national analysis of neighborhood walkability created a model of multi-domain predictors of neighborhood walking, demonstrating the level of complexity characterizing the mature study of a single domain within the field of physical activity and leisure studies (Gallagher et al., 2014).

As reflected in the research describe above, there has been much intellectual refinement and overall growth of scholarly work on activity engagement among older adults within the field of gerontology. Despite these advances, the measurement of activity and innovations in statistical modeling have developed little in the past decades. For the most part, researchers tend to evaluate how a single or small number of activities or roles (such as caregiving, physical activity or volunteering, as noted above) impact health, wellness or other outcomes. To date, very few studies have examined clusters, profiles, or patterns of activities.

While we understand the complexity of studying multiple activity engagement, we believe it is important to do so. The growing literature on active ageing contains a strong critique relating to several issues: older adults perceptions of social pressures to be active or engaged (Martinez, Crooks, Kim, & Tanner, 2011; Pavlova & Silbereisen, 2016), evidence that there are barriers to participation in productive ageing activities such as volunteering related to socio-economic status (Gonzales, Matz-Costa, & Morrow-Howell, 2015); evidence that disengagement from volunteering roles is more likely among older adults who experience health and function declines (Komp, Van Tiburg, & van Groenou, 2012), and the bias against leisure activities, even though reading, home maintenance, watching grandchildren and gardening also contribute to positive health outcomes in later life (Chang, Wray, & Lin, 2014). We believe it is important to investigate the entire portfolio of activities – e.g. productive, leisure, household, personal care – that older adult engage in, and antecedents of these portfolios, in order to better understand the relationship of differing portfolios to global health and wellness outcomes.

There is a developing theoretical argument for studying activity using a more multi-dimensional approach. For example, In the WHO's model of Active Ageing, there are multiple determinants of active ageing that fall across a range of individual, social and environment domains (World Health Organization (WHO), 2007). Based on the WHO's Active Ageing model, we developed a simple framework hypothesizing that activity is an intermediate outcome or a facilitator for global health and wellness among older adults. We retain the idea that activity participation is determined by a variety of factors, but we borrow the idea that there are pathways between activity and global health and wellness outcomes from Fried et al.'s (2004) modeling of social health promotion among older adult volunteers. In this fuller framework, activity is a core intermediate outcome linking a variety of antecedents and wellness outcomes, and, thus, conceptualizing and operationalizing a multi-dimensional nature of activity is crucial to further advance knowledge on active ageing.

As noted below, we have already made contributions to this area of study through a content analysis that identified activity variables across five U.S. data sets (Putnam et al., 2014) and by analyzing data from the Health and Retirement Study (HRS) to successfully create a model approach to using activity portfolios and composite activity measures (Morrow-Howell et al., 2014). We were interested to know how the composite measures we created for the HRS analysis compared to those of other data sets we previously inventoried. In particular, we wanted to know if composite measures suitable for use in activity portfolios could be created using other data sets and how these would be different or similar from those we created in HRS.

Ways activity among older adults is measured and modeled

Research into activity among older adults typically examines a single or small number of activities at one time, usually within a certain conceptual domain. For example, Smith, Gardner, Fisher and Hamer (2015) explored patterns of physical activity among older adults over time to assess changes in levels of intensity physical activity using a measure of inactive, light, moderate, and vigorous activity engagement. In the same area of study, Silverwood, Nitsch, Pierce, Kuh, and Mishra (2011) used a set of physical activities that included gardening, sport, housework, and do-it-yourself to develop three distinct classes of physical activity for middle-aged adults. Similar types of analyses have looked at the social and leisure activities. Seeman, Miller-Martinez, Merkin, Lachman, Tun and Karlamangla (2011) explored patterns of social engagement and their relationship to cognitive functioning by summing three aspects of social engagement.

Consolidation of activities across multiple domains has rarely been explored, but there are a few exceptions. For example, using the Belgian Ageing Studies data, Dury et al. (2016) developed four consolidated measures of activity (helping others, leisure, cultural and civic) to explore how engagement in volunteer work is stimulated or impeded by the types of other activities older adults are engaged in. They found that individuals who volunteered were more likely to also be engaged in other altruistic activities while those who did not volunteer were more engaged in individualistic activities. In another example, Jopp and Hertzon (2010) developed a model of leisure activity using an item reduction approach to identify eleven factors in the Victoria Longitudinal Study (VLS) that can be used to assess engagement in a broad range of physical, social, and household activities among young, middle-aged and older Canadians. Both of the previous studies suggest that moving towards using composite measures and a more comprehensive set of activities provides researchers with the ability to engage in a more holistic, multi-domain assessment of activity in later life.

Contribution of this study

In this study, we analyze three public datasets containing nationally representative populations of older adults in the United States to explore the consolidation of multiple activity items into fewer activity domains and the development of composite measures. This consolidation would enable the inclusion of more activities in any analytic approach. We present our empirical findings here and make comparisons across data sets. We present recommendations for the use of the consolidate measures we identified and discuss how the derived activity domains correspond to the developing framework of active ageing.

At noted above, this work builds on previous work where we studied five data sets, including the three included here, to identify activity domains (Putnam et al., 2014). In this foundational work, we identified activity items, as described in detail below, and conducted content analysis to group the activity items into activity domains. The groupings were conceptually derived; and we identified 13 distinct activity domains across all the data sets, including employment, health risk behaviors, basic living, civic, leisure, household chore, helping others, religious, interpersonal exchange, help-seeking, physical exercise, financial management, and computer. The various data sets differed in the number and type of activities measures included and therefore, in the extent to which the domains were represented. We selected one data set, the HRS, to conduct additional analysis to explore the use of an activity profile in statistical modeling, examining antecedents and outcomes of 5 profiles of activity among older adults (Morrow-Howell et al., 2014). Based on the success of this work, we decided to repeat our approach to consolidating measures with two additional datasets to test the extent to which the items hang together empirically and tie to the conceptual domains and to compare this to the results of our consolidation of HRS activity measures. In sum, the contribution of this analysis is to assess whether this approach to measurement consolidation works across different datasets and to what extent it produces similar or different results.

Method

Data

Three datasets with nationally representative samples of the U.S. population ages 55 and older are utilized in this analysis: (1) Health and Retirement Study Consumption and Activities Mail Survey (HRS CAMS) 2009, (2) Panel Study of Income Dynamics (PSID) 2005, and (3) Midlife in the United States (MIDUS) 1995–1996. The 2009 HRS CAMS data was selected based on its use in our prior analysis (Putnam et al., 2014). We chose the other two data sets based on the results of our prior content analysis that identified them as having substantially different sets of activity measures (Putnam et al., 2014). We selected the data wave year based on our intention to use the derived consolidated measures as baseline measures to predict health and wellness outcomes in future years. We recognize that this technique could be tested on more recent data wave years, but our larger study purposes required that we begin our exploration of consolidating measures on the first year we intended to include in a multi-wave analysis.

The HRS CAMS includes questionnaires assessing individual activities and household patterns of consumption for a sub-sample of the main HRS sample. In this analysis, we only utilized individual activities that were measured by hours per week or month. For the HRS CAMS 2009, the subsample was 7,231. The full version of the CAMS survey included three sections (activities, consumption, and demographics) and was mailed to 4,954 participants and the partial version, which only included the activities section, was mailed to 2,277 participants. A total of 5,530 questionnaires were returned with a response rate of 74%. Six questionnaires had missing observations across all activities; therefore, the final sample size utilized in our study was 5,324 individuals age 55 or older.

The PSID is a longitudinal study of a nationally representative sample of over 22,000 individuals from approximately 9,000 households. Although questions in the PSID focus primarily on household income and employment, survey content covers several domains of activities. Our PSID content analysis identified all activity measures within the 2005, 2007 and 2009 waves of the PSID. We selected the PSID 2005 for the analysis reported here because it included questions on volunteering and religious activities that later waves did not and this fit better with our aim of exploring multi-domain activity portfolios. The PSID is a family-level dataset and contains separate items for the household "Head" and "Spouse". To include both "Head" and "Spouse" aged 55 or older in the analysis, we transformed family-level data into individual-level data. The final sample size utilized in our study was 2,722 individuals aged 55 or older.

The MIDUS survey was first administered in 1995–1996 by phone and mail to a nationally representative sample of non-institutionalized, English-speaking adults aged 25 to 74. A longitudinal follow-up was initiated 10 years later (2004–2006). In addition to a main sample, MIDUS includes over-samples in selected metropolitan areas, a sample of siblings, and a national sample of twin pairs. Our study only utilized the main sample of the first survey wave (1995–1996). The MIDUS was first administered via telephone interviews and then followed up with a mailed questionnaire. Activity measures used in the analysis were drawn from both the phone interview and mailed questionnaire. As with other datasets, we confined our sample to those aged 55 or above, and the final sample size utilized in the study was 1,029.

Measurement

In our prior content analysis that included these three data sets (Putnam et al., 2014), we identified survey items as activities based on a simple test of substituting the phrase "do you do X?" to determine if the survey item qualified as an activity. Based on these findings, 8 activity items were selected for analysis of the PSID 2005, including work (annualized hours), housework (hours per week), eating meals together (number of days per week), heavy physical activity (number of times per year), light physical activity (number of days per year), physical activity to strengthen muscles (number of times per year), volunteering (annualized hours), and attending religious service (number of times per year). The item on eating meals together was originally measured at a family-level, and we assumed "head" and "spouse" in the same family had the same response values. In terms of volunteering activities, annualized hours of volunteering for each of 7 types of organizations, such as religious institutions or organizations serving youth, were summed to create total annualized hours. For heavy physical activity, light activity, physical activity for muscles, and attending religious services, annualized frequencies were created based on the original measures. Descriptive statistics of activity items from the PSID 2005 are presented in Table 1.

For the MIDUS I, we excluded activity items such as sleeping and napping for the same reasons as we excluded items in the HRS CAMS. Activity measures related to household chores were also removed from the analyses because they were only asked to those who have spouses. A total of 18 items were used in the analysis. A list of activities and descriptive statistics for the MIDUS I are presented in Table 2.

For the HRS CAMS 2009, in the prior analysis, thirty-six activity items were identified. Two activity items, "reading newspapers or magazines" and "reading books" were summed into one item. We excluded three items from the analysis: sleep/nap, personal grooming, and eating meals, given the lack of variance in doing these activities. Table 3 presents a detailed description of each HRS CAMS 2009 activity measure which was not previously reported in our prior publication.

Activity items were measured differently within each dataset and across the datasets as well. For example, some were measures with Likert scales, and others asked respondents to report numerical frequencies. To create consistency across items, we recoded activity items into ordinal measures (e.g., low/med/high or no/low/high) based on the distribution of each individual activity item. For the none/low/high category, those respondents who reported no activity for the item were coded as none, and the remaining sample was split evenly into low and high based on response distribution. For the low/med/high measures, where there was no response option of "none" or the proportion of "none" was very low (e.g., less than 5%), we split the sample evenly into thirds. These newly created ordinal activity measures were used in the final analyses. We also recoded activity items into dichotomous measures (e.g., yes/no) and conducted the same analyses. Findings suggested

Table 1. Types and amount of activities: PSID 2005.

Activity	Participation N (%)	Level of Activity [a] M (SD)	Level of Activity [b] M (SD)
Employment [c]	1,465 (49%)	876.35 (1079.64)	1,783.21 (868.57)
Heavy physical activity [f]	1,240 (42%)	101.43 (420.70)	242.95 (624.27)
Light physical activity [f]	2,014 (69%)	163.46 (659.54)	301.40 (593.42)
Activity for muscle [f]	665 (22%)	41.23 (182.00)	215.90 (225.07)
Housework [d]	2,566 (87%)	12.69 (12.38)	14.52 (12.19)
Volunteer [c]	738 (25%)	48.66 (183.75)	195.95 (327.44)
Attend religious service [f]	2,070 (73%)	41.57 (110.58)	56.65 (125.74)
Eat meals together [e]	2,094 (70%)	3.89 (3.06)	5.52 (2.08)

a. Mean and standard deviation for the full sample; b. Mean and standard deviation for those who participated in activity; c. Hours per year; d. Hours per week; e. Days per week; f. Frequency per year

Table 2. Types, and amount of activities: HRS CAMS 2009.

Activity	Participation N (%)	Level of Activity [b] M (SD)	Level of Activity [c] M (SD)
Watch TV	5,132 (97%)	21.47(17.3)	22.07(17.16)
Read Papers/Mag/Books	4,780 (91%)	9.10(10.03)	10.00(10.08)
Listen Music	4,076 (78%)	6.45(11.44)	8.32(12.38)
Walk	4,501 (86%)	6.54(11.47)	7.60 (12.03)
Sports/Exercise	2,096 (40%)	2.20(5.47)	5.54 (7.54)
Visit in person	4,510 (85%)	7.07(11.00)	8.27(11.47)
Phone/Letter/Email	4,874 (92%)	5.33(7.48)	5.79(7.62)
Work for pay	1,625 (31%)	10.07(17.78)	32.64(16.96)
Use computer	2,757 (52%)	7.20(12.31)	13.82(14.12)
Pray/Meditate	4,134 (79%)	4.08(8.41)	5.18(9.17)
House Cleaning	4,211 (80%)	4.53(6.11)	5.65(6.34)
Wash/Iron/Mend	3,648 (69%)	2.48(4.00)	3.59(4.38)
Yard Work	2,757 (52%)	2.31(4.55)	4.44(5.50)
Shop/Run errands	4,597 (87%)	3.70(4.16)	4.25(4.19)
Meals prep/Clean up	4,454 (84%)	6.24(6.61)	7.39(6.57)
Pet care	2,135 (40%)	2.69(9.55)	6.66(14.12)
Show affection	4,210 (81%)	2.89(7.35)	3.58(8.02)
Help others [a]	3,062 (58%)	6.51(21.4)	11.18(27.09)
Volunteering [a]	1,622 (31%)	3.06(11.14)	9.95(18.30)
Religious attendance [a]	2,864 (55%)	3.95(7.89)	7.25(9.50)
Attend meetings [a]	1,628 (31%)	1.62(4.5)	5.22(6.81)
Money management [a]	4,235 (80%)	3.56(6.24)	4.43(6.68)
Manageing medical condition [a]	3,252 (62%)	8.52(46.2)	13.63(57.84)
Play cards/Games/Puzzles [a]	2,509 (48%)	5.6(14.43)	11.76(19.11)
Concert/Movies/Lectures [a]	1.325 (25%)	1.2(3.25)	4.77(5.00)
Sing/Play instruments [a]	1,069 (20%)	1.12(5.64)	5.54(11.53)
Arts/Crafts [a]	1,084 (21%)	2.34(10.76)	11.39(21.43)
Home improvement [a]	2,148 (41%)	3.01(10.34)	7.39(15.16)
Vehicle maintenance [a]	2,534 (48%)	1.44(3.72)	3.00(4.92)
Leisure dining/Eat out [a]	4,083 (78%)	5.53(9.22)	7.13(9.91)
Seeing doctors/nurses/etc. [a]	1,197 (22%)	1.69 (8.49)	7.54 (16.65)
Treating others' medical condition	1,001 (20%)	2.08(9.93)	10.63(20.32)
Manageing medical bills [a]	900 (17%)	0.68(4.23)	4.00(9.62)

a. Hours per month; all other activities were measured by hours per week
b. Average hours of activity for the full sample
c. Average hours of activity for those who participated in activities

that the ordinal measures worked better both conceptually and empirically, compared to dichotomous measures. Thus, we report findings based on the ordinal measures in this study. More information on the dichotomous measures can be obtained by contacting the authors.

Analytic procedure

To test the extent to which conceptual domains empirically group together and to identify underlying factors that cut across domains, we employed exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). A traditional EFA requires all items to be continuous measures. However, activity items in the PSID, HRS, and MIDUS contained categorical measures (e.g., ordinal or binary measures), and thus factor analysis was estimated

Table 3. Types and amount of activities: MIDUS I.

Activity	Participation N (%)	Level of Activity [a] M (SD)	Level of Activity [b] M (SD)
Paid work [c]	511 (50%)	19.33 (22.90)	38.47 (17.50)
Vigorous physical activity [d]	703 (76%)	4.56 (5.09)	6.01 (5.04)
Moderate physical activity [d]	888 (96%)	7.97 (4.96)	8.32 (4.77)
Visit medical doctors/hospital/etc. [e]	767 (84%)	3.58 (6.64)	4.25 (7.03)
Visit mental health professionals [e]	207 (23%)	1.30 (5.50)	5.66 (10.35)
Attend self-help groups [e]	51 (6%)	1.50 (12.74)	27.00 (47.74)
Attend religious services [d]	558 (62%)	3.08 (3.76)	4.97(3.66)
Attend meetings of religious groups [d]	255 (29%)	0.97 (2.26)	3.40 (3.10)
Attend meetings of unions or professional groups [d]	132 (15%)	0.29 (0.89)	1.92 (1.47)
Attend meetings of sports or social groups [d]	263 (30%)	0.99 (2.37)	3.36 (3.32)
Attend meetings of other groups (not related to jobs) [d]	258 (29%)	1.06 (3.36)	3.67 (5.43)
Volunteering [c]	357 (39%)	5.56 (11.96)	14.15 (15.57)
Providing emotional supports [c]	821 (90%)	53.83 (135.19)	60.13 (141.55)
Providing unpaid assistance [c]	679 (74%)	24.20 (64.59)	32.78 (73.30)
Contact with neighbors [f]	-	5.29 (1.01)	-
Conversation with neighbors [f]	-	3.92 (1.34)	-
Contact with family members [g]	-	6.10 (1.39)	-
Contact with friends [g]	-	5.80 (1.41)	-

a. Level of activity for the whole sample
b. Level of activity for those who participated in activity
c. Hours per month
d. Times per month
e. Times per year
f. 1: never or hardly ever, 2: Less than once a month, 3: 1–3 times a month, 4: about once a week, 5: several times a week, 6: almost everyday
g. 1: never or hardly ever, 2: less than once a month, 3: about once a month, 4: 2 or 3 times a month, 5: about once a week, 6: several times a week, 7: about once a day, 8: several times a day
Activities such as light activity, private religious practice, computer use, read books/magazines/newspapers, puzzles or word games, playing cards, attend educational lectures, writings of journal entries/stories/letters, sleeping, napping are not available in wave 1 (only in wave 2)

using diagonally weighted least squares (Flora & Curran, 2004; Woods, 2002). Selecting the optimal number of factors is a crucial issue in conducting EFA. We decided the optimal number of factors based both on data driven criteria such as the Kaiser's eigenvalue-greater-than-one rule (Kaiser, 1960), the Cattell's Scree test (Cattell, 1966), and the Velicer's Minimum Average Partial test (Velicer, 1976) as well as theoretical considerations. In terms of the rotation method in EFA, we used the oblique (quartimin) rotation where correlations among factors are allowed.

Factor structures drawn from EFA were further confirmed by confirmatory factor analysis (CFA) following the procedure we used in our previously reported study (Morrow-Howell et al., 2014). Specifically, given the large sample size in the HRS CAMS 2009, we randomly split the sample into two sub-samples. EFA and CFA were applied to each sub-sample respectively. For the PSID and MIDUS, we ran the EFA and CFA on the entire sample populations respectively. Given the categorical indicators in CFA, we estimated CFA models using diagonally robust weighted least squares. To assess the model-fit in CFA, we used several conventional model-fit statistics such as chi-square tests, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA).

Results

PSID

In the 2005 PSID data set, EFA with ordinal activity items indicated a three or four factor solution. Results from the three and four factor solution are presented in Table 4. In the three-factor solution, work for pay, heavy physical activity, light physical activity, and physical activity for muscles loaded on the first factor, housework loaded on the second, and volunteering and attending religious services loaded on the third factor. The factor loading for eating meals together was quite low across all factors. In the four-factor solution, the first factor in the prior three-factor solution divided into two factors. Work for pay was significantly loaded on one factor, and heavy physical activity, light physical activity, and physical activity for muscle loaded on the other factor.

Following the EFA, we conducted CFA with the solutions derived from EFA. Although model fit statistics of CFA for a three-factor solution with ordinal items were found to be acceptable, CFA for a four-factor solution did not fit to the data well. Factors derived from EFA/CFA were difficult to interpret and did not match with conceptual domains from the content analysis maybe due to the limited number of activity items in PSID (We do not provide detailed information on CFA here, but it is available from authors upon request).

MIDUS

We conducted a series of EFA with ordinal activity items from the MIDUS I. Based on the model fit statistics and substantive judgment, a 7-factor solution with

Table 4. EFA with the PSID: A three and four factor solution with ordinal items.

	3 Factor Solution: Factor Loading			4 Factor Solution: Factor Loading			
Activity	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3	Factor 4
Work	**0.31**	−0.38	0.06	**0.72**	−0.05	0.22	0.03
Meal together	0.18	0.14	0.09	0.06	**0.29**	0.11	0.04
Housework	0.09	**0.63**	0.15	−0.28	**0.47**	0.06	0.04
Volunteering	0.17	−0.07	**0.93**	0.08	0.13	0.16	**1.34**
Attending religious service	0.03	0.16	**0.42**	−0.03	**0.29**	−0.001	**0.26**
Heavy physical activity	**0.88**	−0.08	0.05	0.20	0.13	**0.82**	0.03
Physical activity for muscle	**0.57**	−0.09	0.09	0.08	−0.01	**0.60**	0.08
Light activity	**0.62**	0.13	0.06	0.03	0.25	**0.61**	0.01

Estimation with diagonally weighted least squares (WSLMV); Oblique (quartimin) rotation

Table 5. EFA with the HRS: A nine factor solution with ordinal items.

	1	2	3	4	5	6	7	8	9
Watch TV	**0.48**	−0.16	0.00	0.00	0.02	0.00	−0.05	0.05	−0.01
Read Papers/Mags/Books	**0.42**	0.17	0.20	0.04	0.19	0.22	0.07	0.01	−0.02
Listen Music	0.05	0.09	**0.45**	0.07	0.14	0.11	0.13	0.11	−0.03
Walk	0.03	0.02	**0.43**	0.25	0.15	0.08	0.01	0.11	0.10
Sports/Exercise	0.03	0.13	**0.47**	0.22	0.05	0.26	0.01	−0.13	0.08
Visit in person	0.16	0.08	0.17	0.11	0.13	0.42	−0.02	**0.33**	0.07
Phone/Letter/Email	0.21	0.12	0.23	−0.07	0.37	0.03	0.14	**0.36**	−0.10
Work for pay	−0.55	−0.08	0.18	0.12	−0.03	0.05	**0.53**	0.06	0.08
Use computer	0.03	0.01	0.10	0.11	0.09	0.20	**0.86**	0.03	0.03
Pray/Meditate	0.09	**0.63**	0.25	−0.11	0.14	−0.21	−0.13	0.37	−0.04
House cleaning	0.02	0.05	0.14	0.13	**0.81**	−0.03	−0.03	0.05	−0.01
Wash/Iron/Mend	−0.06	0.09	0.13	−0.13	**0.84**	0.08	−0.01	0.07	−0.06
Yard work/Garden	0.09	0.04	0.15	**0.74**	0.03	0.04	0.01	−0.06	0.12
Shop/Run errands	0.13	0.04	0.09	0.35	**0.48**	0.25	0.12	0.18	−0.05
Meals prep/Clean-up	0.15	0.08	0.03	0.03	**0.79**	0.07	0.06	0.08	0.03
Pet care	−0.06	−0.11	0.05	**0.28**	0.17	−0.06	0.22	0.11	−0.01
Show affection	0.00	0.15	0.32	0.09	0.13	0.12	0.09	**0.35**	−0.04
Help others	−0.11	0.19	0.04	0.33	0.21	0.35	0.01	**0.45**	0.05
Volunteer work	−0.05	**0.67**	0.00	0.14	0.12	0.33	0.12	0.02	0.00
Religious attendance	0.02	**0.82**	0.04	0.02	0.05	0.01	−0.13	0.09	−0.06
Attend meetings	0.03	**0.70**	−0.01	0.06	0.08	0.32	0.05	−0.06	−0.02
Money management	0.07	0.11	0.12	0.23	**0.36**	0.17	0.20	0.17	−0.28
Manageing medical condition	0.18	0.07	0.01	0.01	0.04	0.03	−0.08	0.28	**−0.31**
Play cards/games/puzzles	**0.38**	0.09	0.11	−0.01	0.13	0.37	0.13	−0.02	−0.03
Concert/movies/lectures	−0.07	0.15	0.17	0.09	0.07	**0.66**	0.10	0.00	−0.04
Sing/play instruments	−0.09	**0.50**	0.20	0.06	0.08	0.13	0.04	0.13	−0.05
Arts and crafts	0.13	0.13	0.10	0.01	**0.27**	0.22	0.02	0.04	0.08
Home improvements	0.00	0.04	0.09	**0.68**	0.02	0.15	0.09	0.13	0.00
Vehicle maintenance/cleaning	−0.09	0.10	0.13	**0.70**	−0.02	0.13	0.02	0.04	−0.07
Leisure dining/eating out	0.13	0.17	0.08	0.17	0.02	**0.60**	0.06	0.10	−0.08
Seeing a doctor/nurse/etc	0.00	−0.02	−0.04	−0.06	−0.05	−0.01	−0.07	0.02	**−0.60**
Treating others' medical condition	−0.09	0.13	−0.04	0.22	0.27	0.03	0.17	**0.34**	−0.06
Manageing medical bills	0.00	0.07	−0.03	0.02	0.09	0.03	0.06	−0.02	**−0.69**

Estimation with diagonally weighted least squares (WSLMV); Oblique (quartimin) rotation

ordinal items was selected. The results of a 7-factor solution from EFA with ordinal items are presented in Table 5.

Next, we conducted CFA based on the solutions derived from EFA. Model fit statistics, factor loadings, and their standard errors are presented in Table 8. In terms of the model fit statistics, chi-square test statistics are statistically significant; however, this might be due to a large sample size of this study. Both CFI and TLI are above .90, and RMSEA are below .05, indicating that the model fits the data well. Further, all activity items are significantly loaded on each factor as shown in Table 6.

Based on activity items loaded on each factor, we label each factor as follows: (1) employment (paid work), (2) physical activity (vigorous physical activity, moderate physical activity), (3) manageing medical conditions/help seeking (visit medical doctors, visit mental health professionals, attend self-help groups), (4) religious activity (attend religious services, attend meetings of religious groups), (5) civic activity (volunteering, attend meetings of union

Table 6. CFA with the HRS: A nine factor model with ordinal items.

Factor: Activity category	Item	Estimates	Standard Error
F1 Personal Leisure	Watch TV	1.00	0.00
	Read Papers/Mags/Books	5.28***	1.59
	Play cards/games/puzzles	4.33***	1.33
F2 Civic/Religious activity	Pray/meditate	1.00	0.00
	Volunteering	2.40***	0.19
	Religious attendance	1.61***	0.11
	Attend meeting	2.09***	0.16
	Sing/play instruments	1.77***	0.16
F3 Physical exercise	Listen music	1.00	0.00
	Walk	1.15***	0.08
	Sport/Exercise	1.03***	0.09
F4 Interior household chores	House cleaning	1.00	0.00
	Wash/Iron/Mend	0.84***	0.04
	Shop/Run errands	1.44***	0.07
	Meal prep/clean-up	1.16***	0.05
	Money management	1.12***	0.06
	Art and Craft	0.80***	0.07
F5 Exterior household chores	Yard work/garden	1.00	0.00
	Pet care	0.55***	0.06
	Home improvement	1.49***	0.09
	Vehicle maintenance	1.14***	0.05
F6 Manageing medical conditions	Manageing medical condition	1.00	0.00
	Seeing a doctor/nurse/etc	0.98***	0.15
	Manageing medical bills	1.25***	0.20
F7 Employment/Computer use	Work for pay	1.00	0.00
	Use computer	3.64***	0.88
F8 Interpersonal exchange/Helping others	Visit in person	1.00	0.00
	Phone/letter/email	0.94***	0.05
	Show affection	0.89***	0.06
	Help others	1.31***	0.06
	Treating others' medical condition	0.67***	0.06
F9 Community leisure	Concert/Movies/Lectures	1.00	0.00
	Leisure dining/eat out	0.99***	0.06

$\chi2(df = 199) = 14{,}259.84$***; CFI = .90; TLI = .92; RMSEA = .04; Negative variance in "Use Computer" item is set to zero; Error terms are allowed to be correlated; * $p < .05$ ** $p < .01$ *** $p < .001$

or professional groups, attend meetings of sports or social groups, attend meeting of other groups not related to jobs), (6) helping others (giving emotional support, giving unpaid assistance, contact with family), and (7) interpersonal exchange (contact with neighbors, conversation with neighbors, contact with friends).

HRS

As reported in our prior publication (Morrow-Howell et al., 2014), we also conducted a series of EFA with ordinal activity items from the 2009 HRS CAMS. Based on the model fit statistics and substantive judgment, a 9-factor solution with ordinal items was selected. The results of a 9-factor solution from EFA with ordinal items, not previously reported, are presented in Table 7.

Table 7. EFA with the MIDUS I: A seven factor solution with ordinal items.

	1	2	3	4	5	6	7
Paid work	**0.83**	0.13	0.02	0.04	0.05	0.15	0.05
Vigorous physical	0.19	**0.69**	0.11	0.02	0.05	−0.06	−0.04
Moderate physical	−0.02	**0.68**	0.05	0.11	0.05	−0.03	0.02
Visit medical doctors	−0.04	−0.11	0.01	**−0.45**	0.05	0.03	−0.01
Visit mental health professionals	0.08	−0.03	−0.04	**−0.76**	0.00	−0.02	−0.02
Attend self-help groups	−0.07	0.05	0.28	**−0.48**	0.06	−0.01	−0.13
Attend religious services	−0.04	0.05	0.06	−0.10	0.13	−0.10	**−0.86**
Volunteering	−0.07	0.11	**0.67**	−0.07	0.18	−0.13	−0.26
Attend meetings of religious groups	0.01	−0.03	0.23	−0.03	0.11	−0.10	**−0.83**
Attend meetings of unions or other professional groups	0.47	0.11	**0.55**	−0.05	0.11	−0.08	−0.08
Attend meetings of sports or social groups	0.02	0.12	**0.59**	0.13	0.13	−0.18	−0.08
Attend meetings of other groups (not related to jobs)	0.05	−0.02	**0.76**	−0.21	0.06	−0.07	0.00
Giving emotional support	0.03	0.11	0.18	−0.05	**0.61**	0.07	−0.02
Giving unpaid assistance	−0.03	0.13	0.08	−0.05	**0.82**	−0.05	−0.08
Contact with neighbors	−0.06	0.09	0.09	0.00	0.06	**−0.79**	−0.06
Conversation with neighbors	−0.13	0.05	0.12	0.05	−0.01	**−0.85**	−0.06
Contact with family	0.07	−0.11	0.06	−0.03	**0.41**	−0.14	−0.12
Contact with friends	0.09	−0.05	0.29	−0.05	0.10	**−0.38**	−0.14

Estimation with diagonally weighted least squares (WSLMV); Oblique (quartimin) rotation

Table 8. CFA with the MIDUS I: A seven factor model with ordinal items.

Factor	Item	Estimates	Standard Error
F1	Paid work	1.00	0.00
F2	Vigorous physical activity	1.00	0.00
	Moderate physical activity	0.57***	0.13
F3	Visit medical doctors	1.00	0.00
	Visit mental health professionals	1.16***	0.31
	Attend self-help groups	1.61***	0.42
F4	Attend religious services	1.00	0.00
	Attend meetings of religious groups	1.25***	0.13
F5	Volunteering	1.00	0.00
	Attend meetings of unions or professional groups	0.70***	0.08
	Attend meetings of sports or social groups	0.74***	0.06
	Attend meetings of other groups (not related to jobs)	0.78***	0.06
F6	Giving emotional support	1.00	0.00
	Giving unpaid assistance	1.25***	0.15
	Contact with families	0.63***	0.08
F7	Contact with neighbors	1.00	0.00
	Conversation with neighbors	1.06***	0.10
	Contact with friends	1.27***	0.20

$\chi 2$ (df = 77) = 234.74***; CFI = .92; TLI = .92; RMSEA = .04; Factor 1 has a single indicator (residual variance is set to zero); several indicators are allowed to be correlated.

In that same publication, we indicate that our next step was to conduct a CFA based on the solutions derived from EFA. Model fit statistics, factor loadings, and their standard errors are presented in Table 8, reprinted with permission from the previous publication. In terms of the model fit statistics, chi-square test statistics were noted to be statistically significant; however, this was thought to be due to the large HRS sample size. Both CFI and TLI were above .90, and RMSEA were below .05, indicating that the model fit the data well. Further, all activity items significantly loaded on each factor.

As noted in the prior publication (Morrow-Howell et al., 2014) we label each factor as follows: (1) personal leisure (watching TV, reading newspapers/magazines/books, playing cards/games/puzzles), (2) Civic/Religious activity (pray/meditate, volunteering, attending religious services, attend meetings, singing/playing instruments), (3) Physical exercise (listen to music, walk, sports/exercise), (4) Interior household chores (house cleaning, wash/iron/mend, shop/run errands, meal preparation/clean-up, money management, art and craft), (5) Exterior household chores (yard work/gardening, pet care, home improvement, vehicle maintenance), (6) Manageing medical conditions (manageing medical condition, seeing a doctor/nurse/etc., manageing medical bills), (7) Employment/Computer use (work for pay, use computer), (8) Interpersonal exchange and helping others (visit in person, phone/letter/email, show affection, help others, treating others' medical condition), and (9) Community leisure (concert/movies/lectures, leisure dining/eat out).

Discussion

Based on our analysis, we found that PSID 2005 activity measures were high quality in their construction; however, there were not many activity items (8–9 items depending on the wave) and few activity domains are represented compared to the two other data sets. The approach to consolidating the activity items into factors (EFA/CFA) did not work well, probably because there were too few activity items and single variables represented entire domains. Because the items did not empirically load on conceptual factors, we recommend using the activity items separately. However, the domain of physical activity does have three items (heavy activity, light activity, and strength building activity), which could makes PSID useful for physical-activity related research questions if an investigator was interested in that area alone. Our review of PSID, waves from 2007 through 2012 did not find additional activity measures, thus we believe our findings would not likely change if extended to more recent PSID data.

As for the HRS, factor analysis partially supported the domains identified in our prior content analysis (Putnam et al., 2014). For example, the domains of employment and computer use loaded onto one factor (employment/computer use). The domains of civic activities and religious activities loaded onto a single factor (civic/religious activity) and this factor also included one item that was classified under the leisure domain, singing and playing instruments. The rest of the items in the leisure domain divided into two factors, which represents leisure activities that are likely to be done in the home (personal leisure) and those that are done in a community setting (community leisure). Similarly, the household chores domain split into two factors, with one containing activities that are exterior household chores (exterior household chores) and another representing interior household chores (Interior household chores). The interior factor also included two activities from other domains: money management and arts and crafts. The two items of physical exercise stayed together and also included listening to music (Factor 3). We interpret this to mean that they are listening to music while exercising, considering conceptual interpretability of this domain, although there could be other possible explanations such as those who perform physical exercises also like to listen to music. Managing medical conditions combined items from financial management and help-seeking, but they are related in general management of medical conditions. A single factor of interpersonal exchange/helping others combined two domains, interpersonal exchange and helping others.

Through the factor analysis process, the number of activity variables in HRS 2009 was consolidated from 33 individual measures to 9 composite measures. Each of these 9 composite measures has conceptual validity, and collectively they do not diverge substantially from the conceptual domains identified in our prior content analysis (Putnam et al., 2014). At the same time, the results of the factor analysis are more reflective of how these activities combine in people's lives and offer the opportunity to better assess and understand patterns of engagement. The measures of activity used in the HRS 2009 can be found in later waves of HRS, thus we believe it may be possible to repeat this analysis on later waves in order to examine variations in composite measures based on year of data collection.

Regarding MIDUS I, as seen in Table 8, the factor analysis partially supports the domains identified in the content analysis. Activity domains identified in the content analysis such as employment, physical activity, help seeking, helping others, religious activity, and civic were empirically confirmed by EFA/CFA. There were several slight differences between domains from the content analysis and those from the EFA/CFA. Giving emotional support and giving unpaid assistance were loaded on the "helping others" factor, and this factor also included one activity from other domain: contact with families.

These factor analysis findings make conceptual sense for MIDUS I as they did for the HRS 2009. Through the factor analysis process, the number of activity variables in MIDUS I was consolidated from 18 individual measures to 7 composites measures. Like in the HRS 2009 analysis, each of these 7 composite measures has conceptual validity, and collectively they do not diverge substantially from the conceptual domains we identified in our content analysis (Putnam et al., 2014). Measures of activity in MIDUS I are also found in MIDUS II, making it possible to repeat this empirical consolidation approach for that data wave. However, MIDUS II includes additional activity measures such as leisure-related items and there is a sample attrition between MIDUS I and II, which may have some impact on the composite activity measures identified in it.

Fit for active ageing frameworks

In examining the consolidated measures from all three data sets grouped against the WHO Active Ageing determinants, we find that our consolidated measures did reach across the four other categories of health and social service, behavioral, economics and social. The PSID 2005 activity variables covered the fewest WHO determinants with only three in each. The HRS 2009 activity factors covered the most WHO determinants (health and social services, behavioral, economic and social), however interior and exterior chores did not seem to fit any determinant categories. For MIDUS I, activity factors fell into four of the WHO determinant categories. In sum, we found fairly good overlap between the WHO Active Ageing determinants and the composite activity measures we examined. Each of the three data sets offer some opportunity to empirically explore activity engagement of older adults under the conceptual umbrella provided by the WHO Active Ageing model. The HRS 2009 data set offers the greatest number of factors for this exploration. These factors are similar to those found in the MIDUS I data which suggests that it could be possible to evaluate active ageing frameworks using multiple data sets as a means of assessing the validity and reliability of the theoretical model.

Implications and recommendations for future research

The PSID data set may not be the strongest data set for researchers who want to understand activity profiles mainly due to the limited activity items included in the data set. However, given the strength of the PSID data set in terms of its regular waves, consistency of items over time, and high wave-to-wave response rates, the data set is strong for analyzing any one of the activities as a single item. Also, this data set stands out in terms of its assessment of the three physical activity items. It may be useful for those who want to understand physical activity, in particular, or a single activity in relationship to other life issues and factors like work, income or assets, etc., especially in a longitudinal context. The PSID activity measures should be understood within the context of the survey overall.

The MIDUS data set has a great potential to study multiple activities among older adults since it includes a wider range of activity items. The MIDUS also includes comprehensive sets of psychological, health, and well-being measures which enables researchers to explore determinants and outcomes of activities among older adults. Another advantages of using the MIDUS data set include it oversamples specific segments of population such as twin, sibling, and metropolitan sub-samples (Brim, Ryff, & Kessler, 2004). Although the MIDUS wave 1 and 2 dataset are quite outdated, data collection for wave 3 began in 2013, and the new data are expected to be released in a near future. However, the MIDUS might not be the best option for longitudinal research since it only has three waves and time lags between the waves are almost 10 years. Further, unlike the HRS discussed below, levels and types of measurement in the MIDUS differ substantially across activity measures.

Given the strength of the HRS data set in terms of its regular waves, consistency of items over time, and high wave-to-wave response rates, the data set is strong for analyzing activities as composite measures and multiple activity domains. The HRS data set includes the largest set of activity measures, and they are measured consistently across waves mostly in actual time spent. One point to note is that some activity domains have a small number of measures within them. For example, civic activity has only two measures. The HRS has good potential for the longitudinal analysis of activity items and has a rich set of demographic and socioeconomic factors to use as antecedents. We conclude that the HRS data set would be a strong choice for researchers who want to understand activity profiles and their links to antecedents and various well-being outcomes.

Building on our foundational, measurement work, future research needs to further investigate complex mechanisms of how a variety of antecedents, multiple domains of activities, and health and wellness outcomes are related. As discussed earlier, we selected the HRS to conduct additional analysis to explore the use of an activity profile in statistical modeling, examining antecedents and outcomes of 5 profiles of activity among older adults (Morrow-Howell et al., 2014). We found evidence that activity profiles derived from multiple domains of activities are related to antecedents as well as self-rated health and depression in various ways. Further research should be conducted with various modeling, analytic methods, and datasets to advance knowledge in the area of active ageing, and our measurement study can contribute to these efforts.

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