Title: Measuring Global Cognition in a Pooled Sample using Modified Non-Linear Factor Analysis

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Abstract

Currently, studies of cognition and cognitive decline in the United States are limited by the use of samples that only provide data for respondents during one stage of the adult life course. By using an Integrative Data Analysis (IDA) framework, it is possible to pool multiple national representative samples together in order to create a unified dataset that includes respondents over the entire adult life course. This study applies an IDA framework to two independent public health datasets to create a commensurate measure of cognition using Modified Non-Linear Factor Analysis (MNLFA). The overall goal is to demonstrate the process of using MNLFA for the study of cognition in a pooled dataset.

Introduction

Cognitive decline and Alzheimer's Disease are two public health issues that are of major concern in the United States. By 2050, it is estimated that 13.8 million Americans will be living with Alzheimer's Disease, a substantial increase over the 4.7 million who were living with the disease in 2010 (Herbert et al. 2013). For this reason, further study of the correlates of Alzheimer's disease in the pre-clinical phases of the disease is necessary in order to understand the early-life social circumstances that can both increase and decrease the likelihood of Alzheimer's onset later in the life course. However, data that allow for this analysis over a large swath of the life course is not available, as many samples that include extensive respondent information on cognition and cognitive health are primarily composed of the elderly. And in those samples that do include those in the early-to-mid-life, respondents have not generally been followed into the latest stages of life, when cognitive decline is most present.

In order to account for this data limitation, this study will use Integrative Data Analysis (IDA), or, "the statistical analysis of a single dataset the consists of two or more separate samples that have been pooled into one." (Curran and Hussong 2009). Because of this broad definition, IDA is better understood as a framework than a specific method of statistical analysis, as a wide range of statistical tests can be conducted within a pooled-sample dataset. In this study, we pool together two large, nationally representative samples, the National Longitudinal Study of Adolescent to Adult Health (Add Health, Waves IV and V) and the Midlife Development in the U.S. study (MIDUS, Waves 2 and 3), each of

which encompasses slightly different ages in order to create a dataset that is more generalizable to the entire adult population than either one independently. In our analysis, we use the pooled data in order to create a measure of global cognition that can be used as a dependent variable in subsequent analyses to investigate the social and economic determinants of cognitive functioning. This measure is created using Modified Non-Linear Factor Analysis (MNLFA), a form of factor scoring that accounts for heterogeneity both within and between the independent samples being pooled together. The ultimate goal of this study is to showcase how the use of IDA can be utilized to improve the study of cognitive functioning in the U.S. by addressing the data limitations inherent to an one national survey dataset.

Integrative Data Analysis

Integrative Data Analysis (IDA) is “the statistical analysis of a single data set that consists of two or more separate samples that have been pooled into one.” (Curran and Hussong 2009). Because of this broad definition, IDA is better defined as a framework than a specific method of statistical analysis, as a wide range of statistical methods can be conducted within a pooled-sample data set. Though primarily utilized to date in the study of psychology, IDA has many advantages that are applicable to the study of population health, including the study of cognitive function and the social determinants of cognitive decline. In fact, researchers have noted the potential to use IDA as a means to further explore this important population-health topic (Hofer and Piccinin 2009). These advantages include enhancing the demographic heterogeneity of a sample by pooling together independent samples that include respondents from one or multiple underrepresented populations, increasing the statistical power of a sample by increasing the overall sample size or the sample size of a sub-population within the pooled data set, and allowing for the replication of previous analyses conducted using a pooled sample that, assumedly, overcomes some of the limitations inherent to the independent sample used in the original analyses being replicated (Curran and Hussong 2009).

While the analysis of cognitive functioning in the United States would certainly benefit from these advantages of IDA, perhaps the primary benefit of using IDA to study population-level trends in cognitive health is the ability for analysis within an IDA framework to extend the generalizability of

research findings to a larger swath of the life course. This can be done by creating a unified sample of respondents across a greater range of ages than is possible using any one population health dataset (Curran and Hussong 2009). The current body of literature to cognitive health has overwhelmingly been conducted using samples of elderly populations, perhaps not surprising given that individuals in this period of the life course experience the most rapid cognitive decline and greatest increases in visible cognitive impairment (Hartshorne and Germine 2015). However, research has shown that for some forms of cognitive functioning, decline can occur as early as the 20's or 30's (Hartshorne and Germine 2015), and that early-adulthood decline in cognitive functioning is highly predictive of more severe cognitive impairment in later life (Petersen 2004). Because of this, it is essential to study the association between life-course SES and cognitive functioning in a younger-adult sample of the U.S. population.

While conducting research within an IDA framework is likely of great benefit to the population-health sciences, the correct application of this framework is more complex than just pooling together independent survey data sets before conduct tests of statistical inference. Using IDA, it is imperative to account for heterogeneities that exist between pooled samples in order to ensure that analyses are unbiased due to inherent differences in the individual data sets being pooled together. Two primary causes of between sample heterogeneity are differences in sampling procedures and the differences due to the historical time of sample collection (Hussong et al. 2013). Heterogeneity due to sampling differences can result when two independent samples were collected using different sampling frames, sub-populations within each sampling frame were presented with different sampling probabilities, or the mode through which the data was collected differed between samples (Curran and Hussong 2009). Not accounting for these differences can lead to the misidentification of theoretically interesting results that are in actuality the result of unaccounted for differences between the pooled samples (Hussong et al. 2013).

Heterogeneity due to the historical time in which the data was collected can result from a multitude of factors, many of which are outside of the control of those collecting the data. These included exogenous shocks such as economic depressions or the passing of legislation that can influence the lives of the individuals included in the sample. For longitudinal data that is pooled together, these historical

effects can lead to sample-based heterogeneities both between samples and between waves of data collection *within* a sample. Accounting for within-sample heterogeneity in longitudinal pooled data is particularly important for IDA research on cognition, as retest effects can have been noted as potential sources of measurement error when pooling longitudinal data on cognitive functioning (Hofer and Piccinin 2009). Additional sources of heterogeneity can occur from differences in how latent constructs are measures between studies (Curran and Hussong 2009; Hussong et al. 2013) and differences in the geographic location from which the sample was drawn (Curran and Hussong 2009), though these sources of heterogeneity are less applicable to the current study.

Measuring Cognition in a Pooled Sample using Moderated Non-Linear Factor Analysis

In order to account for the differences inherent between the data sets being pooled together for the current analysis, we will use Modified Non-Linear Factor Analysis (MNLFA). MNLFA is an extension of traditional linear confirmatory factor analysis (CFA). As in the case of CFA, MNLFA leads to a continuous, normally distributed factor score that measures a latent construct understood to underly the values of a set of observed items within a dataset (Curran and Hussong 2009). However, MNLFA allows for the invariance of the model parameters between sub-groups within the sample, and, in the case of a pooled sample, facilitates the creation of a factor score that can account for heterogeneities *between* samples as well. This is in contrast to a traditional CFA model, where the estimated parameters are assumed to be invariant across the sample. This is seen in the general equation for a linear CFA model

$$\mu_{ij} = \nu_i + \lambda_i \eta_j$$

where μ_{ij} is the model implied value of item i for individual j , ν_i is the estimated intercept of item i , λ_i is the estimated factor loading of item i , and η_j is the latent factor score for individual j . Across the entire sample, the latent factor score η is assumed to have a normal distribution, with a set mean (α) of zero and variance (ψ) of one.

Within a MNLFA model, the equations of the traditional CFA model are expanded to allow for heterogeneity within the pooled sample, both as a function of within- and between-sample heterogeneity.

Factor score η is now assumed to be normally distributed with mean α_j and variance ψ_j , in which subscript j again denotes an individual member of pooled dataset. Each individual's latent mean and variance is determined by their values to a set of observed variables that denote heterogeneities within the pooled dataset, such as membership in an individual sample or race and gender. The general equation is also expanded, as shown below:

$$\mu_{ij} = \nu_{ij} + \lambda_{ij}\eta_j$$

Again, the addition of subscript j to the item intercept and item factor loading indicates the statistical moderation of these parameters between individuals as a function of a set of covariates determined by the model. In other words, these model parameters are allowed to vary to account for inherent differences between samples. Heterogeneity between samples in a pooled dataset can lead to considerable invariance in the parameters of a CFA model, thus making MNLFA a necessary method through which to create commensurate measures of any latent factor when using data from multiple sources. Though not necessary in this current study, as all of the observed items being utilized to create the commensurate measure of cognitive functioning are continuous, MNFLA can also be modified to allow for any combination of link functions, including logit for dichotomous items or a negative binomial for count items (Curran et al. 2014).

In the following section of this extended abstract, we will provide an example of how MNLFA can be used to create a continuous latent measure of global cognitive functioning within a pooled sample of two large, publicly available datasets.

Creation of a Global Cognitive Functioning Score in a Pooled Sample Using MNLFA

Data:

For the following example, data come from Waves IV and V of the National Longitudinal Study of Adolescent to Adult Health (Add Health) and Waves 2 and 3 of the Midlife Development in the U.S. study (MIDUS). Add Health is a nationally representative sample of Americans who were in middle school or high school during the 1994-1995 school year, and have since been administered four additional

interviews (Waves II-V). Data for Wave I were collected when respondents were between the ages of 12 and 19 through in-school and in-home interviews. At both Wave IV (2008) and V (2016), several tests of cognitive function were carried out to assess cognitive health on the, now, young adult and adult sample (Wave IV, ages 24-32; Wave V, ages 32-42). MIDUS is another national health-focused data collection effort that collected information from individuals between the ages of 25 and 75, with the first wave of data collection being carried out in 1995/96. Since this initial wave, two additional waves of data have been collected. At each of these latter two waves, MIDUS 2 (2006) and MIDUS 3 (2014), the same tests of cognition utilized in Add Health were conducted within the MIDUS sample.

As stated previously, one of the benefits of MNLFA is the ability to allow for pooled data from samples of different ages, thus broadening the analytical scope of analysis to include a larger swath of the life course. By using Add Health and MIDUS, this analysis will include respondents across the entire adult life span, ranging from the ages of 25-92. Additionally, MNLFA will be necessary in order to account for differences in sampling procedures that introduce heterogeneity into the pooled sample, namely, that measures of cognitive health were collected through different mediums between the studies, and even between waves of the same study. Add Health Wave IV was conducted entirely through in-person, face-to-face interviews, while Add Health Wave V was conducted through a multiple-modes, with some respondents receiving in-person interviews, while others were surveyed using telephone interviewing. For both MIDUS 2 and MIDUS 3, data collection was done over the telephone. By including both study membership and wave of data collection, it is possible to create a commensurate measure of global cognition that accounts for heterogeneities that may result from these different sampling procedures.

For the analytic sample, respondents were included if they had been administered cognitive tests at both ways of data collection. Respondents were also only included if they had full information available for all independent variables utilized in the MNLFA. The final analytical sample included 3,288 respondents, each of which provided two waves of cognitive data, leading to 6,576 total observations.

Table 1 lists the number of observations within each dataset and wave. This table additionally lists these observations in five-year age groups to show the total range of ages in this life course analysis.

[TABLE 1 ABOUT HERE]

Variables:

Cognitive items: Across each dataset and wave, three tests of cognitive functioning were given to respondents; immediate word recall, delayed word recall, and digits backwards recall. In the word recall tasks, respondents were first read a list of 15 words and then asked to relay back as many as they could remember in 90 seconds. The number of words recalled formed the *immediate word recall* score. After a span of about five minutes, during which the respondent was asked additional survey items, they were again asked to recall as many of the same 15 words as they could. The number of words correctly recalled after this delay formed the *delayed word recall* score. In the *digits backward recall* task, respondents were read a series of numbers and asked to recall them back to the interviewer in reverse order. The task was repeated up to seven times, each time with a longer series of numbers. That task was ended after seven series were administered or after two series with incorrect recall responses. Each of these cognitive tests were conducted in a similar manner in both Add Health and MIDUS, though with MIDUS being exclusively done through telephone interviewing and Add Health being done either through in-person and telephone interviewing, depending on the respondent.

Control variables: In order to account for both factors that influence overall cognitive functioning within individual humans, as well as differences in the survey sampling procedures across waves and study membership that would bias uncontrolled for analysis of global cognition within the pooled dataset, additional independent variables were utilized. For the demographic variables, these include age at data collection (along with an age-squared term to account for non-linearity in the decline of cognition over the life course), race, categorized as non-Hispanic White, non-Hispanic Black, or Hispanic, whether the respondent had received a college degree, and gender. In addition, dummy variables were created to indicate the sample the respondent was a part of (Add Health or MIDUS) and the wave of data collection in which their cognitive data was utilized for the MNLFA (Wave 1=Add Health IV or MIDUS 2, Wave 2= Add Health V or MIDUS 3). A full table of descriptive statistics for the full sample, as well as by dataset, can be found in **Table 2**.

[TABLE 2 ABOUT HERE]

Step One – Graphical and Descriptive Analysis of Individual Items:

The first two steps of the MNLFA process are both aimed at determining the validity of the chosen items as observed measures of the focal latent construct. For the first step, this means visually depicting the data to show that all items behave in the same manner. **Figure 1** shows the mean of each cognitive item at each age within each dataset (after the measures have been standardized to fit on the same scale). Results show that no items appear to trend in an aberrant way across age, and that the ages in which there is overlap between the two datasets do not have concerning different scores for the cognitive items.

Figure 1

Step Two – Verification of Construct Validity through Exploratory Factor Analysis

Step two requires that analysis of the observed measures through Exploratory Factor Analysis (EFA) to validate that these observed items are all measuring one single underlying latent variable. Results of these CFA analyses (not shown) support this assumption, with all items loading strongly onto one factor (indicated by factor loadings $>.5$) both within each sample and in the pooled sample.

Step Three – Creation of the Factor Score through MNLFA

After the initial two steps aimed at analyzing whether the observed variables measure one latent construct, the MNLFA analysis is conducted. Because of the assumption that observations are independent within the pooled sample, a calibration sample was created to ensure that no sample participant provided data at multiple waves. This was done by randomly selecting only one wave of data for each participant to be used in construction of the global cognitive score. Thus, every respondent was included, but only contributed data from one wave of data collection. After the creation of the calibration sample the rest of the steps in the MNLFA process could be carried out.

First, CFA in the pooled sample is done with covariates on the mean and variance of the latent factor in order to determine measurement invariance for these two parameters (α, ψ). These covariates were age, age-squared, the dummy variable indicating which dataset each respondent is in (with “Add Health” as the reference category), the dummy indicating the wave from which data was used (with “1” as the reference category), two dummy variables for racial status (“Black” and “Hispanic”, with “White” as the reference category), and a dummy variable for gender (with “Male” as the reference category). After assessing the effect of the covariates on the latent mean and variance, the intercepts and factor loadings of each item are regressed on the covariates in turn to assess the measurement invariance of these parameters (ν_i, λ_i). These additional tests are done while retaining the covariate effects on the mean of the latent factor.

Ultimately, these five tests resulted in a list of covariates that significantly modified the estimated parameters of the MNLFA model. Significance was assessed using a Bonferroni-adjusted p-value of .01

given the five independent test that were carried out (.05/5). **Table 3 and 4** shows the covariates that were found to be significant for each parameter. A final model in which all significant covariates were retained was run, leading to a final set of parameter estimates. This model is shown visually in **Figure 2**. Importantly, there was found to be no significant covariate effects on either the factor loading or the intercept of the Immediate Recall item, indicating that this item exhibits no measurement invariance as a function of respondent demographics or which sample/wave the respondent was drawn from.

[TABLE 3 AND 4 ABOUT HERE]

Figure 2

Step Four - Estimating Factor Scores within the Pooled Sample

Using the regression coefficients produced in the final model, scores of global cognition were produced for each respondent in the entire pooled dataset which account for sample heterogeneity present between Add Health and MIDUS. **Figure 3** shows box plots of the global cognitive score by five-year age groups. As expected, there is a steady decline in cognition as age increases, with a sharper decline at the oldest ages in the sample. **Figure 4** and **Figure 5** show the mean of the global cognitive score across age by two of the covariates utilized in the MNLFA process; sex and college education. These figures show a roughly parallel mean of global cognition between the groups being differentiated (males vs. females in **Figure 3** and non-college graduates vs. college graduates in **Figure 4**), with a slight convergence of these means in the later life course. However, across all ages, there is a distinct advantage in global cognition for females and college graduates respectively.

Figure 3

Figure 4

Figure 5

Comparison of MNLFA global cognitive score and sum-score of cognitive items

In addition to being able to create commensurate measures of latent variables across pooled samples, MNLFA allows for a greater variation in latent construct measurement than is possible with more traditional methods, such as summing the values of the observed items. This is shown in **Figures 6** and **7**. **Figure 6** depicts a scatter plot of the MNLFA global cognitive score (y-axis) and a simpler measure of cognition that would have been created from summing the cognitive items (x-axis) for all respondents in the pooled sample. As can be seen, each value of the summed score is represented by a range of scores on the MNLFA measure. **Figure 7** highlights this by showing a histogram of the MNLFA global cognitive values for all respondents that scored a value of “15” on the summed score, the mean value for this measure. Results show that there is significant variation in the MNLFA score for respondents

who would have normally all scores the same value of “15” on the summed score. This more nuanced measure allows for a more fine-grained analysis of cognitive decline among U.S. adults.

Figure 6

Figure 7

Conclusion

Often, pooling data from multiple sources can provide benefits that improve the study of health and health determinants. However, combining data from multiple, independent samples can also bias statistical results and lead to incorrect conclusions if heterogeneity between samples is not properly accounted for. By using MNLFA within an IDA framework, it is possible to account for sampling differences between data sources and to conduct hypothesis testing on a pooled sample. Using two large, nationally representative datasets, this study was able to use MNLFA to create a commensurate measure of cognitive functioning using several tests of cognition that were collected across the two datasets. As more data becomes available. Future directions for this work include using the commensurate measure to replicate the findings from previous studies on the social determinants of cognition, primarily those that

have been done using only older-American samples or that were done using small, clinical samples that are not representative of the entire U.S. adult population.

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Works cited

- Curran, Patrick J and Andrea M Hussong. 2009. "Integrative data analysis: The simultaneous analysis of multiple data sets." *Psychological methods* 14:81.
- Curran, Patrick J, James S McGinley, Daniel J Bauer, Andrea M Hussong, Alison Burns, Laurie Chassin, Kenneth Sher, and Robert Zucker. 2014. "A moderated nonlinear factor model for the development of commensurate measures in integrative data analysis." *Multivariate behavioral research* 49:214-231.
- Fisher, Gwenith G and Lindsay H Ryan. 2018. "Overview of the Health and Retirement Study and introduction to the special issue." *Work, aging and retirement* 4:1-9.
- Hebert, Liesi E, Jennifer Weuve, Paul A Scherr, and Denis A Evans. 2013. "Alzheimer disease in the United States (2010–2050) estimated using the 2010 census." *Neurology* 80:1778-1783.
- Hofer, Scott M and Andrea M Piccinin. 2009. "Integrative data analysis through coordination of measurement and analysis protocol across independent longitudinal studies." *Psychological methods* 14:150.
- Hussong, Andrea M, Patrick J Curran, and Daniel J Bauer. 2013. "Integrative data analysis in clinical psychology research." *Annual review of clinical psychology* 9:61-89.
- Kirton, Joshua W and Vonetta M Dotson. 2016. "The interactive effects of age, education, and BMI on cognitive functioning." *Aging, Neuropsychology, and Cognition* 23:253-262.
- Petersen, Ronald C. 2004. "Mild Cognitive Impairments as a Diagnostic Entity" *Journal of Internal Medicine* 256(3):183-94
- Ryff, Carol D. and Margie E. Lachman. 2018. "Midlife in the United States (MIDUS3): Cognitive Project, 2013-2017."
- Tun, Patricia A and Margie E Lachman. 2006. "Telephone assessment of cognitive function in adulthood: the Brief Test of Adult Cognition by Telephone." *Age and Ageing* 35:629-632.

Tables

Table 1: Sample-size by Data Source, Wave, and Five-year Age Groups

	25	30	35	40	45	50	55	60	65	70	75	80	85	90	Total
Add Health IV	923	439													1362
Add Health V		13	984	365											1362
MIDUS 2		23	130	227	275	294	310	244	217	122	57	27			1926
MIDUS 3				44	142	246	275	304	287	251	194	113	53	17	1926
Total	923	475	1114	636	417	540	585	548	504	373	251	140	53	17	6576

Table 2

Variable	Full Sample (n=6,576)			Add Health (n=2,724)			MIDUS (n=3,852)		
	Mean	Std. Dev.	Min-Max	Mean	Std. Dev.	Min-Max	Mean	Std. Dev.	Min-Max
Immediate Recall	6.75	2.17	0-15	6.44	1.99	1-15	6.98	2.27	0-10
Delayed Recall	4.74	2.39	0-15	4.93	2.04	0-14	4.61	2.60	0-10
Digits Backwards	4.12	1.48	0-7	4.18	1.53	0-7	4.08	1.45	0-7
Age	48.68	16.17	24-92	33.34	5.13	24-44	59.54	11.96	33-92
Race									
White	0.81			0.61			0.95		
Black	0.11			0.24			0.02		
Hispanic	0.08			0.15			0.03		
College Degree	0.39			0.31			0.45		
Female	0.55			0.52			0.57		

Table 3

Covariate Effect	Estimate (SE)	<i>t</i>	<i>p</i>
Factor mean			
1. Age	-	-	-
2. Age2	-	-	-
3. Data	.053 (.053)	1.011	.000
4. Black	-.452 (.075)	-6.002	.000
5. Hispanic	-.326 (.078)	-4.204	.000
6. College	.474 (.046)	10.304	.000
7. Female	.544 (.048)	11.236	.000
8. Wave	-	-	-
Factor Variance			
1. Age	-	-	-
2. Age2	-	-	-
3. HRS	.285 (.076)	3.766	.000
4. Black	-	-	-
5. Hispanic	-	-	-
6. College	-	-	-
7. Female	.212 (.067)	3.181	.001
8. Wave	-	-	-

Table 4		
Item Covariate Effect	Intercept (SE)	Loading (SE)
1. Immediate Word Recall	6.087 (.076)	1.516 (.055)
<i>Age</i>	-	-
<i>Age2</i>	-	-
<i>Data</i>	-	-
<i>Black</i>	-	-
<i>Hispanic</i>	-	-
<i>College</i>	-	-
<i>Female</i>	-	-
<i>Wave</i>	-	-
2. Delayed Recall	4.524 (.077)	1.000 (.000) (fixed)
<i>Age</i>	-	-
<i>Age2</i>	-	-
<i>Data</i>	.-	.277 (.058)
<i>Black</i>	-	-
<i>Hispanic</i>	-.262 (.088)	-
<i>College</i>	.398 (.051)	-
<i>Female</i>	-.201 (.051)	-
<i>Wave</i>	-	-
3. Category Fluency	3.944 (.046)	.0360 (.025)
<i>Age</i>	-	-
<i>Age2</i>	-	-
<i>Data</i>	-.943 (.064)	-
<i>Black</i>	-	-
<i>Hispanic</i>	-	-
<i>College</i>	-	-
<i>Female</i>	-	-
<i>Wave</i>	-	-