HRS 2016 - Core & HCAP Cognition, HCAP Classification

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ABSTRACT
This reports summarizes data prepared for analysis regarding HRS Core Classification. Data are (primarily) from the 2016 HRS and HCAP surveys.

variable	label
HHID	HOUSEHOLD IDENTIFICATION NUMBER
PN	RESPONDENT PERSON IDENTIFICATION NUMBER
SECU	SAMPLING ERROR COMPUTATION UNIT
STRATUM	STRATUM ID
PWGTR	2016 WEIGHT: RESPONDENT LEVEL
HCAP16WGTR	HCAP 2016 WEIGHT: RESPONDENT LEVEL
PINSAMP	2016 SAMPLE STATUS
PIWWAVE	2016 WHETHER INTERVIEWED IN THE WAVE
PIWYEAR	2016 INTERVIEW YEAR
PMARST	2016 MARITAL STATUS
PNURSHM	2016 NURSING HOME STATUS
PPROXY	2016 PROXY TYPE STATUS
rage	R CURRENT AGE CALCULATION
PA019	R CURRENT AGE CALCULATION
PAGE	AGE AT 2016 INTERVIEW
female	Female from trk2022tr_r
black	Black or African-American (not Hispanic) from trk2022tr_r
hisp	Hispanic from trk2022tr_r
SCHLYRS	
HISPANIC	HISPANICITY TYPE
RACE	RACE/ETHNICITY
vdori	Orientation to Time - number correct

variable	label
vdlfl1z	Animal naming (correct - errors)
vdlfl2	Object naming - Scissors, cactus
vdlfl3	Naming - President, Vice-president
vdwdimmz	Word recall - Immediate
vdwddelz	Word recall - Delayed
vdexf7z	Number series
vdsevens	Serial 7’s - Number correct
vdcount	Count backwards from 20
nPG014	recoded: DIFFICULTY- DRESSING
nPG021	recoded: DIFFICULTY BATHING
nPG023	recoded: DIFFICULTY EATING
nPG030	recoded: DIFFICULTY USING TOILET
nPG040	IADL: Difficulty Using Maps
nPG041	IADL: Difficulty Meal Prep
nPG044	IADL: Difficulty Grocery Shopping
nPG047	IADL: Difficulty Making Phone Calls
nPG050	IADL: Difficulty Taking Meds
nPG059	IADL: Difficulty Managing Money
PD102	RATE MEMORY PAST
jorm	Jorm score (HRS)
vs1hcapdx	HRS HCAP Dementia and MCI Classification (BPV version, HRS HCAP variable set 1)
vs1hcapdxeap	HRS HCAP Dementia and MCI Classification (EAP version, HRS HCAP variable set 1)
nonzeroweight	
inHCAP	
age65up	
cogfunction2016	2016: Cognition Category: 1=Normal, 2=CIND, 3=Demented
PrDem	Probability of dementia, point estimate
PrCIND	Probability of CIND, point estimate
PrNorm	Probability of normal cognition, point estimate
Cog	Latent cognition, point estimate

variable	label
CogSd	Latent cognition, std of estimate
Hudomiet_classification	Hudomiet classification by highest class proportion
SCHLYRSimp	Number of years in school (imputed)
DEGREE	HIGHEST DEGREE OF EDUCATION
spage1	R CURRENT AGE CALCULATION
spage2	R CURRENT AGE CALCULATION
spage3	R CURRENT AGE CALCULATION
rage_cat	Age group, y
Sex	Sex
RaceAndEthnicity	Race and ethnicity
Educational_Attainment	Educational attainment
x1	Source: spage1
x2	Source: spage2
x3	Source: spage3
x4	Source: female
x5	Source: black
x6	Source: hisp
x7	Source: SCHLYRSimp
x1x4	
x1x5	
x1x6	
x1x7	
x2x4	
x2x5	
x2x6	
x2x7	
x3x4	
x3x5	
x3x6	
x3x7	

variable	label
x4x5	
x4x6	
x4x7	
x5x6	
x5x7	
x6x7	

Variables and labels

Summary of data

Cognitive performance variables

variable	label
vdori	Orientation to Time - number correct
vdlfl1z	Animal naming (correct - errors)
vdlfl2	Object naming - Scissors, cactus
vdlfl3	Naming - President, Vice-president
vdwdimmz	Word recall - Immediate
vdwddelz	Word recall - Delayed
vdexf7z	Number series
vdsevens	Serial 7's - Number correct
vdcount	Count backwards from 20

Cognitive variables and labels in age 65+ sample

Data summary

Name	dplyr::select(data, all_o…
Number of rows	9763
Number of columns	9
_______________________	
Column type frequency:	
numeric	9
________________________	
Group variables	None

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
vdori	571	0.94	3.64	0.75	0	3.00	4.00	4.00	4	▁▁▁▂▇
vdlfl1z	637	0.93	0.17	0.08	0	0.11	0.16	0.22	1	▇▃▁▁▁
vdlfl2	571	0.94	1.90	0.32	0	2.00	2.00	2.00	2	▁▁▁▁▇
vdlfl3	572	0.94	1.62	0.55	0	1.00	2.00	2.00	2	▁▁▂▁▇
vdwdimmz	634	0.94	0.50	0.17	0	0.40	0.50	0.60	1	▂▆▇▃▁
vdwddelz	635	0.93	0.39	0.21	0	0.30	0.40	0.50	1	▅▃▇▅▁
vdexf7z	1867	0.81	0.61	0.19	0	0.53	0.62	0.73	1	▁▁▆▇▂
vdsevens	571	0.94	3.31	1.77	0	2.00	4.00	5.00	5	▅▂▂▃▇
vdcount	608	0.94	0.92	0.27	0	1.00	1.00	1.00	1	▁▁▁▁▇

Functional variables, self-report, and informant variables

variable	label
nPG014	recoded: DIFFICULTY- DRESSING
nPG021	recoded: DIFFICULTY BATHING
nPG023	recoded: DIFFICULTY EATING
nPG030	recoded: DIFFICULTY USING TOILET
nPG040	IADL: Difficulty Using Maps
nPG041	IADL: Difficulty Meal Prep
nPG044	IADL: Difficulty Grocery Shopping
nPG047	IADL: Difficulty Making Phone Calls
nPG050	IADL: Difficulty Taking Meds
nPG059	IADL: Difficulty Managing Money
PD102	RATE MEMORY PAST
jorm	Jorm score (HRS)

Functional, self-report, and informant variables in age 65+ sample

Data summary

Name	dplyr::select(data, all_o...
Number of rows	9763
Number of columns	12

________________________	
Column type frequency:	
numeric	12
________________________	
Group variables	None

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
nPG014	17	1.00	0.13	0.34	0	0	0.00	0.00	1	▇▁▁▁▁
nPG021	6	1.00	0.10	0.30	0	0	0.00	0.00	1	▇▁▁▁▁
nPG023	6	1.00	0.05	0.21	0	0	0.00	0.00	1	▇▁▁▁▁
nPG030	14	1.00	0.08	0.26	0	0	0.00	0.00	1	▇▁▁▁▁
nPG040	848	0.91	0.17	0.37	0	0	0.00	0.00	1	▇▁▁▁▂
nPG041	531	0.95	0.08	0.28	0	0	0.00	0.00	1	▇▁▁▁▁
nPG044	556	0.94	0.10	0.31	0	0	0.00	0.00	1	▇▁▁▁▁
nPG047	113	0.99	0.06	0.24	0	0	0.00	0.00	1	▇▁▁▁▁
nPG050	19	1.00	0.05	0.23	0	0	0.00	0.00	1	▇▁▁▁▁
nPG059	528	0.95	0.08	0.26	0	0	0.00	0.00	1	▇▁▁▁▁
PD102	571	0.94	2.25	0.53	1	2	2.00	3.00	9	▇▃▁▁▁
jorm	9193	0.06	3.59	0.80	1	3	3.18	4.25	5	▁▁▇▂▃

Analytic covariates

These variables have been constructed to not have any missingness. This is accomplished with the use of absorbing null categories (not Black or African-American, not Hispanic), and single imputation using predictive mean matching (years of educational attainment).

These covariates are all centered. x1, which is spage1, is age at 2016 interview centered at 70. x2 and x3 are two additional splines for age that are 0 at age 70. x7 is years in school, with missing values imputed, and centered at 12 years. In keeping with analytic decisions made in the HRS/HCAP analyses (Manly et al 2022) we do not use restricted cubic splines for education. x4, x5, and x6 code for female sex, Black or African-American (vs all other racial groups) and Hispanic (vs not Hispanic), and are mean centered using the HCAP sample and weighted. Interaction terms involving continuous predictors (x1-x3, x7) are not re-centered, and are computed before centring. Interaction terms involving discrete predictors (e.g., x4x5, the interaction of female sex and Black or African-American) are computed before centring, and are centered to the HCAP weighted mean.

variable	label
x1	Source: spage1
x2	Source: spage2

variable	label
x3	Source: spage3
x4	Source: female
x5	Source: black
x6	Source: hisp
x7	Source: SCHLYRSimp
x1x4	
x1x5	
x1x6	
x1x7	
x2x4	
x2x5	
x2x6	
x2x7	
x3x4	
x3x5	
x3x6	
x3x7	
x4x5	
x4x6	
x4x7	
x5x6	
x5x7	
x6x7	

Analytic covariates in age 65+ sample

Data summary

Name	dplyr::select(data, all_o…
Number of rows	9763
Number of columns	25
________________________	
Column type frequency:	

numeric	25
________________________	
Group variables	None

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
x1	0	1	5.76	7.57	-5.00	-1.00	5.00	11.00	37.00	▇▇▂▁▁
x2	0	1	2.31	4.68	0.00	0.00	0.22	2.31	47.33	▇▁▁▁▁
x3	0	1	0.35	1.10	0.00	0.00	0.00	0.05	14.00	▇▁▁▁▁
x4	0	1	0.03	0.49	-0.56	-0.56	0.44	0.44	0.44	▇▁▁▁▇
x5	0	1	0.07	0.37	-0.09	-0.09	-0.09	-0.09	0.91	▇▁▁▁▂
x6	0	1	0.03	0.32	-0.08	-0.08	-0.08	-0.08	0.92	▇▁▁▁▁
x7	0	1	0.64	3.28	-12.00	0.00	0.00	3.00	5.00	▁▁▂▇▇
x1x4	0	1	3.49	6.63	-5.00	0.00	0.00	7.00	37.00	▇▂▂▁▁
x1x5	0	1	0.66	3.25	-5.00	0.00	0.00	0.00	37.00	▇▁▁▁▁
x1x6	0	1	0.47	2.84	-5.00	0.00	0.00	0.00	33.00	▇▁▁▁▁
x1x7	0	1	1.25	32.99	-312.00	-5.00	0.00	10.00	140.00	▁▁▁▇▁
x2x4	0	1	1.47	4.05	0.00	0.00	0.00	0.60	47.33	▇▁▁▁▁
x2x5	0	1	0.25	1.64	0.00	0.00	0.00	0.00	47.33	▇▁▁▁▁
x2x6	0	1	0.20	1.56	0.00	0.00	0.00	0.00	39.33	▇▁▁▁▁
x2x7	0	1	0.32	18.84	-304.00	0.00	0.00	0.14	146.67	▁▁▁▇▁
x3x4	0	1	0.24	0.95	0.00	0.00	0.00	0.00	14.00	▇▁▁▁▁
x3x5	0	1	0.03	0.38	0.00	0.00	0.00	0.00	14.00	▇▁▁▁▁
x3x6	0	1	0.03	0.36	0.00	0.00	0.00	0.00	11.33	▇▁▁▁▁
x3x7	0	1	0.00	4.20	-80.00	0.00	0.00	0.00	40.00	▁▁▁▇▁
x4x5	0	1	0.05	0.30	-0.06	-0.06	-0.06	-0.06	0.94	▇▁▁▁▁
x4x6	0	1	0.02	0.25	-0.05	-0.05	-0.05	-0.05	0.95	▇▁▁▁▁
x4x7	0	1	0.30	2.43	-12.00	0.00	0.00	1.00	5.00	▁▁▁▇▂
x5x6	0	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	▁▁▇▁▁
x5x7	0	1	0.02	1.22	-12.00	0.00	0.00	0.00	5.00	▁▁▁▇▁
x6x7	0	1	-0.36	1.85	-12.00	0.00	0.00	0.00	5.00	▁▁▁▇▁

Cognitive classification

HCAP Cognitive Classification

There are two versions of the HCAP Cognitive Classification. Both follow the algorithm outlined in Manly et al (2022), but one relies upon Bayesian plausible values (BPV) as estimates of the underlying cognitive ability (`vs1hcapdx`), and with the other Expected A Posteriori (EAP) (`vs1hcapdxeap`). Here's what the HRS/HCAP Technical Documentation has to say about BPV vs EAP.

> We have generated factor score estimates as expected a posteriori (EAP) estimates and single draws from a Bayesian posterior distribution (Bayesian plausible values, PV). Both of these estimates were derived using Mplus software (version 8.8, Muthén & Muthén, Los Angeles CA)(Asparouhov, 2010; https://www.statmodel.com/download/Plausible.pdf). Factor scores are estimates of a latent variable. And latent variables are, by definition, not directly observable. Therefore, any estimate of that latent variable has some level of imprecision. In the context of categorical data item factor analysis (or item response theory), the imprecision is determined by the number of items used in the factor model, the strength of the correlation between the items and the underlying factor, and the distribution of difficulty levels of the items. Factors with more items, items with strong relationships with the underlying factor, and many widely dispersed difficulty levels will have less imprecision than factors with only a few items with weak relationships with the underlying factor and coarse and skewed responses. If a factor is measured by all continuous indicators, imprecision is constant across the level of the latent trait. But if a factor is measured with at least one categorical indicator, imprecision will vary across the level of the latent trait, generally being higher at the extremes.

> When we generate factor score estimates as plausible values, each person's score is a draw from the posterior distribution of their factor score estimate, which is determined by the level of imprecision of the factor score. These are analogous to imputations in multiple imputation. In fact, it might be desirable to use multiple plausible values generated for each participant as if they were multiply imputed values in a data analysis. If we were to take many draws from the posterior for each participant, and then compute the mean of each persons' plausible values - that mean would approach the EAP estimate we obtain for each person.

> In addition to factor scores, we produce results of the classification algorithm using single draws from the Bayesian posterior distribution of factor scores (vs1hcapdx) and expected a posteriori (EAP) factor scores (vs1hcapdxeap) for data users to include in their analysis as they determine is appropriate. We recommend using plausible values (or multiple plausible values) in any circumstance where population-level parameter estimation and inference is desired. Use of EAP estimates in such circumstances is anti-conservative and may result in biased low standard errors in inflated type-I error levels. In some situations, such as descriptive analysis, or in a high-stakes decision making procedure (e.g., selecting participants for a module or sub-study) the EAP estimates would be preferable. For example, when we are interested in generating a prevalence estimate for older adults living in the US, we prefer the classification algorithm that uses the single draws from the plausible values, because that version incorporates uncertainty in the estimation of cognitive ability. On the other hand, when we are interested in comparing how the HCAP algorithm compares to a reference standard classification, we make use of the EAP factor score derived algorithmic results. The latter example involves a "high stakes" decision about agreement at the individual participant level, and we would not like that decision to be clouded by random fluctuations in assignment due to measurement imprecision in the cognitive assessment.

Think carefully about whether you want to use the EAP or BPV versions of the HCAP cognitive classification.

Criterion measures

variable	label
vs1hcapdx	HRS HCAP Dementia and MCI Classification (BPV version, HRS HCAP variable set 1)
vs1hcapdxeap	HRS HCAP Dementia and MCI Classification (EAP version, HRS HCAP variable set 1)

variable	label
cogfunction2016	2016: Cognition Category: 1=Normal, 2=CIND, 3=Demented
PrDem	Probability of dementia, point estimate
PrCIND	Probability of CIND, point estimate
PrNorm	Probability of normal cognition, point estimate
Cog	Latent cognition, point estimate
CogSd	Latent cognition, std of estimate
Hudomiet_classification	Hudomiet classification by highest class proportion

Analytic covariates in age 65+ sample

Data summary

Name	dplyr::select(data, all_o...
Number of rows	9763
Number of columns	9
________________________	
Column type frequency:	
numeric	9
________________________	
Group variables	None

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
vs1hcapdx	6293	0.36	1.46	0.69	1.00	1.00	1.00	2.00	3.00	▇▁▂▁▁
vs1hcapdxeap	6293	0.36	1.45	0.68	1.00	1.00	1.00	2.00	3.00	▇▁▂▁▁
cogfunction2016	0	1.00	1.39	0.65	1.00	1.00	1.00	2.00	3.00	▇▁▂▁▁
PrDem	0	1.00	0.09	0.24	0.00	0.00	0.00	0.01	1.00	▇▁▁▁▁
PrCIND	0	1.00	0.26	0.29	0.00	0.01	0.11	0.49	0.95	▇▂▂▂▂
PrNorm	0	1.00	0.66	0.38	0.00	0.31	0.84	0.98	1.00	▂▁▁▁▇
Cog	0	1.00	1.26	0.85	-3.82	0.83	1.38	1.84	3.67	▁▁▂▇▁
CogSd	0	1.00	0.38	0.04	0.25	0.35	0.36	0.39	0.58	▁▇▂▂▁
Hudomiet_classification	0	1.00	1.40	0.63	1.00	1.00	1.00	2.00	3.00	▇▁▂▁▁

Langa-Weir classification (`cogfunction2016`)

Langa et al write:

> The Langa-Weir Classifications map onto the 27-point scale (variable name `cogtot27_imp` [not in our data set]) thus: Normal (12 – 27); Cognitively Impaired but not Demented (CIND) (7 – 11); and Demented (0 – 6) (variable name `cogfunction`). Crimmins et al. (2011) documents the methods used to make these classifications based on diagnostic information from the ADAMS.

They go on to explain coding for Proxy respondents, and for dealing with web administration and cross-wave differences in assessment. The value levels correspond to `Cognition Category: 1=Normal, 2=CIND, 3=Demented`.

Hudomiet classification (`Hudomiet_classification`, `PrDem`, `PrCIND`, `PrNorm`, `Cog`, `CogSd`)

Hudomiet and colleagues (2022) write (emphasis added):

> We use a longitudinal latent variable model and jointly model the clinical dementia diagnosis in the ADAMS subsample and the cognitive measures in the HRS. Changes in dementia over time are primarily identified from wave-to-wave differences in the averages of individuals' performance on the HRS cognitive tests, while the clinical diagnosis of dementia in ADAMS plays a critical role in calibrating the HRS cognitive tests to measure dementia. Importantly, ***our model allows the relationship between the ADAMS and HRS measures to vary across population subgroups, essentially calibrating the measures for each subgroup.*** (page 2/9)

> …the model is constructed to ensure the dementia classification is calibrated accurately within population subgroups, and therefore, it is equipped to produce accurate estimates of dementia prevalence by age, sex, education, race and ethnicity, and a measure of lifetime earnings. (page 2/9)

Details beyond this are difficult to parse from Hudomiet et al (2022) and supplementary materials.

The provided data are:

`PrDem` Estimated probability of dementia
`PrCIND` Estimated probability of cognitive impairment not dementia (CIND)
`PrNorm` Estimated probability of normal cognitive status
`Cog` Expected value of latent cognitive ability
`CogSd` The standard deviation of latent cognitive ability

In addition, I have generated `Hudomiet_classification`, which is a normal/cind/dementia three-level variable where a respondent is classified according to their highest class probability.

Design Variables and convenience variables

variable	label
HHID	HOUSEHOLD IDENTIFICATION NUMBER
PN	RESPONDENT PERSON IDENTIFICATION NUMBER
SECU	SAMPLING ERROR COMPUTATION UNIT
STRATUM	STRATUM ID
PWGTR	2016 WEIGHT: RESPONDENT LEVEL
HCAP16WGTR	HCAP 2016 WEIGHT: RESPONDENT LEVEL
nonzeroweight	
inHCAP	

variable	label
age65up	

Analytic covariates in age 65+ sample

Data summary

Name	dplyr::select(data, all_o...
Number of rows	9763
Number of columns	9
_______________________	
Column type frequency:	
character	2
numeric	7
________________________	
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
HHID	0	1	6	6	0	7399	0
PN	0	1	3	3	0	14	0

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
SECU	0	1.00	1.51	0.50	1	1.00	2	2.00	2	▇▁▁▁▇
STRATUM	0	1.00	30.06	15.19	1	18.00	32	43.00	79	▅▅▇▂▁
PWGTR	0	1.00	4941.63	3614.38	0	2387.00	4064	5936.00	28961	▇▂▁▁▁
HCAP16WGTR	6293	0.36	14298.28	10730.18	756	6723.25	11203	17902.25	59020	▇▃▂▁▁
nonzeroweight	0	1.00	0.99	0.09	0	1.00	1	1.00	1	▁▁▁▁▇
inHCAP	0	1.00	0.36	0.48	0	0.00	0	1.00	1	▇▁▁▁▅
age65up	0	1.00	1.00	0.00	1	1.00	1	1.00	1	▁▁▇▁▁

For analyses involving the sampling weight, you must use `SECU`, `STRATUM`, and either of the available weights (`PWGTR` and `HCAP16WGTR`.) The number of records passed to analysis will be either N = 19,699 or N = 3,496. Since the cognitive classifications based on HCAP are only relevant to those 65+, in the Core even 'tho the analysis involves 19,699 we must identify the `SUBPOPULATION` (analogous toa filter) to which the analysis is relevant, and that's where the `age65up` convenience variable comes in. `nonzeroweight` is a indicator for purposes of people in the N = 19,699 sample who were "officially" in the HRS 2016 sampling frame, as indicated by their having a non zero weight on `PWGTR`. There were 79 people in the HRS/HCAP sample with a non-zero `HCAP16WGTR` but a zero `PWGTR`.

Table 1 and 2 variables

A number of variables have been created to be used in descriptive tables.

Descriptive variables for reporting

variable	label	value_labels
rage_cat	Age group, y	65-69 = 1; 70-74 = 2; 75-79 = 3; 80-84 = 4; 85-89 = 5; 90 and over = 6
rage	R CURRENT AGE CALCULATION	
Sex	Sex	Male = 0; Female = 1
RaceAndEthnicity	Race and ethnicity	White = 1; Black or African-American (Not Hispanic) = 2; Hispanic (any racial group) = 3; All other racial groups = 4
Educational_Attainment	Educational attainment	< High school = 1; High school = 2; Some college = 3; Education beyond college = 4; Unknown = 5
SCHLYRSimp	Number of years in school (imputed)	

Strobe diagram