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Heterogeneity in Normal Neurocognition: A Latent Profile Analysis of the Expanded Halstead-Reitan Battery Normative Dataset

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Heterogeneity in Normal Neurocognition:
A Latent Profile Analysis of the Expanded Halstead-Reitan Battery Normative Dataset

A dissertation submitted in partial satisfaction of the
requirements for the degree of Doctor in Philosophy

in

Clinical Psychology

by

Virginie Marie Patt

Committee in charge:

University of California, San Diego

Professor Gregory G. Brown, Chair
Professor Robert K. Heaton
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2017

The Dissertation of Virginie Marie Patt is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

Chair

University of California, San Diego

San Diego State University

2017

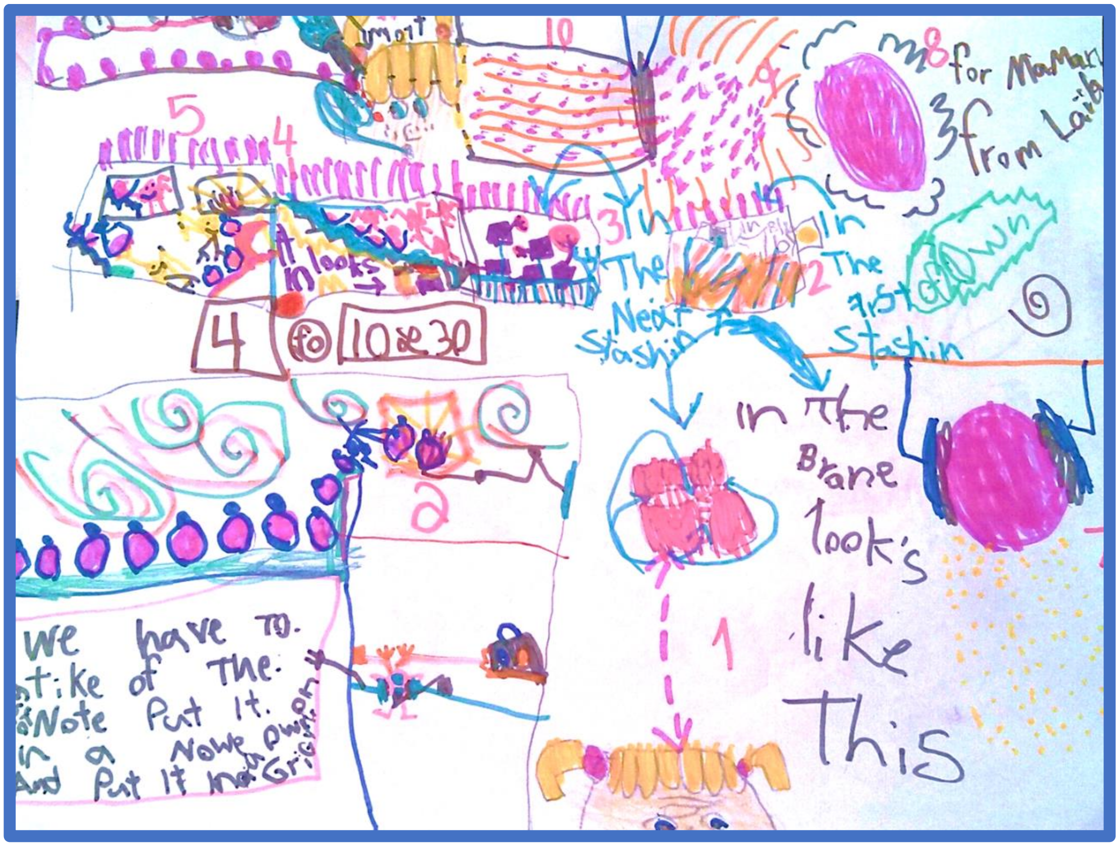
DEDICATION

To Odette, Solange, Genevieve, Laïla, and Cyan, my anchors to the present and masters of mindfulness.

To Leigh, who has inspired this journey.

And to Dan, who has made it possible.

EPIGRAPH



"In the Brane looks like this" *by Laïla Patt (May 2015)*

"Gray Matter Decomposition" *by Cyan Patt (April 2017)*

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Archives of Clinical Neuropsychology, in press. The dissertation author was the primary investigator and author of this material. Part of the material in this dissertation is also currently being prepared for submission for publication: Patt, V. M., Brown, G. G., Thomas, M. L., Roesch, S. C., Taylor, M. J., & Heaton, R. K. “Heterogeneity in normal neurocognition: A latent profile analysis of the expanded Halstead-Reitan Battery normative dataset.” The dissertation author will be the primary investigator and author of this material.

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2013 **M.S. in Clinical Psychology**
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Thesis: Disentangling Spatial Working Memory Processes: A Modeling Analysis of Preferred Eye Movement Strategies during Neurocognitive Testing. March, 2013. (Committee: Drs. William Perry, Arpi Minassian, Martin Paulus, & Sarah Mattson)

2007 **M.A. in Clinical Psychology with an emphasis on Marriage and Family Therapy (MFT)**
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2015-2016 **Walter Reed National Military Medical Center**, Bethesda, MD
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2014 **Rady Children's Hospital**, San Diego, CA
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Conducted neuropsychological evaluations.

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Interpreted extended Halstead-Reitan neuropsychological batteries.

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Conducted group psychotherapy for substance dependence and depression.

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2001-2002 Tuition Waiver for selective international exchange student program - University of Michigan

PROFESSIONAL ORGANIZATIONS

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PUBLICATIONS IN PSYCHOLOGY
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Peer-Reviewed Journal Articles

(1) **Patt, V. M.**, Brown, G. G., Thomas, M. L., Roesch, S. C., Taylor, M. J., & Heaton, R. K. (2017). Factor structure of the expanded Halstead-Reitan neuropsychological battery. *Archives of Neuropsychology, in press*.

(2) Brown, G. G., Thomas, M. L., & **Patt, V. M.** (2017). Parametric model measurement: Reframing traditional measurement ideas in neuropsychological practice and research. *The Clinical Neuropsychologist, in press.*

(3) Thomas, M. L., **Patt, V. M.**, Bismark, A., Sprock, J., Tarasenko, M., Light, G. A., & Brown, G. G. (2017). Evidence of systematic attenuation in the measurement of cognitive deficits in schizophrenia. *Journal of Abnormal Psychology, 126*, 312-324.

(4) Brown, G. G., **Patt, V. M.**, Sawyer, J., & Thomas, M. L. (2016). Double dissociation of a latent working memory process. *Journal of Clinical and Experimental Neuropsychology, 38*, 59-75.

(5) Thomas, M. L., Brown, G. G., Gur, R. C., Moore, T. M., **Patt, V. M.**, Nock, M. K., Naifeh, J. A., Heeringa, S., Ursano, R. J., Stein, M. B. (2015). Measurement of Latent Cognitive Abilities Involved in Concept Identification Learning, *Journal of Clinical and Experimental Neuropsychology, 37*, 653-669.

(6) **Patt, V. M.**, Thomas, M. L., Minassian, A., Geyer, M. A., Brown, G. G., & Perry, W. (2014). Disentangling working memory processes during spatial span assessment: A modeling analysis of preferred eye movement strategies. *Journal of Clinical and Experimental Neuropsychology, 36*, 186-204.

(7) Henry, B. L., Minassian, A., **Patt, V. M**., Hua, J., Young, J. W., Geyer, M. A., & Perry, W. (2013). Inhibitory deficits in euthymic bipolar disorder patients assessed in the Human Behavioral Pattern Monitor. *Journal of Affective Disorders, 150, 948-954.*

Manuscripts in Preparation or Under Review

(1) Thomas, M. L., Moore, T. M., Baker, D., **Patt, V. M.**, Risbrough, V., Gur, R. C., & Brown, G. G. (*submitted*). Psychometric Applications of an Item Response-Signal Detection Model.

(2) **Patt, V. M.**, Brown, G. G., Thomas, M. L., Roesch, S. C., Taylor, M. J., & Heaton, R. K. (*in preparation*). Heterogeneity in normal neurocognition: A latent profile analysis of the expanded Halstead-Reitan Battery normative dataset.

Peer-Reviewed Abstracts and Oral Presentations

(1) **Patt, V. M.**, Brown, G. G., Thomas, M. L., & Heaton, R. K. (2017, February). *Digit Vigilance Test: Speed versus Accuracy Tradeoff Revealed*, Poster session at the International Neuropsychological Society (INS) 45th annual meeting, New Orleans, LO.

(2) **Patt, V. M.**, Brown, G. G., Thomas, M. L., Roesch, S. C., Taylor, M. J., & Heaton, R. K. (2016, February). *Characterizing Heterogeneity in Normal Neurocognition*, Poster session at the International Neuropsychological Society (INS) 44th annual meeting, Boston, MA.

(3) **Patt, V. M.**, Jernigan, T. L., & Brown, G. G. (2015, November). *Heterogeneity in Normal Neurocognition*, Poster session at the UCSD Frontiers of Innovation Scholars Program (FISP) symposium, La Jolla, CA.

(4) **Patt, V. M**., Thomas, M. L., Minassian, A., Geyer, M. A., Brown, G. G., & Perry, W. (2013, November). *Parsing Working Memory Processes: The Impact of Eye Movement Strategy on Neurocognitive Test Performance*, Poster session at the National Academy of Neuropsychology (NAN) 33rd conference, San Diego, CA.

(5) Kloezeman, K., Henry, B. L., **Patt, V. M**., Minassian, A., & Perry, W. (2013, November). *Inhibitory Deficits and Everyday Functional Ability in Bipolar Disorder*, Poster session at the National Academy of Neuropsychology (NAN) 33rd conference, San Diego, CA.

(6) **Patt V.,** Minassian A., Henry B.L., Geyer M.A., & Perry W. (2011, December), *Objective Assessment of Social Disinhibition using the Human Behavioral Pattern Monitor (hBPM) in Bipolar Disorder and Schizophrenia Patients*, Poster Session at the American College of Neuropsychopharmacology (ACNP) 50th meeting, Waikoloa, HI.

(7) **Patt, V.**, Minassian, A., & Perry, W. (2011, November). *Spatial Span Assessment: Beyond Target Number*, Poster session at the National Academy of Neuropsychology (NAN) 31st conference, Marco Island, FL.

PUBLICATIONS IN SPACE SCIENCE
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Peer-Reviewed Journal Articles

(1) Mandt, K. E., Gell, D. A., Perry, M., Waite, J. H. Jr., Crary, F. A., Young, D., Magee, B. A., Westlake, J. H., Cravens, T., Kasprzak, W., Miller, G., Walhlund, J.-E., Ågren, J., Edberg, N. J. T., Heays, A. N., Lewis, B. R., Gibson, S. T., **De La Haye, V.**, & Liang, M.-C. (2013), Ion densities and composition of Titan's upper atmosphere derived from the Cassini Ion Neutral Mass Spectrometer: Analysis methods and comparison of measured ion densities to photochemical model simulations, *Journal of Geophysical Research*, 117(E10006), 22p.

(2) Bell, J. M., Bougher, S. W., Waite, J. H. Jr., Ridley, A. J., Magee, B. A., Mandt, K. E., Westlake, J., DeJong, A. D., Bar-Nun, A., Jacovi, R., Toth, G., **De La Haye, V.**, Gell, D., & Fletcher, G. (2011). Simulating the one-dimensional structure of Titan's upper atmosphere: 3. Mechanisms Determining Methane Escape. *Journal of Geophysical Research. 116(E11002),* 16p.

(3) Bell, J. M., Bougher, S. W., Waite, J. H. Jr., Ridley, A. J., Magee, B. A., Mandt, K. E., Westlake, J., DeJong, A. D., **De La Haye, V.**, Bar-Nun, A., Jacovi, R., Toth, G., Gell, D., & Fletcher, G. (2010). Simulating the one-dimensional structure of Titan's upper atmosphere: 2. Alternative scenarios for methane escape. *Journal of Geophysical Research. 115(E12018),* 20p.

(4) Bell, J. M., Bougher, S. W., Waite, J. H. Jr., Ridley, A. J., Magee, B. A., Mandt, K. E., Westlake, J., DeJong, A. D., Bar-Nun, A., Jacovi, R., Toth, G., & **De La Haye, V.** (2010). Simulating the one-dimensional structure of Titan's upper atmosphere: 1. Formulation of the Titan Global Ionosphere-Thermosphere Model and benchmark simulations. *Journal of Geophysical Research. 115(E12002),* 20p.

(5) **De La Haye, V.**, Waite, J. H., Jr., Cravens, T. E., Bougher, S. W., Robertson, I. P., & Bell J. M. (2008). Heating Titan's Upper Atmosphere. *Journal of Geophysical Research, 113(A11314),* 314-335.

(6) **De La Haye, V.**, Waite, J. H., Jr., Cravens, T. E., Robertson, I. P., & Lebonnois, S. (2008). Coupled Ion and Neutral Rotating Model of Titan's Upper Atmosphere. *Icarus, 197(1),* 110-136.

(7) Cravens, T. E., Robertson, I. P., Waite, J.H., Jr., Yelle, R. V., Vuitton, V., Coates, A. J., Wahlund, J.-E., Agren, K., Richard, M. S., **De La Haye, V.,** Wellbrock, V. A., & Neubauer, F. M. (2008). Model-Data Comparisons for Titan's Nightside Ionosphere, *Icarus, 199(1),* 174-188.

(8) **De La Haye, V.**, Waite, J. H. Jr., Johnson, R. E., Yelle, R. V., Cravens, T. E., Luhmann, J. G., Kasprzak, W. T., Gell, D. A., Magee, B., Leblanc, F., Michael, M., Jurac, S., & Robertson, I. P. (2007). Cassini Ion and Neutral Mass Spectrometer Data in Titan's Upper Atmosphere and Exosphere: Observation of a Suprathermal Corona. *Journal of Geophyical Research, 112(A07309),* 309-324.

(9) **De La Haye, V.,** Waite, J. H., Jr., Cravens, T. E., Nagy, A. F., Yelle, R. V., Johnson, R. E., Lebonnois, S., & Robertson, I. P. (2007). Titan's Corona: The Contribution of Exothermic Chemistry. *Icarus, 191(1),* 236-250.

(10) Yelle, R. V., Borggren, N., **De La Haye, V.**, Kasprzak, W. T., Niemann, H. B., Muller-Wodarg, I., & Waite, J. H., Jr. (2006). The Vertical Structure of Titan's Upper Atmosphere from Cassini Ion Neutral Mass Spectrometer Measurements, *Icarus. 182(2),* 567-576.

(11) Cravens, T. E., Robertson, I. P., Waite, J. H., Jr., Yelle, R. V., Kasprzak, W. T., Keller, C. N., Ledvina, S. A., Niemann, H. B., Luhmann, J. G., McNutt, R. L., Ip, W.-H., De La Haye, V., Müller-Wodarg, I., Wahlund, J.-E., Anicich, V. A., & Vuitton, V. (2006). The Composition of Titan's Ionosphere. *Geophysical Research Letters, 33(7),* L07105.

(12) Waite, J. H., Niemann, H. B., Yelle, R. V., Kasprzak, W. T., Cravens, T. E., Luhmann, J. G., McNutt, R. L., Ip, W.-H., Gell, D. A., **De La Haye, V.**, Müller-Wordag, I., Magee, B., Borggren, N., Ledvina, S., Fletcher, G., Walter, E., Miller, R., Scherer, S., Thorpe, R., Xu, J., Block, B., & Arnett, K. (2005). Ion Neutral Mass Spectrometer Results from the First Flyby of Titan. *Science, 308(5724),* pp. 982-986.

(13) Cravens, T. E., Robertson, I. P., Clark, J., Wahlund, J.-E., Waite, J. H., Jr., Ledvina, S. A., Niemann, H. B., Yelle, R. V., Kasprzak, W. T., Luhmann, J. G., McNutt, R. L., Ip, W. – H., **De La Haye, V.**, Müller-Wodarg, I., Young, D. T., & Coates, A. J. (2005). Titan's Ionosphere: Model Comparisons with Cassini TA data. *Geophysical Research Letters*, *32(12)*, L12108.

Peer-Reviewed Abstracts and Oral Presentations (sub-selection)

(1) **De La Haye, V.,** Bell, J., Yu, J., Bougher, S., Waite, J. H., Jr., Clark, J., Cravens, T. E., Yelle, R. V., Chassefière, E., Leblanc, F., Lebonnois, S. (2004, July). *The Thermal Structure of Titan's Upper Atmosphere in the Cassini Flyby Regions*. Presentation at the COSPAR Scientific 35th Assembly, Paris, France.

(2) **De La Haye, V.** & Waite, J. H., Jr. (2005, April), *Suprathermal Populations in Titan's Upper Atmosphere Extracted from INMS Cassini Data*. Poster Session at the Michigan Geophysical Union (MGU) conference, Ann Arbor, MI.

ABSTRACT OF THE DISSERTATION

Heterogeneity in Normal Neurocognition:
A Latent Profile Analysis of the Expanded Halstead-Reitan Battery Normative Dataset

by

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Doctor of Philosophy in Clinical Psychology

University of California, San Diego, 2017
San Diego State University, 2017

Professor Gregory G. Brown, Chair

Are you right-brained or left-brained? The belief that individual cognitive differences may be characterized in terms of right or left hemispheric dominance is often accepted as conventional wisdom, but has never been clearly supported. Perhaps as a result, "normal neurocognition" has been almost invariably assumed to constitute one large homogenous group and modeled using a flat neuropsychological profile (i.e., using unimodal normal distributions across neuropsychological domains). The current project tested this assumption by exploring and characterizing heterogeneity in a cognitively healthy population.

The neuropsychological profiles of cognitively-healthy individuals were characterized using latent profile analysis (LPA) on a normative dataset of the expanded Haltstead-Reitan neuropsychological Battery (eHRB). Participants were included that had been administered at least half of the eHRB measures with a memory test (N=982, age=20-85, education=7-20, 618

African-American, 364 Caucasian). The neurocognitive domains underlying performance on the eHRB were characterized and quantified using exploratory and confirmatory factor analyses on demographically-uncorrected eHRB test scores. Two series of LPAs were conducted on composite factor scores that were (1) corrected for demographics and (2) corrected for both demographics and general cognitive ability.

Seven factors were identified: ‘working-memory’, ‘fluency’, ‘verbal episodic memory’, ‘language’, ‘visuospatial cognition’, ‘perceptual speed’, and ‘perceptual attention’. The first LPA revealed individual differences in general neurocognitive ability, with some individuals performing better than others across domains. After correcting for general neurocognitive ability, the second LPA revealed patterns of individual differences best described by four pairs of latent classes with opposite patterns of relative strengths and weaknesses. These patterns were characterized by tradeoffs along two dimensions: verbal-to-perceptual and analysis-to-attention/speed.

When demographic characteristics are controlled, individual differences in normal neurocognition are dominated by general cognitive ability. At equivalent general cognitive ability, individual differences are characterized by relative tradeoffs along two almost orthogonal dimensions, verbal-to-perceptual and analysis-to-attention/speed. These findings suggest that different cognitive strategies or neuronal routes may be employed to attain similar general performance on neurocognitive testing. Based on brain function theories, these neuronal routes may involve differential activation of the left-versus-right cerebral hemispheres and of the ventral-versus-dorsal brain pathways, perhaps suggesting right- and left- but also top- and bottom-brained phenotypes.

INTRODUCTION

The main goals of neuropsychological assessment have been identified as detecting acquired brain dysfunction, monitoring neurocognitive functioning over time, and characterizing patterns of cognitive strengths and weaknesses that can affect every day functioning (Heaton & Marcotte, 2000). These goals have been traditionally achieved through the formal administration and interpretation of a battery of tests, ideally covering most domains of cognitive function, including attention, memory, executive function, language, visuospatial skills, and sensory-perceptual and motor skills (e.g., Benton et al. 1983; Christensen, 1975; Heaton, Grant, & Matthews, 1991; Heaton, Miller, Taylor, & Grant, 2004; Luria, 1973; Reitan & Wolfson, 1985; Wechsler, 1983). Access to adequate norms has been key to interpreting performance on those tests, ideally permitting comparison of raw scores to scores that might be expected of any specific individual if they were free of brain disorder, taking into account their demographic, cultural, and educational backgrounds (Heaton, Grant, & Matthews, 1986; Heaton, Ryan, Grant, & Matthews, 1996). A concerted campaign of effort has been undertaken to develop adequate norms for neuropsychological tests, usually now stratified at least by age, and often by education and gender (e.g., Strauss, Sherman, & Spreen, 2006). Stratification by cultural factors (or ethnicity as its closest proxy) also started being published in the last decade. Although still scarcely available or used, this latter stratification has been shown to be important to avoid misclassification of large demographic groups as impaired (Heaton et al. 2004; Norman et al. 2000, 2011; Taylor & Heaton, 2001).

It has been strongly suggested that diagnostic interpretations never be based on a single impaired test performance (Heaton & Marcotte, 2000). Indeed, intact individuals have been shown to obtain impaired scores on average across 10% of all administered tests, with 90% of people obtaining a least one impaired score in a battery of 40 tests (Heaton et al. 1991). This seemingly high occurrence of impaired scores has stemmed in part from a well-accepted definition of impairment as scores under one standard deviation below the mean. This threshold was suggested by Heaton et al. (1991) as bringing the best compromise between sensitivity – a test's ability to detect actual impairment, and specificity – a test's ability to correctly classify intact individuals. Their study examined Average Impairment Ratings, a summary score of the Halstead Reitan Battery (e.g., Reitan & Wolfson, 2009), on large samples of healthy subjects and verified patients. They reported optimal sensitivity and specificity of 80% and 88% for the Average Impairment Ratings. Of course, using a one standard deviation threshold to define impairment also means that any single test, taken on its own, will systematically classify about 15% of intact individuals as impaired.

Instead of single impaired performances, neuropsychologists have thus been encouraged to draw diagnostic impressions based on patterns of scores across tests and domains of function (Heaton & Marcotte, 2000; Kaufman, 1994; Meehl, 1950). Such patterns of scores, or neuropsychological profiles, have been examined for a wide variety of disorders in hundreds of studies. For example, detailed neuropsychological profiles have been published for mild and major neurocognitive disorders, including Alzheimer's disease, alcoholic Korsakoff's syndrome, Huntington's disease, dementia with Lewy bodies, frontotemporal lobar degeneration, and vascular dementia (e.g., Delis, Massman, Butters, Salmon, Cermak, & Kramer, 1991; Jak et al. 2009; Smits et al. 2012; Weintraub, Wicklund, & Salmon, 2012); movement disorders, including Parkinson's disease and progressive supranuclear palsy syndrome (e.g., Rohrer, Paviour, Bronstein, O'Sullivan, Lees, & Warren, 2010; Zgaljardic, Borod, Foldi, & Mattis, 2003); psychiatric disorders, including schizophrenia, bipolar disorder, attention deficit hyperactivity disorder, obsessive compulsive disorder, depression, and anxiety (e.g., Castaneda, Tuulio-Henriksson, Marttunen, Suvisaari, & Lönnqvist, 2008; Kim, Jang, & Kim, 2009; Kurtz & Gerraty, 2009; McLean, 2004; Tan & Rossell, 2014); developmental disorders, including autism, fetal alcohol syndrome, corpus callosum agenesis, and the effects of childhood maltreatment (e.g., Kavanaugh, Holler, & Selke, 2015; Mattson et al. 2010, Meyer & Minshew, 2002; Siffredi, Anderson, Leventer, & Spencer-Smith, 2013); and infectious disorders such as HIV (e.g., Cysique, Maruff, & Brew, 2006). Interestingly, though, among this wealth of research, neuropsychological profiles have never been published for intact individuals. In fact, a March 2014 PsychINFO search of “neurocognitive profile” or “neuropsychological profile” returned 613 results, almost all referring to studies characterizing patterns of neuropsychological scores in specific disorders. Therefore, although great resources have been available for comparing clinical neurocognitive profiles to profiles for known conditions, comparison with neurocognitive normality has remained mostly limited to the use of single test norms, one score at a time.

The lack of research on normal neuropsychological profiles stems, perhaps, from the traditional construction of norms for each neuropsychological test independently from the others. That is, even when a battery of tests was administered to the same large group of people, Gaussian curves and tables of standard scores or T-scores have been systematically constructed for every measure separately, including test performances, comparison indices, and summary scores (e.g., difference between Verbal and Performance Intellectual Quotients – Matarazzo & Herman, 1984; Wechsler, 1997; Global Deficit Score of the expanded Halstead Reitan Battery – Heaton et al. 1991, 2004; discriminability indices in the California Verbal Learning Test, II – Delis, Kramer, Kaplan, & Ober, 2000). Perhaps as a result of norm construction using unimodal normal distributions for each measure, cognitively healthy individuals have been almost invariably modeled as one large group, with an overall flat neuropsychological profile (i.e., a profile characterized by performances centered on T-scores of 50 across cognitive domains). These models do not assume, per say, that most people have a flat neuropsychological profile. In fact, within-individual variability has been recognized as common across cognitive domains (Schretlen & Sullivan, 2013) and “everyone has strengths and weaknesses” is often proposed as feedback in clinical settings (Spangenberg Postal, & Armstrong, 2013). However, by gathering all healthy individuals together into one large group, most models of neurocognitive normality have mathematically assumed a random distribution of those strengths and weaknesses across the general population. But is this assumption justified? Or could there be specific patterns of individual cognitive differences within the normal population, with particular strengths and weaknesses occurring more commonly within subgroups of cognitively intact individuals?

The present study explores the question of heterogeneity in normal neurocognition, starting with a literature review of the theories and empirical research that have contributed to examining individual differences in cognition. The review covers research that was undertaken in two parallel fields: the field of cognitive psychology, with the development of theories of cognitive styles and information processing; and the fields of neuropsychology and cognitive neuroscience, with considerations of the brain functional organization and associated cognitive processes, investigated under the two traditional right/left and dorsal/ventral brain divisions. The present study then proposes to take a neuropsychological approach and contribute to this research by characterizing patterns of individual differences across neurocognitive domains, using the expanded Halstead Reitan Battery normative dataset.

Cognitive Styles

The development of cognitive styles started in the 1930s, reflecting the work of experimental psychologists examining individual differences in cognitive and perceptual functioning (Bartlett, 1932). Many cognitive styles have been proposed over the years, often defined in terms of a dimension with two poles (Messick, 1976; Rayner & Riding, 1997). Examples of these dimensions include: analytical versus non-analytic processing (i.e., the extent to which one may focus on specific attributes rather than overarching themes – Kagan, Rosman, Day, Albert, & Philips, 1964), field-independency versus dependency (i.e., the ability to distinguish structures or forms from their surrounding field – Witkin & Asch, 1948), impulsivity versus reflectiveness (i.e., the extent to which one makes decisions quickly or carefully deliberates in uncertain conditions – Kagan et al. 1964; Messer, 1976), serialist versus holist processing (i.e., the tendency of learning and problem solving by using incremental versus global assimilation of details – Pask, 1976), adaptive versus innovative problem solving (i.e., the preference for using established procedures versus new perspectives – Kirton, 1976), abstract versus concrete thinking (i.e., the extent to which one prefers or is able of using abstraction – Harvey, Hunt, & Schroder, 1961), and verbal versus imagery processing (i.e., the use of verbal or imagery strategies when processing information – Paivio, 1971). These cognitive style dimensions have been noted to overlap significantly. For example, individuals with imagery cognitive styles were found to be more holistic and field-independent, whereas individuals with verbal cognitive styles were found to be more analytic and field-dependent (e.g., Kirby, Moore, & Schofield, 1988). Taking into account these overlaps, an integration of the various cognitive styles was proposed into two fundamental dimensions: “verbal-imagery” and “wholist-analytic” (Riding & Cheema, 1991). The verbal-imagery dimension – perhaps the most relevant to neuropsychological evaluation which traditionally distinguishes between verbal and perceptual ability assessment – is developed further in the following sections.

Dual Coding Theory. The development of the verbal-imagery cognitive style must be understood within the framework of Paivio’s (1971) Dual Coding Theory. The theory proposes two systems for the representation and processing of information: the verbal system (or symbolic system), which deals with language and concepts that are abstract; and the nonverbal system (or imagery-based system), which deals with nonlinguistic concrete objects and events (Paivio, 1971, 1991). Both systems were emphasized to be processing- and not stimulus-dependent, and may each deal with information presented in different modalities, including auditory, visual, tactual, and motor (Paivio 1971, 1991). Per Paivio, the verbal and nonverbal systems are assumed be structurally interconnected and functionally independent. The structural interconnection assumption implies the efficient spread of information from one system to the other, for example permitting evocation of objects from names and names from objects. The functional independence assumption suggests parallel activation of the systems, either one at a time or simultaneously, implying advantages such as additive memory effects. Such effect was verified in many experiments, where events presented simultaneously using both a name and a picture were shown to be more readily remembered than pictures or names alone (Paivio, 1971). It was also proposed that the verbal and non-verbal systems may be activated differentially depending on three parameters: the stimulus variables (e.g., a concrete word would activate the non-verbal system more than an abstract word), the task instructions (e.g., having to remember a word might recruit the non-verbal system more than simply reading it), and individual differences in terms of verbal and multi-modal imagery abilities (Paivio, 1971, 1991).

Verbalizers versus Imagers. Individual differences in terms of habits and abilities for using verbal versus imagery-based representations have been the subject of much research in the early years of the field of psychology. Galton (1883) conducted the first systematic empirical investigation of individual differences in symbolic habits, using a questionnaire designed to measure imagery vividness. He specifically asked subjects to imagine their breakfast tables, inquiring about levels of illumination, definition, and coloring. To his surprise, many people (especially scientists) reported little or no use of visual imagery, likely using abstract and verbal thinking instead. Binet (1894) also pursued the question of individual reliance on vivid imagery by interrogating blind folded chess players. He noted that amateurs tended to use very concrete imagery techniques – for example visualizing the chess board with its black and white squares – but that more experimented players used increasingly abstract strategies, mentally retaining only the chessmen's friend or foe characteristics and their geometric configurations.

On the basis that most people experience a certain degree of both verbal and imagery-based representations, it was suggested early-on that individual differences should be considered on a continuum instead of types, with distributions that were likely normal instead of multi-modal (e.g., Thorndike, 1914, pp.272). Ensuing studies have thus divided their subjects into groups with varying degrees of verbal or imagery habit or ability, with individual differences characterized by predominance of one type (e.g., Fernald, 1912). It is within this framework that the relation between cognitive styles and functional abilities has been subsequently investigated, often with the examination of representational differences across professional groups (Paivio, 1971 for a review). For example, Roe (1951) showed that biologists and experimental physicists tended to prefer visual imagery, whereas theoretical physicists, psychologists, and anthropologists reported habitual use of verbal symbolization. In a similar way, Uznadze (1966, p.131) reported that drama students had higher imagery abilities than other students, based on findings that they were more susceptible to a verbally-aroused tactile illusion.

In his Dual Coding Theory, Paivio (1971,1991) proposed that the verbal and non-verbal systems may be activated differentially depending on individual differences in verbal and imagery abilities (Paivio, 1971, 1991). The study of Kuhlman (1960) supported this proposition by showing a double dissociation in concrete versus abstract task performance in children classified as high or low imagers. Findings suggested that high imagers were better at recalling concrete visual stimuli and pairing them with names but worse at categorizing objects into abstract categories. By contrast, low imagers were better at categorizing objects into abstract categories, but worse in tasks involving concrete visual stimuli. It was thus concluded that imagery facilitates the memory and labeling of concrete objects but interferes with abstract concept-formation (Kuhlman, 1960). Another example of trade-off between concrete imagery and verbal symbolization abilities was presented by Luria (1968). In this rather extreme case study, a gifted young man was described with his thoughts being dominated by extremely vivid imagery, mostly in the visual modality but also accompanied by tactual kinesthetic and taste sensations. After observing for a few seconds tables featuring fifty numbers or letters, this young man could remember any designated cell and could do so for years afterwards (Luria, 1968). Upon questioning, he explained he could mentally see the tables and simply read off the characters. Luria noted, however, that this gift also came with disadvantages, notably due to the formation of concrete imagery without his control (e.g., concepts elicited by the word "justice" might be dominated by concrete evocations of a court room). As a consequence, extreme deficits were also observed in this young man for comprehending abstract concepts and using higher levels of cognition.

One of the greatest challenges for studying individual differences in cognitive styles has been to devise instruments that could adequately assess individual utilization of verbal versus imaginal modes of thinking. For that purpose, Paivio (1971) devised an individual differences questionnaire designed to evaluate preferential habits for using verbal versus imaginal representations (Paivio, 1971; Paivio & Harshman, 1983). The questionnaire, composed of 86 true-false items, included questions such as "I can easily picture moving objects in my mind", "I find it difficult to form a mental picture of anything", "most of my thinking is verbal, as though talking to myself", or "I have difficulty producing associations for words"

(Paivio, 1971, p. 496). Richardson (1977) later selected the 15 most discriminative items in this questionnaire to form the "Verbalizer-Visualizer Questionnaire", with proposed verbal and imagery subscales, and suggested the existence of three groups: "verbalizers" who prefer verbal over imagery strategies, "visualizers" who prefer imagery over verbal strategies, and "mixers" who do not have preference for one mode over the other. Attempts to relate the questionnaire results to cognitive performances have reached mixed conclusions. Although scores on the verbal subscale were shown to relate to measures of verbal ability, scores on the imagery subscale showed weak or no correlation with performance on visuospatial tasks and ratings of imagery vividness (e.g., Alesandrini, 1981; Green & Schroeder, 1990). Another approach suggested to rate individuals depending on their self-reported use of imagery while solving mathematical problems (Krutetskii, 1976; Lean & Clements, 1981). However, again, no clear relationship was found between imagery preferences during mathematical operations and spatial performance – in fact a trend was even noted suggesting that verbalizers tended to outperform visualizers on both spatial and mathematical tests (Lean & Clements, 1981).

A group of researchers recently proposed an explanation to the lack of correlation between imagery styles and performance on spatial tests, arguing that two types of cognitive styles needed to be distinguished, separating imagery strategies based on spatial representations from those based on figural representations (e.g., Blazhenkova & Kozhevnikov, 20008; Kozhevnikov, Hegarty, & Mayer, 2002; Kozhevnikov, Kosslyn, & Shepard, 2005). Specifically, they found that individuals who tended to use imagery for solving mathematical problems rather than verbal methods could be divided into two groups: individuals who scored high on spatial imagery tasks (e.g., mental rotation and mental paper folding) but poorly on object imagery task (e.g., judgment of fine texture and grain density, object identification in a degraded picture, ratings of vividness of mental images); and individuals who scored high on object imagery tasks but poorly on spatial imagery tasks (Kozhevnikov et al. 2005). In addition, when interpreting scientific graphs, a tendency to generate abstract images was found in imagers with high spatial ability, while detailed pictorial images were generated by imagers with low spatial ability (Kozhevnikov et al. 2002). Following the tradition started by Galton (1883) and Binet (1894), Kozhevnikov et al. (2005) also verified whether individual differences in preferred imagery strategies were related to individual differences in occupation. They found that visual artists (N=10) preferred and excelled at figural imagery and strategies, whereas scientists (10 physicists and 4 engineers) preferred and excelled at spatial imagery and strategies.

Interestingly, inconsistent with observations of possible trade-off between verbal and imagery abilities (e.g., Kuhlman, 1960; Luria, 1968), these studies did not report striking differences in visuospatial performances when comparing individuals who preferred verbal compared to imagery strategies (whether spatial or figural). In fact, verbalizers were found to perform at an intermediate level on all visuospatial tasks (Kozhevnikov et al. 2002, 2005). The comments provided by Paivio (1971, p.508) three decades prior when discussing Kuhlman's (1960) results may apply again to these recent considerations: "low imagers may have a greater preference for verbal thinking without being superior to high imagers in verbal ability." In other words, Paivio suggested that preference for one representational mode over the other may not imply greater ability in that domain compared to individuals with the opposite preference.

Right Brain versus Left Brain

Research on the brain's anatomy and functional organization has rather closely paralleled the research efforts on the verbal versus imagery cognitive styles, notably with considerations that associated brain functions may be lateralized to the right or left cerebral hemisphere. A review of these lateralized brain functions is provided here and the question of whether functional differences across hemispheres may translate into individual differences is addressed.

Functional Asymmetry of the Brain. Asymmetry between the right and left brain hemispheres has been demonstrated in decades of scientific studies in terms of structure, neurochemistry, and function (e.g., Springer & Deutsch, 2001; Toga & Thompson, 2003). In the vast majority of right-handers and in many left-handers, the left hemisphere has been shown to be dominant in mediating language functions, while the right hemisphere dominates for processing spatial relations and emotional control (e.g., Broca, 1861; Milner, 1971; Sperry, 1975; Spring & Deutsch, 2001). The production and understanding of language were initially proposed to be left lateralized by Broca (1861) and Wernicke (1874), respectively, based on their observation of patients who had lost those abilities following lesions of the left middle frontal gyrus and of the left upper posterior temporal lobe. The lateralization of language production was perhaps most strikingly confirmed in the first human split brain experiments (Sperry, 1975). In those studies, epileptic patients who had undergone a corpus callosum resection were presented with objects in either their right or their left visual field. Results showed that objects presented to the right visual field could be readily named (left hemisphere processing), whereas objects presented to the left visual field could not be named but could be identified in an array by left hand pointing (right hemisphere processing). During that time period, groups of researchers also started pointing out the unique and essential specialization of the right hemisphere in visuospatial and tactile-perceptual processing (e.g., Milner, 1971). For example, Milner & Taylor (1972) tested subjects in a delayed matching-to-sample task, with stimulus consisting of four tactile shapes made of wire. They found that patients with a corpus callosum resection were able to learn tactile matching-to-sample more efficiently with their left hand (right hemisphere processing) compared to their right hand (left hemisphere processing).

Examination of learning and working memory abilities in patients with lateralized brain lesions confirmed a left/right and verbal/visuospatial double-dissociation: that is, patients with left-lesions were shown to be impaired in verbal but not visuospatial tasks, and patients with right lesions were shown to be impaired in visuospatial but not verbal tasks (e.g., Corsi, 1972; Milner, 1971). The lateralization of verbal and visuospatial working memory processes to the left and right hemispheres was also confirmed by imaging, with reliable demonstrations of differential left activation for the short term retention of verbal information, compared to right activation for the retention of visuospatial information such as locations, line orientation, and faces (e.g., McDermott, Buckner, Petersen, Kelley, & Sanders, 1999; Owen, McMillan, Laird, & Bullmore, 2005; Rothmayr et al. 2007; Rämä, Sala, Gillen, Pekar, & Courtney, 2001; Smith & Jonides, 1997). Interestingly, consistent with Paivio (1971, 1991)'s dual coding theory, hemispheric specialization has been shown to be processing-dependent (i.e., making verbal versus visuospatial decisions) rather than stimulus-dependent, with lateralization of cognitive control operations such as response selection, response inhibition, or conflict monitoring to the same hemisphere as task execution (Stephan et al. 2003).

Although right lateralization has been reliably demonstrated for processing spatial information and faces, findings have been rather mixed for processing information pertaining to object feature such as shape and color, with suggestions of bilateral activation and even sometimes left lateralization of those processes (e.g., Brown, Sawyer, Nathan, & Shatz, 1987; Owen, McMillan, Laird, & Bullmore, 2005; Ragland et al. 2002; Smith & Jonides, 1997). For example, using position emission tomography, Smith & Jonides (1997) showed a double dissociation of visual and spatial working memory to the left and right hemispheres, with left-lateralized activation demonstrated during the retention of abstract shapes, compared to right-lateralized activation during the retention of spatial information. Further, in an n-back study requiring the short term retention of fractal shapes, differential left activation was demonstrated in the lingual gyrus (Ragland et al. 2002). These demonstrations of bilateral and even left brain activation during figural information processing have remained poorly understood, with the leading tentative explanations suggesting some degree of verbalization or symbolization of figural information (e.g., Smith & Jonides, 1997). Interestingly, the distinction between spatial and figural information processing is consistent with the finding of two distinct types of imagery-based cognitive styles, separating individuals preferring strategies based on spatial representations from those preferring strategies based on figural representations (Kozhevnikov et al. 2005). The distinction between spatial and figural processes will be further examined in a subsequent section on the functions of the brain's dorsal and ventral pathways.

Functional specializations have also been attributed to the left and right cerebral hemispheres beyond verbal and visuospatial processing (Bogen, 1969; Bradshaw & Nettleton, 1981). Notably, analytic and serial information processing have been shown to involve the left hemisphere differentially, while gestalt and synthetizing processing have been shown to involve the right hemisphere (e.g., Cohen, 1973; Efron 1963; Levy 1974; Nebes, 1978). Left hemispheric specialization has also been associated with abstract categorization (e.g., Levy, 1974); while right hemispheric specialization has been associated with emotional judgment and face recognition (e.g., Benton, 1980; Carey & Diamond, 1977).

Right-brainers versus Left-brainers. Although it is clear that the right and left cerebral hemispheres hold different functional specialty; it is less clear whether these anatomic differences translate into individual cognitive differences. Following Sperry's (1975) human split brain experiments, a surge of enthusiastic lay articles were published, extrapolating from his research and suggesting differences between people as being either left-brained or right-brained (e.g., Time magazine, 1974). In particular, it was suggested that left-brained individuals were more verbal, logical, and analytical whereas right-brained individuals were more intuitive, artistic, and creative. Despite warnings from Sperry himself, reminding readers that his research was based on patients and that "the two hemispheres in the normal intact brain tend regularly to function closely as a unit" (Sperry, 1984, p.668), the popular-culture version of the left/right brain theory built on itself through a wealth of magazine and book publications and became widely accepted (Kosslyn & Miller, chapter 5). Today, dozens of popular self-help books, websites, and apps can still be found, for example aiming at self-diagnosing whether one is more right-brain or left-brain or providing methods for re-establishing hemispheric equilibrium (e.g., Buzan, 1991; Edwards, 2012; Meindl, 2012; Psychtests, 2014).

Contrasting with widely held popular theories, scientific evidence has remained scarce supporting clear cut right-brained versus left-brained differences in terms of personality or cognitive styles within the general population. In fact, a recent fMRI study that examined resting state functional connectivity concluded against a left-brained versus right-brained phenotype (Nielsen et al. 2013). In that study, publically-available scans of 1011 individuals (ages 7 to 29) were analyzed. Nielsen et al. (2013) reported significant lateralized functional connectivity at rest in several regions of the brain, including regions specializing in language (left-lateralized) and attention control (right-lateralized). However, they found no evidence of greater left versus right network strength across individuals and concluded against left-brained versus right-brained individual characteristics.

Within the field of neuropsychology, the properties associated with the functional asymmetry of the brain have been mostly used to identify neurocognitive impairment rather than characterizing individual differences in the general population. This emphasis on impairment in neuropsychology may have naturally unfolded from the focus of its early pioneers. For example, Halstead, who published seminal studies of the brain basis of human higher cognitive functions, dedicated his life's work to studying individuals with known brain lesions, selecting his initial battery of tests on the sole basis of sensitivity to brain damage (Halstead, 1947). Following in the same spirit, Reitan, who was Halstead's student, undertook the challenging task of expanding and modifying the battery until it could provide correct diagnostic inferences for an entire range of known brain damage and diseases (Reitan & Wolfson, 1985, 2009). This process, which took 15 years and involved the systematic testing of thousands of cases, resulted in the early 1960s in the comprehensive instrument known as the Halstead Reitan Battery (HRB). During this process, tests were only added or kept if they contributed significantly to inferences for distinguishing between known patients and controls. Notably, tests were selected based on their sensitivity in indicating right versus left hemispheric involvement, anterior versus posterior involvement, focal versus diffuse lesion localization, acute versus chronic course, and type of damage or disease (Reitan & Wolfson, 2009). Among other summary indices, an intra-individual lateralization index was devised based on performance comparison across tests involving left versus right hemispheric cognitive specialties (i.e., verbal versus visuospatial abilities) and across tests of sensory-perceptual and motor functions involving the right versus left side of the body. Again, this lateralization index was solely used for the purpose of detecting brain dysfunction, based on the rationale that "many, if not most, brain disorders affect one hemisphere to a greater extent than the other hemisphere" (Reitan, 1955a; Reitan & Wolfson, 2009, p.8).

The Wechsler intelligent scales, another set of widely employed neuropsychological assessment tools introduced by Wechsler (1939), also looked into using lateralized brain function to help diagnose neurocognitive impairment (Kaufman & Lichtenberger, 2006, Chapter 11). Notably, in the original and revised versions of the Wechsler Adult Intelligent Scale (WAIS, WAIS-R, WAIS-III, Wechsler, 1955, 1981, 1997), two summary indices were proposed: the verbal intelligence quotient (VIQ) that averaged performances across all verbal subtests, and the performance intelligence quotient (PIQ) that averaged performances across all visuospatial subtests. An enormous amount of research has been conducted that related disparities between VIQ and PIQ performances to lateralized brain lesions and disorders (Kaufman & Lichtenberger, 2006, Chapters 8 & 9). In general, profiles with PIQ lower than VIQ have been associated with unilateral right hemisphere lesions, whereas VIQ lower than PIQ has been associated with unilateral left hemisphere lesions (e.g., Fields & Whitmyre, 1969; Satz, 1966). Profiles with VIQ lower than PIQ have also been related to conditions such as mental retardation, autism, learning disability, delinquency, and bilingualism (Kaufman & Lichtenberger, 2006, Chapter 9). Based on these findings, clinicians were initially taught that a "significant" VIQ/PIQ difference (i.e., 10 points and above from an instrumental reliability perspective) had diagnostic utility in identifying brain damage (e.g., Jones & Butters, 1983; Walsh, 1978). Kaufman (1976) and Matarazzo & Herman (1984, 1985), however, cautioned that a distinction should be made between "significant" and "abnormal" differences. That is, they pointed out that VIQ/PIQ differences that were reliably measured (or "significant") said nothing about their rates of occurrence in the normal population. In fact, using the WAIS-R test scores of 1880 cognitively healthy subjects, Matarazzo & Herman (1984, 1985) calculated base rates for VIQ/PIQ differences and found that discrepancies between indices were larger and more common than previously anticipated. They reported VIQ/PIQ differences that were strictly greater than 0 in 96% of the subjects, > 3 in 74% of the subjects, > 9 in 37% of the subjects, >15 in 15% of the subjects, > 21 in 6% of the subjects, and > 25 in 2% of the subjects. These results were striking, suggesting that 37% of intact individuals presented with a "significant" difference between their VIQ and PIQ scores, and that a minimum of 22 points were necessary to define unusual differences (i.e., occurring in less than 5% of the standardization sample).

Beyond issues of cutoff, the predictive validity of the VIQ/PIQ difference for identifying lesion lateralization has also been questioned (e.g., Iverson, Mendrek, & Adams, 2004; Lezak, 1995). Lezak (1995) noted that PIQ subtests, which consist mostly of activities that are unusual and timed, tend to be more sensitive than VIQ subtests to diffuse neuropathologies, thus making a PIQ<VIQ profile more likely as a result of traumatic brain injury or dementia. Further, Iverson et al. (2004) directly examined the sensitivity of the VIQ/PIQ difference in diagnosing lesion lateralization by testing 49 patients with cleanly lateralized right or left hemispheric lesions on the WAIS-R. Although they reported overall VIQ/PIQ differences in the expected direction when averaging across each patient group, they found that 61% of right-lesion patients had “significant” PIQ<VIQ differences (13% using the base rate cutoff) and only 23% of left-lesion patients had “significant” VIQ<PIQ differences (4% using the base rate cutoff). They concluded that VIQ/PIQ differences had no diagnostic predictive validity for left hemispheric lesions and had only very limited predictive validity for right hemispheric lesions. Taking into account these more recent studies, clinical interpretations of VIQ/PIQ differences continue to be encouraged, but with a strong caution that base rates be considered for abnormality interpretations and that this index never constitute the sole basis of a diagnosis (Kaufman & Lichtenberger, 2006, Chapter 11).

Research aimed at characterizing base rates of abnormal VIQ/PIQ discrepancies has provided valuable information for characterizing normal VIQ/PIQ differences with the general population. Notably, Matarazzo & Herman (1984) published a distribution of VIQ - PIQ scores, showing a frequency curve that was deemed overall normal and centered on zero, but that was flatter (with greater standard deviation) than previously expected. Further, Matarazzo & Herman (1985) examined factors that might impact the distribution of VIQ/PIQ differences. They found that greater overall intellectual abilities, as measured by the Full Scale Intelligent Quotient

(FSIQ), were associated with greater base rates of large VIQ/PIQ differences. For example, they reported VIQ/PIQ differences of more than 9 points in 33% of individuals with FSIQ=80-89, 46% of individuals with FSIQ=90-109, and 49% of individuals with FSIQ=110-119; and differences of more than 15 points in 10% of individuals with FSIQ=80-89, 19% of individuals with FSIQ=90-109, and 25% of individuals with FSIQ=110-119. With the goal of fitting these base rate data, a mathematical model of the VIQ-PIQ distribution was constructed more recently, assuming quadratic FSIQ dependence and normal VIQ-PIQ distributions at fixed FSIQ (Hsu, Hayman, Koch, & Mandell, 2000). The model provided a good fit of Matarazzo & Herman's (1985) data, and suggested distributions of VIQ-PIQ scores that were sharp and centered on zero at low FSIQs and became rapidly flatter with increasing FSIQ. These results, specifically the normal properties of the VIQ-PIQ distributions, appear also inconsistent with the existence of a dichotomous right brain versus left brain phenotype. It is notable, however, that a bimodal distribution model was never tested and the possibility that it could have provided a better fit of the flatter VIQ-PIQ distribution profiles at higher FSIQ may not be discarded.

In summary, lateralized brain functions appear to map rather well on the "verbal-imagery" and "wholist-analytic" fundamental cognitive style dimensions suggested by Riding & Cheema (1991); with the left hemisphere specializing in verbal and analytic information processing and the right hemisphere in spatial and gestalt processing. However, cognitive styles defined in terms of preferred strategy for processing information, have failed to reliably translate into individual differences in cognitive ability (e.g., Lean & Clements, 1981) or hemispheric dominance (e.g., Arndt & Berger, 1978). In fact, despite popular beliefs, solid evidence has been lacking for a right- versus left-brained phenotype (e.g., Nielsen et al. 2013) or for a bimodal classification of individuals in terms of verbal- versus perceptual-dominant cognitive abilities (e.g., Kozhevnikov et al. 2002, 2005; Matarazzo & Herman, 1984; Paivio, 1971).

Top Brain versus Bottom Brain

Having considered the limitations associated with the right-brained versus left-brained distinction, a new theory was recently proposed suggesting that individual cognitive differences may be understood along a vertical rather than lateral brain axis (Kosslyn & Miller, 2013). Kosslyn's theory of "cognitive modes" notably suggests that individuals may be divided into four groups depending on their differential usage of their "top-brain" versus "bottom-brain" systems. The foundation of the theory is examined in this section, followed by a description of these proposed cognitive modes.

Dorsal and ventral pathways. Kosslyn's theory of cognitive modes takes roots in decades of neurological and neuropsychological research aiming at identifying and characterizing the functions of the dorsal versus ventral portions of the brain, roughly separated by the Sylvian fissure. The ventral and dorsal pathways were first distinguished within the field of visual processing, with the functional and anatomic identification of brain regions specializing in object property versus spatial relations (e.g., Haxby et al. 1991; Ungerleider & Mishkin, 1982). The ventral system, or "what" pathway, was shown to process information such as shape, size, color, or texture, and to project from the primary visual cortex in the occipital lobe to the inferior temporal lobe. By contrast, the dorsal system, or "where" pathway, was shown to specialize in object location and orientation in space and to project from the primary visual cortex to the posterior parietal lobe.

Since the publication of those studies, the definition of the ventral and dorsal pathways has been extended both in terms of brain region and function. First, the dorsal and ventral pathways have been found to project actively to the dorsolateral and ventrolateral prefrontal cortices, where they have been shown to mediate object and spatial working memory, respectively (e.g., Wilson, Scalaidhe, and Goldman-Rakic, 1993). These findings were also supported by demonstrations of independent store and rehearsal mechanisms in working memory for remembering figural information such as shape and color compared to location and orientation in space (Della Sala, Gray, Baddeley, Allamano, & Wilson, 1999; Klauer & Zhao, 2004). The dual pathway of information processing was also shown to generalize to other modalities. For example, in the auditory modality, a dorsal stream was proposed, projecting from the primary auditory cortex (Heschl's gyrus within the lateral sulcus transverse to the superior temporal gyrus) to the inferior parietal and posterior frontal regions, and specializing in auditory-motor integration; and a ventral stream was proposed, projecting from the primary auditory cortex down to the middle and inferior temporal cortices, and specializing in processing the meaning of sounds (Hickok & Poeppel, 2004, 2007). Finally, the dorsal and ventral pathways have also been distinguished as mediators of top-down versus bottom-up processes. For example, dorsal fronto-parietal connections have been proposed to mediate actions (Goodale & Milner, 1992) and to play an essential role in the voluntary allocation of attention (e.g., Posner, 1980; Sereno, Pitzalis, & Martinez, 2001). By contrast, ventral fronto-parietal connections, especially in the right hemisphere, have been proposed to control attention to unexpected stimuli as detected by the senses (Corbetta & Shulman 2002; Vossel, Geng, & Fink, 2013).

Theory of cognitive modes. Kosslyn proposed a summary and extension of the research on the brain dorsal and ventral pathways by using an information processing model (Borst, Thompson, & Kosslyn, 2011; Kosslyn & Miller, 2013). As part of the theory of "cognitive modes", a "bottom-brain system" was suggested, encompassing the occipital, temporal, orbito-frontal, and ventromedial frontal cortices, that deals with organizing information perceived by the senses, comparing it with memory content, and classifying and interpreting that information to form an input signal. The inclusion of the limbic system was also proposed as part of the bottom-brain system, subserving the transmission of information pertaining to emotional reactions and needs (e.g., eating, drinking). Interacting closely with this bottom-brain system, a “top-brain system” comprising the parietal and remaining portion of the frontal lobes was suggested as manager of executive functions, including devising goals and plans, generating expectations, and monitoring and adjusting the carrying-out of plans. Such a summary of the brain functional organization in terms of two interacting systems is not new. In fact, in 1970, Luria had proposed a division of the higher cortex into blocks with very similar functions and reasonably close neuroanatomy. Luria’s “block 2”, composed of the parietal, occipital, and temporal lobes, was suggested to play a central role in the analysis, coding, and storage of information; and his “block 3”, consisting of the frontal lobes, was proposed to mediate attention regulation and the generation of intentions and behavioral programs (Luria, 1970). It is notable that Luria had also proposed a subcortical “block 1”, comprising the brain stem, thalamus, and hypothalamus, with function to regulate wakefulness and the intensity of the brain’s response to stimuli.

Kosslyn went yet a step further in his theory by proposing that individuals could be categorized depending on their utilization of their top- versus bottom-brain systems on a low-to-high continuum (Kosslyn & Miller, 2013). Four cognitive modes were defined, each with implications for the personality of individuals who tend to preferably think with this pattern: (1) the “mover mode” (i.e., high top- and bottom-brain use), encompassing individuals likely to make plans, act on them, see the consequences of their actions, and adjust plan accordingly; (2) the “perceiver mode” (i.e., low top-brain versus high bottom-brain use), encompassing individuals that are good at perceiving and making sense in depth of their experiences, but display less of a tendency to initiate plans; (3) the “stimulator mode” (i.e., high top-brain versus low bottom-brain use), encompassing individuals who tend to initiate plans, but display limited awareness and adjustment of their behavior, and may therefore present as creative and original but also disruptive; and (4) the “adaptor mode” (i.e., low top- and bottom-brain use), encompassing individuals with low tendency for initiating plans or interpreting and classifying their experiences, but may adapt without resistance to new environmental demands. As pointed out by Kosslyn & Miller (2013), if their description of the brain functional organization into top- and bottom-brain systems was derived based on a wealth of research, their categorizing of individuals into groups depending on their dominant cognitive mode is purely theoretical and has yet to be supported by data. The current project proposes to utilize neuropsychological data to evaluate this theory.

This Study: Hypotheses and Implications

The present study proposes to identify and characterize patterns of individual differences in neuropsychological abilities within the general population. Specifically, it is proposed to characterize the neuropsychological profiles of cognitively-healthy individuals by using latent profile analysis on the expanded HRB normative database (Heaton et al. 2004). This method will test the general assumption that normality is homogeneous by deciphering whether healthy individuals all belong to one group with average cognition and random between-subject variability or whether they can be separated into a number of smaller homogeneous groups with well-defined neurocognitive profiles.

The proposed work is suggested to have significant implications for validating theories of brain function, as well as potential applications in domains including education, neuropsychological assessment, and neuropsychological research methods. First, if as hypothesized, cognitively intact individuals can be separated into homogeneous groups with well-defined neurocognitive profiles, the patterns of those profiles may allow inferences on dominant theories of brain function. For example, Kosslyn's theory of cognitive modes may suggest that four separate groups will be found, distinguished in terms of their high/high, high/low, low/high, and low/low performances on tests involving information perception, organization, classification, memory, and interpretation ("bottom-brain" tests) compared to tests involving voluntary attention allocation, executive function, and spatial skills ("top-brain" tests). By contrast, Paivio's dual coding theory and research on lateralized brain functions and VIQ/PIQ differences may suggest four groups distinguished in terms of their high/high, high/low, low/high, and low/low performances on tests involving verbal versus perceptual abilities.

As an alternate hypothesis, it is also possible that individual differences within the general population may be better characterized by horizontal divisions separating groups of individuals with high, average, or low abilities in all cognitive domains. Such a ladder-like configuration would support the hypothesis that flat neuropsychological profiles represent the cognitive norm within the general population. In that case, cognitive heterogeneity would be essentially defined in terms of level of general cognitive ability, with some individuals simply having more brain reserve capacity (Satz, 1993), pool of mental energy (Spearman, 1904), or intelligence (Wechsler, 1955) than others. Such a ladder-dominated configuration has been reported in previous studies that performed cluster analysis on the normative samples of child or adult neurocognitive batteries (e.g., Donders, 1996; Konold, Glutting, McDermott, Kush, & Watkins, 1999; McDermott, Glutting, Jones, & Noonan, 1989). For example, McDermott et al. (1989) performed sequential minimum-variance cluster analysis using the scaled scores of the WAIS-R normative dataset (N=1,880, Age=16-74). They reported 9 core profile types essentially distinguished by their overall ability levels, with 6 flat profiles characterized as "Low", "Below average", "Slightly below average", "Average", "Above average", and "High", and 3 profiles with some variations characterized as “Slightly below average with higher Digit Symbol”, “Slightly above average with VIQ>PIQ”, and “Above average with VIQ>PIQ”. In a similar fashion, Konold et al. (1999) performed a multistage cluster analysis using the normative dataset (N=2,200, Age=6-17) of the Wechsler Intelligence Scale for Children – Third Edition scaled scores (WISC-III, Wechsler, 1991). They reported 8 core profile types also essentially distinguished by ability levels, including four types displaying some profile pattern (“High ability”, “Above average”, “Above average and VIQ>PIQ”, “Average and VIQ>PIQ”, “Average and PIQ>VIQ”, “Below average and VIQ>PIQ”, “Below average”, and “Low”). Methodological limitations associated with cluster analysis have been argued to be partially responsible for these ladder-like findings, with large differences in profile elevations commonly obscuring more subtle differences in profile patterns (Moses, Pritchard, & Faustman, 1994). To circumvent these problems, other techniques were subsequently suggested, including modal profile analysis (MPA), a mixture of cluster analysis and Q-factor analysis, and profile analysis via multidimensional scaling (PAMS), which solely reflect differences in profile shape rather than profile elevation, (e.g., Davidson, Gasser, & Ding, 1996; Kim, Frisby, & Davison, 2004; Moses et al. 1994; Pritchard, Livingston, Reynolds, & Moses, 2000). However, a downside of these methods has been indeed the loss of information in overall ability levels, which likely rightfully represent a non-negligible portion of between-individual variance in cognitive abilities. Another possible explanation for the ladder-like findings in previous cluster analyses may be the presence of confounding factors, such as education and culture, which might have impacted cognitive test performance beyond cognitive ability (e.g., Heaton et al. 1986, 1996; Manly et al. 2005; Reynolds, Chastain, Kaufman, & McLean, 1987). For example, Konold et al. (1999) found that their “high ability” group tended to be over-represented by Caucasian children and have parents with higher educational levels. In other words, it is possible that by failing to control for demographic factors beyond age, previous studies have clustered together individuals that had similar demographic and cultural backgrounds rather than solely similar cognitive styles.

Characterizing normal neuropsychological profiles has evident applications to the field of clinical neuropsychology. First, in clinical settings, the description and frequency of normative profiles could provide information at the pattern level on how unusual a patient's profile may be, beyond considerations of single scores being within normative expectations. Such comparison would be especially important if, as hypothesized, normal cognition is better described by clusters of individuals sharing similar patterns of strengths and weaknesses rather than by a continuous ladder of homogeneous flat profiles. Second, in research settings, normative profiles may provide new points of comparison for evaluating neuropsychological patterns associated with specific disorders. For example, it is possible that neurocognitive profiles associated with certain psychiatric illnesses may differ significantly from the flat profile obtained after averaging indiscriminately over all comparison subjects, but may be similar to the profile of one cluster of comparison subjects.

Various methodological applications may also be envisioned. First, neuropsychological studies frequently encounter difficulties with the recruitment of their comparison subjects, who often consist of undergraduate students and unemployed individuals due to scheduling constraints. The characterization of clusters of normative neuropsychological profiles could help decipher whether a group of recruited healthy comparison subjects is indeed representative of cognitive normality, or whether it is only representative of a subset of clusters. Further, in brain imaging studies where between-subject variability represents a great source of signal noise (e.g., Wong et al. 2008), the proposed profile analysis may permit classification of healthy comparison subjects into cognitively homogeneous groups and thus contribute to signal improvement.

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METHOD

Participants

The present study uses the extensive dataset collected as part of the expanded HRB (eHRB) normative effort, a multi-center collaborative effort conducted over a period of 25 years (Heaton et al. 1991; 2004). The subjects were recruited from both urban and rural areas in the context of several studies that took place in various North American states, including California, Washington, Colorado, Texas, Oklahoma, Wisconsin, Illinois, Michigan, New York, Virginia, and the Canadian province of Manitoba. Among others, these studies included a large multisite study on supplemental oxygen treatment for severe chronic obstructive pulmonary disease (Heaton, Grant, McSweeny, & Adams, 1983), an epidemiologic study of organophosphate pesticide poisoning (Savage et al. 1988), studies on neuropsychological functioning associated with HIV infection (Heaton et al. 1995), and work specifically conducted for the eHRB norming project, associated with the construction of African American norms (Norman et al. 2000, 1011). The same standardized procedures and testing and scoring guidelines were promoted and emphasized across studies, with close supervision carried out by senior staff members and systematic double-checking of scores by experienced examiners (Heaton & Heaton, 1981). Most participants were paid for their time. Subjects were excluded based on structured interviews if they endorsed any history of neurological disorder, medical condition that might affect the brain, significant head trauma, learning disability, serious psychiatric disorder, and substance use disorder. Effort during testing was also assessed to be sufficient based on formal effort testing and/or examiner's ratings.

Among individuals who were administered at least half of the eHRB measures (N= 1319, age=20-85, education=7-20), the normative sample consisted of 580 female and 739 male participants, and of 628 African American and 691 Caucasian participants, with sizeable representation of all age and education groups. This sample composition has constituted the largest African American recruitment by far of any neuropsychological normative study, permitting demographic corrections pertaining to age, education, and gender, but also ethnicity (Heaton et al. 2004). Because memory was deemed a potentially important criteria of classification, only the participants that had been administered at least one of the three possible eHRB memory measures were included in the present study. The final sample – N= 982, age = 47.2 years (SD = 18.0), education = 13.7 years (SD = 2.5) – was composed of 443 female and 539 male participants, and 618 African American and 364 Caucasian participants. Because memory tests were more systematically administered during the second wave of the eHRB normative effort which also focused on establishing African American norms (Heaton et al. 2004) as compared to the first wave (Heaton et al. 1991), the focus sample of the present study is notable for including 26% more African American than Caucasian participants. This distribution, although not representative of the overall U.S. population in terms of proportions, provides a unique framework for comparing neuropsychological profiles across ethnicity and culture. Information on handedness was also available, and the final sample included 876 right-handed and 106 left-handed individuals with demographically similar compositions (i.e., left-handers were 64 male / 42 female, 62 African American / 44 Caucasian).

The demographic distribution of the sample was examined using Pearson Chi-square tests and univariate analyses of variance on age and education with gender, ethnicity, and handedness as independent variables. The proportion of females was significantly greater (χ^2=44.4, p<.001) in the African American sample (329 females / 289 males) compared to the Caucasian sample (114 females / 250 males). The sample did not differ significantly in age across ethnicity ($F(1,974)$=2.327, p=.127, η^2=.002) or handedness ($F(1,974)$=1.578, p=.209,

η^2=.002), but there was a small-effect age difference (*F(1,974)*=13.289, *p*<.001, η^2=.013) between males (*M*=44.3, *SD*=17.2) and females (*M*=50.8, *SD*=18.4). Further, the sample did not differ significantly in education across gender (*F(1,974)*<.001, *p*=.983, η^2<.001) or handedness (*F(1,974)*=.001, *p*=.971, η^2<.001), but there was a small-effect education difference (*F(1,974)*=21.538, *p*<.001, η^2=.022) between Caucasian (*M*=14.4, *SD*=2.5) and African American (*M*=13.4, *SD*=2.5). There was no significant interaction between gender, ethnicity, or handedness on the distributions of age and education (*ps*=.148 to .893). Because corrections for age and education are carried out in the study, the small effect-differences noted in the demographic composition of the sample are not expected to have affected the conclusions of the study.

Neuropsychological Test Battery

The number of tests that were systematically administered to the same individuals as part of the eHRB normative effort was considerable, likely constituting the most comprehensive neuropsychological dataset available to date. This section describes these tests, dividing them into three parts: the tests that were part of the original HRB (Reitan & Wolfson, 1985, 2009), the tests that were added to form the eHRB (Heaton et al. 1991, 2004), and the Wechsler scales' subtests (Wechsler, 1955, 1981). The measures derived from each test are presented in Table 1 with a breakdown of the abilities they likely represent.

The Halstead-Reitan Battery (HRB). The HRB has been one of the first widely used test batteries for assessing brain dysfunction (Reitan & Wolfson, 1985), and continues to enjoy widespread utilization with a 6th place rank in 2005 among instruments most frequently used in clinical neuropsychological evaluations (Rabin, Barr, & Burton, 2005). The HRB is unique in that it was developed with a solely practical intent of detecting brain disorder, rather than based on a theory. A model of neuropsychological functioning – the Reitan-Wolfson model – was only later related to it, essentially derived from the selection of tests that had emerged as sensitive indicators of brain damage (Reitan & Wolfson, 1993). The tests that constitute the HRB are described and organized in this section following the theoretical framework of the Reitan-Wolfson model (Reitan & Wolfson, 2009). Interestingly, this model suggests steps of information processing that are representative of both the right-left and top-down models of brain function described in previous sections.

The first phase of central information processing in the Reitan-Wolfson model is the “registration phase”, involving alertness, attention, concentration, and the ability to sort information relative to prior experiences using immediate, intermediate, and remote memory. To evaluate alertness and attention, two HRB tests were proposed: the *Speech-Sounds Perception Test,* consisting of 60 trials requiring discrimination between four tape-recorded nonsense syllables (e.g, “weem”, “weer”, “weez”, or “weeth”); and the *Seashore Rhythm Test*, consisting of 30 trials requiring discrimination between two rhythmic beats.

The second phase in the Reitan-Wolfson model suggests verbal information processing in the left hemisphere and visuospatial processing in the right hemisphere. To evaluate verbal functions, the *Reitan-Indiana Aphasia Screening Test* was proposed, consisting of short tasks such as naming common objects, reading, writing, and repeating simple words, explaining a short sentence, and performing simple arithmetic calculations. To evaluate visuospatial functions, *Spatial Relations* tasks were proposed, consisting of spontaneously drawing simple shapes (e.g., a square and a triangle) and copying drawings (e.g., a cross and a key) – these tasks were also administered as part of the *Reitan-Indiana Aphasia Screening Test*. The WAIS verbal and performance subtests were also suggested to be included as part of the evaluation of verbal and visuospatial abilities (Reitan & Wolfson, 1985, 2009).

To further assess right versus left hemisphere functioning, a series of sensory-perceptual and motor tests was also included in the HRB, with the idea of comparing performances on the left versus right sides of the body. Two sensory-perceptual tests were proposed: the *Reitan-Kløve Sensory-Perceptual Examination (SPE),* which assesses tactile, auditory, and visual perception through the presentation of stimuli on either or both sides of the body; and the *Tactile Form Recognition Test (TFR)*, requiring identifying shapes successively held in one hand. Two tests of gross motor skills were also proposed: the *Finger Tapping Test*, requiring quickly tapping a lever with the forefinger of each hand; and the *Grip Strength Test*, involving squeezing a handle forcefully. The *Tactual Performance Test (TPT)* was also proposed as part of the assessment of lateralized functions. The test requires quickly fitting a number of wood or foam shapes into their proper spaces on a vertical board while blindfolded. It is carried out in three trials, successively testing the dominant hand, non-dominant hand, and both hands. After the blindfold is removed, participants are asked to remember the shapes and their spatial location by drawing the vertical board with its cut-out shapes. This test was suggested to involve a series of complex abilities, including tactile form discrimination, kinesthesis, motor coordination, manual dexterity, the association of shape configurations with spatial locations, problem-solving and organizational skills, and memory (Reitan & Wolfson, 2009).

The third phase in the Reitan-Wolfson model is suggested to be the highest level of processing, consisting of abstract reasoning, concept formation, and logical analysis. Two tests were proposed to assess these skills: the *Category Test* and *Trail Making Test*. In the *Category Test*, participants are presented with geometric figures and must decide whether they remind them of the numbers 1, 2, 3, or 4. The test is divided into four 52-picture subtests, each with a different principle to uncover. Feedback is provided after each response. The test has been suggested to recruit complex abilities including abstraction, problem solving, logical analysis, organized planning, and organized memory (Reitan & Wolfson, 2009). In the *Trail Making Test*, participants must trace lines as fast as possible linking circled numbers or letters scattered on a page. The test is divided into two parts, the first one requiring simple number sequencing (Part A), and the second requiring number and letter sequencing and set-switching (Part B). The test was suggested to involve simultaneous integration of several key abilities, including visual scanning, processing speed, and cognitive flexibility; and was identified as one of the best indicator of general brain function (Reitan, 1955b; Reitan & Wolfson, 2009).

The expanded Halstead-Reitan Battery (eHRB). One of the main aims of the eHRB normative effort was to improve diagnostic accuracy in neuropsychological assessment by providing simultaneous corrections for demographic variables known to impact neuropsychological test performance (Heaton et al. 1991, 2004). In the context of this effort, a series of tests was added to the HRB, including tests of language, executive function, attention, processing speed, and memory.

The added language tests included the *Boston Naming Test (BNT)*, requiring naming 60 visually-presented pictures (Kaplan, Goodglass, & Weintraub, 1983); the *Complex Ideational Material Subtest of the Boston Diagnostic Aphasia Examination* (BDAE), a test of auditory comprehension requiring yes/no responses to 12 two-part questions, including four questions about commonly known facts and 8 questions about brief read-aloud stories (Goodglass & Kaplan, 1972); and the *Reading Recognition, Spelling, and Reading Comprehension subtests* of the *Peabody Individual Achievement Test (PIAT)* (Dunn & Markwardt, 1970), respectively requiring reading words aloud, choosing correct word spelling among multiple-choices, and choosing scenes best depicting a short story presented in writing immediately before among four picture-drawings. Beside language abilities, the *PIAT Reading Comprehension subtest* was also suggested to involve memory processes, making this subtest particularly sensitive to acquired brain dysfunction (e.g., Heaton, Schmitz, Avitable, & Lehman, 1987).

Several fluency tests were added assessing language production skills but also fundamentally involving executive function: the *Thurstone Word Fluency Test*, a test of written fluency, requiring writing down as many words as possible first starting with the letter “S” and then both starting with the letter “C” and composed of four letters (Pendleton, Heaton, Lehman, & Hulihan, 1982); and *Letter and Category Fluency*, tests of oral fluency, requiring saying as many words as possible either starting with a specific letter (“F”, “A”, and “S”) or representing names of animals (Gladsjo et al. 1999). Another test involving high attentional and executive demands was also added, the *Paced Auditory Serial Addition Test (PASAT)*, a test of verbal working memory and processing speed, requiring continuously adding the two most recent digits in a series of audio-taped digits presented at increasing speeds (Diehr, Heaton, Miller, & Grant, 1998; Gonzalez et al. 2006; Tombaugh, 2006).

To assess simple attention and psychomotor speed, the *Digit Vigilance Test* was added, requiring crossing out as rapidly as possible the number 6 in two large digit arrays. The two measures derived from this test – number of errors and completion time– were found to be essentially unrelated, reflecting abilities of visual attention and processing speed, respectively (Lewis, 1995). The *Grooved Pegboard* test was also added as part of the eHRB to assess fine motor skills and psychomotor processing speed; the test requires placing 25 pegs into a board using either the dominant or non-dominant hand (Reitan & Davison, 1974).

Finally, three comprehensive memory tests were added as part of the eHRB, assessing abilities for learning and recalling verbal and figural material after a delay. First, in the *California Verbal Learning Test* (*CVLT*, Delis, Kramer, Kaplan, & Ober, 1987), a word list (List A) is presented in five learning trials, each time requiring immediate recall of as many items as possible. A single interference trial is then administered, requiring immediate recall of a second word list (List B). Delayed recall of the first word list is assessed twice, immediately after the interference trial (short delay) and after a 20 minute delay (long delay). Second, in the *Story Memory Test* (Berry, Heaton & Kirby, 1977), a short story authored by Reitan and containing 29 pieces of information is presented requiring immediate recall. The story is repeated until retention of at least 15 out of 29 pieces of information is demonstrated with a maximum of 5 allowed trials. Delayed recall is assessed four hours later. The *Figure Memory Test* employs a procedure similar to that of the *Story Memory Test*, but requiring remembering material consisting of figures from the Visual Reproduction subtest of the Wechsler Memory Sale (Wechsler, 1945). During the learning trials, the entire visual material is presented on three successive cards up to five times, until participants are able to draw the figures with a level of accuracy of at least 15 points. Delayed recall is again assessed four hours later.

The WAIS and WAIS-R subtests. Over the 25 year course of the eHRB normative effort, two versions of the Wechsler scales were administered, the WAIS (Wechsler, 1955) and the WAIS-R (Wechsler, 1981). Both versions consist of 11 subtests divided into two subscales, the Verbal and the Performance subscales.

In the Verbal subscale, the three first subtests involve skills highly related to general knowledge and past experiences. These subtests include: *Information*, requiring answering questions of general factual knowledge; *Vocabulary* requiring defining words presented visually or orally; and *Comprehension*, assessing understanding of general principles and social situations, requiring common sense and the ability to use past experiences. The *Similarities* subtest may be distinguished from the three previous ones for recruit abstraction and reasoning skills beyond sheer word knowledge. In this test, participants are presented with pairs of words and required to perceive common elements between them and find underlying common concept.

Answers are rated on a scale varying between 0, 1, and 2 based on level of abstraction. The two last subtests included as part of the verbal subscale involve higher levels of attention, concentration, and working memory. These tests are the *Digit Span* subtest, requiring participants to repeat increasingly long series of digits, first forward and then backward; and the *Arithmetic* subtest, requiring mental solving of orally-presented arithmetic problems. The *Arithmetic* subtest was shown to be particularly related to educational and occupational attainments (Kaufman & Lichtenberger, 2006).

The Performance subscale first includes two tests shown to significantly relate to individual experiential and cultural backgrounds: *Picture Completion*, a test of essential detail differentiation requiring identifying missing parts in a series of pictures in a timely manner (e.g., a slit in a screw); and *Picture Arrangement*, a test of nonverbal social intelligence requiring arranging a set of pictures in order so that they tell a sensible story. Two tests of visuospatial assembly are also included, both involving organizational abilities: *Block Design*, which requires arranging bi-color blocks together in a timely manner so that they form patterns similar to presented pictures; and *Object assembly*, which requires assembling parts of cut-up drawings of objects (similar to puzzles). The last test forming the Performance subscale is *Digit Symbol-Coding*, a test of processing speed requiring efficiently copying symbols paired with specific digits.

The WAIS-R has been described as an improved version of the WAIS with a new standardization sample (Kaufman & Lichtenberger, 2006, Chapter 3). The content of the subtests was indeed very similar between the WAIS and WAIS-R, with percentage of items retained of 69% for *Information*, 83% for *Vocabulary*, 86% for *Comprehension* and *Arithmetic*, 77% for *Similarities*, 67% for *Picture Comprehension*, 75% for *Picture Arrangement*, 90% for *Block Design*, and 100% for *Object Assembly*, *Digit Symbol-Coding*, and *Digit Span* (Kaufman

& Lichtenberger, 2006). Several correlation studies were carried out by testing individuals on both the WAIS and WAIS-R administered after a 3 to 6 week interval in a counterbalanced order (Ryan, Nowak, & Geisser, 1987). From these studies (N=420 in eight groups), it was concluded that nine of the 11 subtests correlated sufficiently well to support continuity of measurement from the WAIS to the WAIS-R. Highest correlations were reported for *Information, Vocabulary, Arithmetic, Similarities,* and *Block Design*. Only two subtests, *Picture Completion* (.68) and *Picture Arrangement* (.58), showed inadequate correlations across WAIS and WAIS-R versions, likely related to greater change in subtest content across versions. Considering this lack of supported measurement continuity across WAIS versions, caution should be exercised in the current project when interpreting results from these two subtests in analyses involving merging the WAIS and WAIS-R databases.

In terms of normative samples, differences are noted between the WAIS and WAIS-R education level distributions. For example, 36% of individuals in the WAIS normative sample compared to 16% in the WAIS-R had 8 years of education or less; and 14% of individuals in the WAIS sample compared to 25% in the WAIS-R had some college education or more (Kaufman & Lichtenberger, 2006). Differences in education levels between the WAIS and WAIS-R normative samples were verified to match the 1950s and 1970s U.S. Census data, and are thus representative of a real increase in the population's educational level between those times. Nonetheless, these differences must be kept in mind when comparing age-corrected scaled scores between the WAIS and WAIS-R. Indeed, if one was to administer both the WAIS and WAIS-R to similar groups of people in the 1980s using the raw to scaled score conversion tables published in Wechsler (1955) and Wechsler (1981), respectively, higher IQ scores might be expected in individuals who were administered the WAIS compared to those who were administered the WAIS-R, for the sole reason that they would be compared to an overall less educated population. Such findings were reported in a study comparing performance on British versions of the WAIS and WAIS-R in two U.K. samples matched for age, gender, and education (Crawford et al. 1990). Results suggested Full Scale IQs higher by 8.2 points on average when using the WAIS compared to the WAIS-R version. This point will be particularly relevant to the current project in considerations of merging the WAIS and WAIS-R databases. (Further discussion is provided in the Data Analysis section.)

Data Analysis

To test the hypothesis of heterogeneity in cognitive normality, the present project used latent profile analysis on the extensive dataset collected over the course of the eHRB normative project. A series of preliminary factor analyses and complementary post-hoc analyses was also carried out to evaluate the domains of cognitive functions covered by the various test measures, limit methodological confounds, and provide demographic comparison of resulting profiles.

Latent Profile Analysis. Mixture modeling techniques such as latent profile analysis, latent class analysis, or latent growth modeling are statistical methods that aim to uncover unobserved heterogeneity in a population by identifying meaningful groups of people sharing similar patterns of scores on measured variables (e.g., Lazarfeld, 1950; McCutcheon, 1987; Muthén, 2004). These approaches are person-centered rather than variable-centered in that they focus on describing relationships among individuals rather than among variables as in regression or classic R factor analysis. Because population heterogeneity cannot be observed, it is modeled using a latent categorical variable that represents the number of homogeneous groups (or latent classes) underlying the population. Among other mixture modeling techniques, Latent Profile Analysis (LPA) is deemed particularly adapted to the present study as it permits analysis of continuous rather than categorical observed measures (Lanza, Flaherty, & Collins, 2003). In addition, because it is model-based (i.e., involving probability estimates), LPA has been gauged superior to classic clustering analyses such as K-means clustering involving centroid calculations (Vermunt and Magidson, 2002). LPA has been increasingly used in behavioral and social sciences in recent years, for example in characterizing profiles of eating disorders, child maltreatment, fetal alcohol syndrome, frontotemporal lobar degeneration, and executive functioning (e.g., Borroni et al. 2007; Mattson et al. 2010; Rau, 2013; Roesch, Villodas, & Villodas, 2010; Wade, Crosby, & Martin, 2006).

The LPA mathematical model has been described in detail by Vermunt & Magidson (2002). The model is based on expressing the probability of obtaining a certain pattern of scores on a number of continuous observable measures as:

$$f(Y = y) = \sum_{i=1}^{N} P(lc = i) f(Y = y|gp = i), \qquad (1)$$

where $f(Y = y)$ is the probability density of obtaining the pattern of scores $y=\{y_1, y_2, \ldots, y_q\}$ on q continuous observable measures, N is the number of latent classes, $P(lc = i)$ is the probability of belonging to the i^{th} latent class (or proportion of individuals in the i^{th} latent class), and $f(Y = y|gp = i)$ is the probability density of obtaining the pattern of scores y for individuals in the i^{th} latent class. In classic LPA, a local independence assumption is combined to this model. This assumption, which supposes independence of the observed measures within each latent class, may be expressed as:

$$f(Y = y|lc = i) = \prod_{j=1}^{q} f\left(Y_j = y_j \middle| lc = i\right), \qquad (2)$$

where $f\left(Y_j = y_j \middle| lc = i\right)$ is the probability density of obtaining a score y_j on the j^{th} observable measure for individuals in the i^{th} latent class. Within each latent class, the distribution of scores on all q measures is also assumed to be multivariate normal. Maximum likelihood techniques are then employed to find latent grouping that will maximize homogeneity within classes and heterogeneity between classes. This goal may also be expressed in the terms of maximizing the likelihood of obtaining N specific patterns of scores, one for each latent class, with the logarithm of this likelihood expressed as:

$$ln(L) = \sum_{i=1}^{N} n_i \ln\left(f(Y = \overline{y_i})\right), \quad (3)$$

where n_i represents the proportion of individuals in the i^{th} latent class, $\overline{y_i} = \{\overline{y_{1i}}, \overline{y_{2i}}, \ldots, \overline{y_{qi}}\}$ the mean scores of the i^{th} latent class on the q observable measures, and $f(Y = \overline{y_i})$ the probability density of occurrence of that pattern of scores. Model parameters include the proportion of individuals in each latent class, and the mean and variance on each measure for each latent class. (Variance parameters were allowed to vary across classes in the present study.) Once the best data fit is achieved, posterior membership probabilities (i.e., probabilities of belonging to each latent class) are calculated for each individual, using the Bayes rule:

$$P(lc = i|Y = y) = P(lc = i)f(Y = y|lc = i)/f(Y = y), \quad (4)$$

where $P(lc = i|Y = y)$ is the probability to be in latent class i given a pattern of score y. Each individual is then assigned to the latent class corresponding to the greatest $P(lc = i|Y = y)$.

To guide the decision on the number of latent classes that may provide the best and most meaningful fit of the data, models with incremental number of classes are tested. For each incremental step, a number of criteria are considered, including measures of model fit such as the Akaike's Information Criterion (AIC, Akaike, 1987), Bayesian Information Criterion (BIC, Schwartz, 1978), and sample adjusted BIC (adjBIC, Hagenaars & McCutcheon, 2002; Sclove, 1987), and an entropy index, which provides information on how well the latent classes are distinguished (good>0.8, Ramaswamy et al., 1993). Two significance tests are also carried out at every step, the Lo-Mendell-Rubin adjusted likelihood ratio test (LMR, Lo, Mendell, and Rubin, 2001) and bootstrapped parametric likelihood ratio test (BP, McLachlan & Peel, 2000), to determine whether the new model provides a significantly better fit than the previous model with one fewer class. Among these various criteria, the BP likelihood ratio test has been suggested to provide the most consistent indicator of number of latent classes across mixture models (Nylund, Asparouhov, & Muthén, 2007). Because theoretical meaning should also weigh in guiding decisions on the number of latent classes, neuropsychological profiles and frequencies are calculated and compared for each class at every incremental step of the analysis. Desirable criteria supporting meaningful results include some stability across incremental models of neuropsychological profiles and frequencies of at least 5% for every latent class. The present study proposes to run these analyses using Mplus™ (Muthén & Muthén, 2009), including options Tech11 and Tech14 to provide the afore-mentioned model fit criteria and likelihood ratio tests (Asparouhov & Muthén, 2012).

The selection of variables to be included as input into the LPA was the subject of careful examination to limit risks of methodological confound. Notably, the inclusion of too many variables derived from the same test or too many variables assessing the same construct was deemed to have a potential impact on latent grouping. For example, if the scores obtained on trial 1, trial 5, trials 1-5, short delay recall, and long delay recall of the CVLT were all included in the LPA, performance on the CVLT may have a much greater effect on latent grouping than if trial 1 only was included. In the same way, if five variables were included assessing memory and only one variable assessing executive function, grouping would likely be biased toward grouping individuals with high or low memory scores before considering executive function performance. To circumvent the issue of variable selection and explore the cognitive domains covered by the test measures, a series of preliminary factor analyses was carried out. The goal of these analyses was the construction of composite factor scores representative of meaningful cognitive constructs to be then used as input into the LPA. To explore individual differences in terms of both absolute and relative neuropsychological profiles, two series of LPAs were conducted, the first one on full composite factor scores and the second on composite factor scores corrected for general cognitive ability level. The second set of LPAs allowed to explore patterns of individual differences in cognition that might be otherwise masked if variations in general cognitive ability were to be dominant.

Preliminary Factor Analyses. To create composite factor scores representative of the cognitive constructs involved during eHRB testing, a two-step approach was taken. An Exploratory Factor Analysis (EFA) was first conducted to explore the dimensionality of the eHRB without imposing a priories. A Confirmatory Factor Analysis (CFA) was then carried out to compute the composite factor scores, with factor structure guided by the prior EFA results. Both analyses were run using Mplus™ (Muthén & Muthén, 2009).

First, EFA was chosen over Principal Component Analysis (PCA) as it deals solely with the shared variance among observed variables (as opposed to the total amount of variance in PCA), thus permitting theoretical interpretation of factors as underlying or "causing" the variables (Meyers, Gamst, Guarino, 2006). These characteristics were deemed better adapted to modeling the constructs underlying cognition from imperfect instrumental measures. Oblique factor rotation (*Geomin*; Yates, 1987) was carried out to maximize high correlations and minimize low correlations between observable variables and factors. This type of rotation was selected over an orthogonal factor rotation such as *Varimax* (Kaiser, 1958) to permit maximization of model fit – the factors are positioned closer to the original variables – and a more realistic representation of the relationship between cognitive domains – the factors can be correlated (Browne, 2001; Thurstone, 1947). Among models with increasing number of factors, the final solution was selected by comparing statistical indices of model fit (e.g., Hooper, Coughlan, & Mullen, 2008), including Akaike's Information Criterion (AIC, Akaike, 1987), Bayesian Information Criterion (BIC, Schwartz, 1978), sample adjusted BIC (adjBIC, Hagenaars & McCutcheon, 2002; Sclove, 1987), Chi-square indice (χ^2, Hu & Bentler, 1999), Comparative Fit Index (CFI, Bentler, 1990), Root Mean Square Error of Approximation (RMSEA, Steiger, 1990), and Standardized Root Mean Square Residual (SRMR, Byrne, 1998). The variance accounted for by the solution (i.e., the sum of the solution's eigenvalues divided by the number of variables), the variance accounted for by each individual factor (i.e., approximated as the sum of squared factor loadings for that factor divided by the number of variables), and the interpretability of the factors were also evaluated to determine the initial plausibility of the factor structure. Factor interpretability was determined by verifying the presence of loadings greater than 0.3 on each factor with limited cross-factor loadings. Because the goal of this analysis was not data reduction per se, but the exploration and identification of underlying and potentially overlapping cognitive constructs, criteria based on Scree plot characteristics such as solely retaining eigenvalues greater than one and above the curve's elbow shape were not deemed determinant.

Because several of the eHRB measures were derived from the same tests, caution must be exercised in the EFA to avoid obtaining instrument factors – i.e., factors arising from correlations related to task demands rather than to underlying cognitive ability (Cattell, 1961). For example, *delayed recall* performance on the *CVLT* is likely to be more correlated to the *CVLT T1-T5 learning trials* than with *delayed recall* on the *Story Memory Test* for the sole reason that they involve the same verbal material. Similarly, right- and left-hand performances on the *Grooved Pegboard* are likely more closely related to each other than to any other fine motor measures due to involving the same instrumental constraints. A preliminary EFA conducted on all the eHRB measures confirmed the risk of instrument factors. For example, in the four factor solution of this preliminary analysis, two of the factors were defined solely by loadings from the *Tactual Performance Test* and *Reitan- Kløve Sensory Perceptual Examination*, respectively. A second EFA was thus conducted, this time including only one measure per test.

Because the goal of the EFA was solely to guide the factor structure of the subsequent CFA, the process for selecting which measure to keep per test was somewhat arbitrary. Exceptions were made and same-test variables were kept only for measures that have been suggested to involve markedly different cognitive constructs: *Trail Making Test Part A* and *Part B*, with *Part B* requiring set-switching compared to simple sequencing required during *Part A* (Reitan, 1955b; Reitan & Wolfson, 2009); and *Digit Vigilance Time* and *Error*, which assess speed and accuracy (or error-monitoring), respectively, and have been found to be essentially unrelated (Lewis, 1995).

In a second step, a CFA was conducted on all eHRB variables using a factor structure guided by the EFA results. Correlation parameters were included to model relatedness between factors and provide a realistic representation of relatedness between cognitive domains. The factor means were set to 0 and factor variances to 1. To account for within-instrument relations, correlation parameters were also included in the CFA model relating any two measures derived from the same test. The CFA model was progressively simplified by running several analyses in an iterative process, starting with parameters for all loadings that were greater than 0.22 in the EFA (corresponding to a 5% proportion of variance), and progressively keeping only loadings greater than 0.3, and finally 0.4. Loading sizes were interpreted based on criteria proposed by Comrey & Lee (1992) – i.e., excellent for loadings >.71 (50% overlapping variance), very good for loadings >.63 (40% overlapping variance), good for loadings >.55 (30% overlapping variance), fair for loadings >.45 (20% overlapping variance), and poor for loadings >.32 (10% overlapping variance). Each iterative CFA model was verified to provide adequate fit of the data by using the same statistical indices as for the EFA (i.e., AIC, BIC, sample-adjusted BIC, χ^2, CFI, RMSEA, and SRMR) and was gauged in terms of factor interpretability. Factor scores were computed for the final model using Bartlett's method as employed by Mplus™ for continuous variables (Bartlett, 1937, Estabrook, & Neale, 2013; Lawley & Maxwell, 1971, Chapter 8; Muthén, 1998-2004, Appendix 11).

Attrition and Variable Selection. In general, most subjects were administered most measures as part of the eHRB normative project. However, because the normative project represented a multi-study and multi-site effort with main goal to provide norms for every test separately, it was not uncommon for a single subject to have a few missing measures. Most latent variable statistical techniques are reasonably robust to attrition (Hagenaars & McCutcheon, 2002). However, because including too many subjects with too few test scores might affect the reliability of factor score estimation (Estabrook, & Neale, 2013), only subjects who had been administered at least half of the eHRB measures including at least one memory test, were selected for the present statistical analyses. The demographic characteristics of the remaining sample (N=982) were examined for each test separately and are presented in Table 2. As shown in the table, three of the test measures were found to have been administered to less than 25% of the remaining sample, namely the *BDAE Complex Ideational Material* (the BDAE normative sample was recruited entirely separately), *PIAT spelling* (only 125 subjects tested who were all Caucasian), and *PIAT comprehension* (only 217 subjects tested, including 203 Caucasian and 14 African American participants). These three measures were excluded from all analyses.

Significant differences in demographic distributions are also shown for the WAIS and WAIS-R data in Table 2: WAIS data were only available for Caucasian individuals, and WAIS-R data were available for 3.5 times as many African American compared to Caucasian individuals. This demographic imbalance is explained by the timely administration of the two WAIS versions over the 25 year course of the eHRB normative effort. That is, the WAIS was essentially administered during the first wave of the eHRB normative effort focusing on establishing Caucasian norms (Heaton et al. 1991), whereas the WAIS-R was administered during the second wave focusing on establishing African American norms (Heaton et al. 2004). To avoid introducing too many confounds in the main analyses (i.e., WAIS version and ethnicity), the WAIS and WAIS-R data were excluded from the factor analyses, and thus from the LPA. The WAIS and WAIS-R data were used, however, in post-hoc analyses to help compare and interpret neuropsychological profiles resulting from the LPA.

Most remaining tests were found to have been administered to more than 80% of the selected sample, with consistent demographic distributions in terms of gender, ethnicity, age, and education (Table 2). Attrition in the remaining tests was thus assumed to occur at random and was dealt with in the EFA and CFA using Full Information Maximum Likelihood (e.g., Collins, Schafer, & Kam, 2001; Muthén & Muthén, 2009).

A few other test measures were excluded from the main factor analyses and LPA but included for interpretation purposes in post-hoc analyses, notably measures that were not normally distributed (i.e., *Spatial Relations, Story Memory-Percentage Loss,* and *Figure Memory-Percentage Loss*), and to avoid multicolinearity, measures that linearly combined or were included in other measures – i.e., *CVLT Trial 5*, which is included in a combination of *CVLT Trials1-5* and *CVLT Trial 1*; *SPE total*, which is a combination of *SPE right hand* and *SPE left hand*; and *TPT dominant, non-dominant,* and *both hands*, which are summarized in *TPT total*. Pure motor tests (i.e., *Grip Strength* and *Finger Tapping*) were also excluded from the factor analyses and LPA to limit the introduction of gender differences related to physiological rather than cognitive factors. These test measures are presented in gray font in Table 1.

Demographic and Ability Corrections. Most if not all previous data analyses involving the HRB and WAIS or WAIS-R measures have used scores that were either raw or corrected for age (e.g., McDermott et al. 1989; Ross, 2013). Yet, demographic factors such as education, ethnicity, and sometimes gender have been shown to be significantly related to neurocognitive test performance, potentially leading to large scale misdiagnosis of specific demographic groups if not taken into account (Heaton et al. 1986, 1996; Manly et al. 2005; Norman et al., 2000; Reynolds et al., 1987). For example, using norms that were not education-corrected on the HRB has led to misclassifying 42% of healthy adults with lower educational levels as cognitively impaired (Heaton et al. 1986). Further, despite norms corrected for age, education, and gender on the *CVLT*, failure to control for ethnicity has led to misclassifying 36% of healthy African-American individuals as impaired (Norman et al. 2000). Demographic factors may therefore represent a dominant source of individual differences in uncorrected neurocognitive test performance, perhaps masking more subtle patterns of strengths and weaknesses across individuals in neurocognition. In the LPA, lack of demographic corrections might thus result in unwanted clustering of individuals based on demographic and cultural factors rather than cognitive styles.

In the present study, scaled scores generated from raw test scores were first inputted without demographic correction into the factor analyses. Scaled scores have a mean of 10, standard deviation of 3, and were computed so that higher scores always indicate better performance (e.g., faster trial completion, fewer errors, or more correct answers). These scaled scores were published by Heaton et al. (2004) to permit comparison of patient performance in absolute terms to the entire population, a comparison often relevant for inferences on professional and everyday functioning. They were deemed particularly useful in the factor analyses of the present study for recruitment of maximal available sources of reliable variance when identifying cognitive constructs, while permitting same-scale comparisons across tests.

Because the goal of this study is to examine individual differences in neurocognitive profiles, and not the impact of age, education, or cultural background on cognitive performance, the factor scores resulting from these factor analyses were then corrected for age, education, and ethnicity before being inputted into the LPA. Demographic corrections were carried out using multiple linear regression, with models including quadratic and linear terms for age and education and a linear term for ethnicity. The regression models are expressed as:

$$FS = FS_{cor} + b_{1a} age + b_{2a} age^2 + b_{1e} edu + b_{2e} edu^2 + b_{ethn} ethn, \qquad (5)$$

where *FS* and FS_{cor} represent the original and corrected factor scores, *age* the age of participants in years, *edu* the education level of participants expressed in years of education, *ethn* the ethnicity of participants dummy-coded using *0* for Caucasian and *1* for African American, and b_{1a}, b_{2a}, b_{1e}, b_{2e}, and b_{ethn} the regression coefficients. All independent variables were centered so that *FScor* and *FS* would retain the same mean. When a quadratic term was not significant, the regression was run a second time without that quadratic term.

Because there are no known large effect size a priori differences in neurocognitive performance between right-handed and left-handed individuals and between males and females (Hyde, 2005, 2014; Zell, Krizan, & Teeter, 2015), these demographic variables were deemed unlikely to mask subtle patterns of individual differences in neurocognition. In addition, there might arguably be fewer environmental confounds associated with gender and handedness than with other demographic variables such as education or ethnicity – e.g., males and females and right- and left-handers are found in equal proportions in all cultures and socio-economic status. These demographic variables were therefore deemed unlikely to lead to unwanted clustering of individuals based on demographic and cultural factors, and no corrections for gender or handedness were carried out.

To also explore individual differences in terms of relative neurocognitive profiles, a second set of composite factor scores was computed with corrections for level of general cognitive ability in addition to demographic corrections. Using the psychometric definition of general intelligence initially introduced by Spearman (1904), or g-factor, level of general cognitive ability was defined as the direction of maximum common variance between cognitive abilities – i.e., the direction of the eigenvector with largest eigenvalue for the covariance matrix of demographics-corrected factor scores. Controlling for g has been done in previous factor analytic studies to isolate processes unique to single tasks (e.g., Vernon, 1964). Correction for level of general cognitive ability was calculated by projecting demographics-corrected factor scores onto the vector space orthogonal to the eigenvector with largest eigenvalue, using the system of equations:

$$\begin{cases} FS_{ab,i} \,.\, V_1 = 0 \\ \left\{FS_{ab,i} \,.\, V_j = FS_{cor,i} \,.\, V_j\right\}_{j=2:n_F} \end{cases}, \tag{6}$$

where $FS_{cor,i}$ is the row-vector of factor scores corrected for demographic variables for individual i, $FS_{ab,i}$ is the row-vector of factor scores corrected for both demographic variables and ability for individual i, n_F is the overall number of factors, and V_1, V_2, ... V_{nF} are the eigenvectors (column-vectors) of the covariance matrix of demographics-corrected factor scores in order of decreasing eigenvalue. This system of equations was solved as:

$$FS_{ab,i} = FS_{cor,i}\left[(0)\; V_2 \;\dots\; V_{n_F}\right]\left[V_1\; V_2 \dots V_{n_F}\right]^{-1}. \tag{7}$$

Two sets of LPAs were therefore run using either FS_{cor} or FS_{ab} as input, permitting exploration of individual differences in cognition in terms of both absolute and relative neurocognitive profiles. In the second set of LPAs, because correcting for level of general cognitive ability essentially removed one dimension of variance, including all the ability-corrected factor scores would have resulted in the multicolinearity of the input variables. To avoid multicolinearity, the ability-corrected factor with smallest remaining variance was selected to not be included in the set of LPA inputs. That ability-corrected factor, although not directly influent in clustering individuals together, was nonetheless calculated for each latent class of the LPA solution and used for result interpretation.

Post-Hoc Analyses. A series of post-hoc analyses was carried out for further interpretation of the LPA results, notably for comparison of factor scores, test scores, and demographic composition across latent classes.

For further characterization of the latent classes' neuropsychological profiles, factor scores and test-scores were compared across latent classes using multivariate and univariate analyses of variance. Notably, results were provided for all available eHRB and Wechsler scales test measures, including those previously excluded from the factor analyses (e.g., Wechsler scales tests, motor tests). For consistency, eHRB test scores were corrected for age, education, and ethnicity using a similar multiple linear regression procedure as described for the factor scores. These corrected scores were converted into Z-scores with mean of 0 and standard deviation of 1 to permit same-scale comparisons across tests. For the WAIS and WAIS-R measures, scaled scores were used providing population-based comparison to the published normative samples (Wechsler, 1955, 1981). To control for age, education, ethnicity, and IQ-score drift across WAIS versions, three separate regression analyses and conversions to Z-scores were conducted: for Caucasian individuals who had been administered the WAIS (N=126, age: M=35.4, SD=12.8), Caucasian individuals who had been administered the WAIS-R (N=97, age: M=67.2, SD=11.1), and African-American individuals who had been administered the WAIS-R (N=362, age: M=39.0, SD=12.6). Because of the large difference in age found between the WAIS-R Caucasian and African American participants ($F(1,457)$=403.9, p<.001, η^2=.469), this method was deemed preferable than correcting for ethnicity using dummy coding within one regression model to limit confounding factors. The three distribution of Z-scores with mean of 0 and standard deviation of 1 were then merged to compare performance on the Wechsler scales across latent classes.

In terms demographic composition of the latent classes, differences in age and education were tested using univariate analyses of variance with most likely class membership as independent variable. Differences in gender, ethnicity, and handedness composition were tested using logistic regression with dummy coding of the latent classes. Although composite factor scores inputted into the LPA were each controlled for age, education, and ethnicity, it was still deemed possible to find demographic differences along these variables due to profile variation. For example, one could imagine that middle age individuals may present with marked variations in their neurocognitive profiles due to years spent developing and maintaining specialized cognitive work skills; while younger individuals may present with flatter profiles, perhaps resulting from exercising a less deep but wider range of cognitive functions throughout their school years.

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RESULTS

Factor Analyses Results

Exploratory Factor Analysis. An EFA using *geomin* rotation was first conducted on a selection of test measures to explore the cognitive constructs underlying the eHRB normative database. Considerations of indices of model fit (see Tables 3) and factor interpretability suggested that a 7-factor solution best explained the data ($\chi^2(84)=137.5$, *CFI=.994, AIC=79,326, BIC=80,148, adjBIC=79,614, RMSEA=0.025, SRMR=0.014*). An 8-factor solution was also considered due to improvement of some of the model fit indices (i.e., $\chi^2(70)=85.9$, *CFI=.998, AIC=79,302, BIC=80,192, adjBIC=79,614, RMSEA=0.015, SRMR=0.011*), but was discarded based on difficulties with convergence (i.e., tolerance had to be decreased from .00005 to .0005 to obtain a set of results), BIC indices indicative of worse fit (i.e., *BIC=80,192, adjBIC=79,614)*, and lack of interpretability of the solution (i.e., only one item loaded on the 8th factor and the 7th factor was poorly identified).

The variance explained by the 7-factor solution was 74.1%. The sums of squared structure coefficients, a proxy for the overlapping proportions of variance covered by each factor after rotation, were 22.1%, 12.7%, 26.1%, 13.5%, 31.3%, 25.0%, and 23.2% for factors 1 to 7, respectively (see Table 4). The *geomin*-rotated factor loadings are presented in Table 4. Loadings greater than 0.22, highlighted by gray-shading, were kept for the initial CFA model. Loadings greater than 0.45, highlighted in bold font, were considered in priority for factor interpretation. Based on these loadings and on a review of the cognitive processes theoretically involved in each test measure, the factors were interpreted as representing the following underlying cognitive abilities: "attention/working memory" (factor 1), "fluency" (factor 2), "language" (factor 3), "verbal episodic memory" (factor 4), "visuospatial cognition" (factor 5), "perceptual speed" (factor 6), and "sensory-perceptual processing" (factor 7). Correlations between factors (see Table 5) were for the most part positive with small to large effect sizes (*r* =.212 to *r* =.642). Exceptions were found for the correlations between "language" and "sensory-perceptual processing" (*r* =.120) and between "language" and "perceptual speed" (*r* =.085) which were weak to negligible.

Confirmatory Factor Analysis. A series of CFAs was conducted on a larger selection of eHRB test measures. The CFA models were initially guided by the factor structure resulting from the EFA and were progressively simplified so as to keep only loadings greater than 0.3 and then 0.4. Indices of goodness of fit for the initial, intermediate, and final models are presented in Table 6. The final model was found to fit well the data ($\chi^2(454)=1134.5$, *CFI=.965, AIC=120,682, BIC=121,366, adjBIC=120,922, RMSEA=0.039, SRMR=0.050*), with loadings deemed good to excellent per the Comrey & Lee (1992) criteria for all but two test measures (Figure 1). The factor structure in the final model is as follows: Factor 1 is defined by loadings from *Trails Making-Part B* (.87), *PASAT* (.80), and *Digit Vigilance-Error* (.40); Factor 2 is defined by loadings from *Thurstone Word Fluency* (.88), *Letter Fluency* (.80), and *Category Fluency* (.69); Factor 3 is defined by loadings from the *BNT* (0.78), *Aphasia Screening Test* (0.70), and *PIAT Reading Recognition* (0.62); Factor 4 is defined by loadings from the *CVLT* (.60 to .78) and *Story Memory Test* (.61 to .80), with greatest loadings from the averaged learning trials in both tests; Factor 5 is defined by loadings from the *Figure Memory Test* (.56 to .82) with greatest loading from the averaged learning trials, and by loadings from the *Category Test* (.83) and the two *TPT* memory measures (.62 and .67); Factor 6 is defined by loadings from *TPT-total* (.85), *Grooved Pegboard* (.76 and .78), *Trail Making-Part A* (.72), and *Digit Vigilance-Time* (.59); and Factor 7 is defined by loadings from *Speech-Sounds Perception* (.71), the *Reitan- Kløve Sensory Perceptual Examination* (.67 and .67), *Tactile Form*

Recognition (.60 and .62), and *Seashore Rhythm* (.49). A competing model was considered with a loading for *TPT-total* on Factor 5 rather than 6. That model was not selected based on a poorer fit of the data (χ^2*(454)=1158.3, CFI=.964, AIC=120,706, BIC=121,390, adjBIC=120,946, RMSEA=0.040, SRMR=0.051*) and a less elegant theoretical factor interpretation – *TPT total* would have been the only measure with a speed component loading on Factor 5.

Based on the loadings and structure of the final solution, most CFA factors were deemed to represent underlying cognitive abilities similar to those of the EFA factors, but with noticeable changes in Factors 1 and 7. First, Factor 1, which included loadings in the EFA from tests involving basic attention (i.e., *Seashore Rhythm*, *Aphasia Screening Test*, and *Trail Making Test –Part A*), included loadings in the CFA solely from tests requiring online executive processes, specifically information manipulation, cognitive flexibility, and error monitoring. Further, Factor 7, which was dominated in the EFA by loadings from sensory-perceptual tests (i.e., *Speech-Sounds Perception* and *Tactile Form Recognition*), presented in the CFA with a highest loading from the *Speech-Sounds Perception Test* and an increased loading from the *Seashore Rhythm Test*, two tests test originally designed to measure alertness and attention (Reitan & Wolfson, 2009). Taking into account these considerations, the CFA factors were interpreted as representing the following underlying cognitive abilities: “working memory” (factor 1), “fluency” (factor 2), “language” (factor 3), “verbal episodic memory” (factor 4), “visuospatial cognition” (factor 5), “perceptual speed” (factor 6), and “perceptual attention” (factor 7).

The correlations between factors in the final model (see Table 7) were all positive and significant (p<.001), with medium to large effect sizes (r =.46 to r =.91). Residual correlations between same-test measures (see Figure 1) were also for the most part positive and significant (p<.001), with effect sizes ranging from small to large (r =.18 to r =.76). There were a few exceptions, with weak to negligible associations found between *Story Memory-Delayed Recall* and *Story Memory-Trial 1* (r =.09, p =.023), and between *Story Memory-Delayed Recall* and *Story Memory-Learning* (r =.13, p =.003). Further, *Digit Vigilance-Time* and *Digit Vigilance-Error* were moderately and negatively associated (r = -.29, p <.001), suggesting a trade-off between performances on these two measures. Interestingly, similar patterns of residual correlations were found across the three memory tests (i.e., *Figure Memory, Story Memory,* and *CVLT*), with weak to small associations found between performances on *trial 1* and *delayed recall* (r = .20, .09, and .25, respectively), somewhat increased associations between *averaged learning* and *delayed recall* (r=.24, .13, and .55, respectively), and large associations between *trial 1* and *averaged learning* (r= .74, .76, .64, respectively).

Demographic Contributions and Corrections of the Factor Scores. Factor scores were computed using the final CFA model and were corrected for age, education, and ethnicity using multiple linear regression. The multiple linear regression statistical results are presented in Table 8. The regression models including age, education, and ethnicity accounted for 63.0%, 42.1%, 42.5%, 59.2%, 63.9%, and 67.0%, of the variance in the factors "working memory" (R^2=.630, $F(5,976)$=333.0, p <.001), "fluency" (R^2=.421, $F(5,976)$=142.1, p <.001), "language" (R^2=.425, $F(4,977)=180.3$, $p<.001$), "verbal episodic memory" (R^2=.592, $F(5,976)$=283.4, p <.001), "visuospatial cognition" (R^2=.670, $F(5,976)$=396.6, p <.001), "perceptual speed" (R^2=.676, $F(5,976)$=408.1, p <.001), and "perceptual attention" (R^2=.639, $F(5,976)$=345.8, p <.001), respectively. The regression coefficients for the quadratic effects of age were negative and significant (p<.05) for all factors except "language", indicating accelerated decrease of performance with age in most domains of cognition (see Figure 2). The linear regression model was re-run for "language" without the quadratic term for age. Results also suggested a significant linear decrease of "language" performance with age, but with a very small effect size

(b_{1a} = -5.14×10^{-3} in units of number of standard deviations per year, p<.05). Education was found to have significant positive linear and negative quadratic effects on all factors, indicating increased performance with years of education in all cognitive domains, with dampening at higher educational levels (see Figure 3). The effect of ethnicity was also significant, indicating better performance for Caucasian subjects over African American subjects across cognitive domains.

For further information on the differential effects of the various demographic variables, hierarchical multiple regression was carried out, using models progressively including age, education, and ethnicity. Results suggested that age, education, and ethnicity each contributed significantly to incremental portions of variance in the factors, but with contributions varying in effect size depending on the cognitive domain (see statistics in Table 8). The incremental contributions of age, education, and ethnicity were 43.5%, 9.4%, and 10.1%, respectively, of the variance in “working memory”; 18.8%, 14.7%, and 8.6% of the variance in “fluency”; 4.1%, 22.1%, and 16.3% of the variance in “language”; 30.5%, 15.3%, and 13.4% of the variance in “verbal episodic memory”; 48.2%, 7.9%, and 10.9% of the variance in “visuospatial cognition”; 53.9%, 5.7%, and 8.0% of the variance in “perceptual speed”; and 48.4%, 7.3%, and 8.2% of the variance in “perceptual attention”. Notably, using Cohen’s criteria to evaluate effect sizes (Cohen et al. 2003), age had a small effect on “language”, a medium effect on “fluency”, and a large effect on all other factors; education had a medium incremental effect on “fluency”, “language”, and “verbal episodic memory”, but a small incremental effect on other factors; and ethnicity had a medium incremental effect on “language” and “verbal episodic memory” but a small incremental effect on all other factors.

The effect of gender was also examined in an additional model. Females were found to significantly outperform males in “working memory”, “language”, “fluency”, and “verbal episodic memory", but all effect sizes corresponding to the incremental contribution of gender were negligible. There was no significant incremental effect of gender on "visuospatial cognition", "perceptual speed", or "perceptual attention".

Latent Profile Analyses Results

Two series of LPAs were conducted investigating individual differences in cognitive profiles in terms of absolute and relative abilities.

First LPA series. The first series of LPAs was carried out, using factor scores corrected for age, education, and ethnicity as input. Models were run with number of latent classes iteratively increasing between 1 and 8. The maximum loglikelihood of the model with 8 classes could not be replicated despite increase of the number of starts to 10,000 – the results that were obtained are therefore unreliable (they could correspond to a local maximum) and are not presented here. Among the measures of goodness of fit (Table 9), the *AIC*, *BIC*, and *adjBIC* indices suggested systematic improvement of model fit with increasing number of classes. Entropy indices were equivalent across models, ranging between .88 and .91 and suggesting adequate distinction of the latent classes in all model. The LMR likelihood ratio test suggested that the two-latent class model improved significantly upon the one-class model (*Likelihood Ratio*: LR=3365, p <.001), and that the three-class model improved significantly upon the two-class model (LR =1666, p <.001). The LMR likelihood ratio test suggested that improvement in fit was not significant between models with four versus three, five versus four, six versus five, and seven versus six latent classes (p = .173, .173, .604, and .137, respectively). This lack of significant improvement, however, could not be confirmed by the BP likelihood ratio test, not reported here due to lack of replication in all bootstrap draws of the best loglikelihood value. The average neurocognitive profiles obtained for models with 2 to 7 latent classes are plotted in

Figure 4. The resulting variance parameters, separate for each latent class and each factor, are indicated in the figure using line-width. In the LPA solutions with two- to five-classes, a ladder-like distribution of latent class profiles emerged, with profiles that were primarily flat and mostly differing in their level of general cognitive ability. Interestingly, in the solution with six latent classes, individuals with average general cognitive ability (about 40% of the sample population) became divided into two groups with complementary neurocognitive profiles,: one group with relatively better performance on factors involving verbal abilities (i.e., “fluency”, “language”, and “verbal episodic memory”) and relatively worse on factors involving perceptual abilities (i.e., “visuospatial cognition”, “perceptual speed”, and “perceptual attention”); and one group with relatively better performance on factors involving perceptual abilities and relatively worse performance on factors involving verbal abilities. In the solution with seven latent classes, a similar division became apparent for individuals with high-average cognitive abilities. The examination of these profiles, added to considerations of all fit indices, suggested the presence of a continuum of individual differences rather than the existence of a specific number of groups with differing neurocognitive profiles. This continuum is predominantly characterized by level of general cognitive ability, even after correcting for age, education, and ethnicity. A secondary level of individual differences also appeared at average and high-average ability levels, characterized by relative performance on verbal versus perceptual tasks. Further investigations are necessary to determine whether this secondary division is present at all levels of cognitive abilities and whether it also varies along a continuum.

Second LPA series. To examine individual differences in relative cognitive abilities, a second series of LPA was conducted on factors scores corrected for level of general cognitive ability as well as for age, education, and ethnicity. This method allowed to explore patterns of individual differences in cognition that might be otherwise masked by the dominant variation along general cognitive ability. Because one dimension of variance was removed by correcting for level of general cognitive ability, only six of the seven ability-corrected factor scores were used as input into the LPA to avoid multicolinearity. The ability-corrected factor with smallest remaining variance, i.e., "working memory", was selected to not be included in the LPA inputs. The scores on this factor were nonetheless calculated for the latent classes identified in the LPA solution and were used for result interpretation. LPA models were run with number of latent classes iteratively increasing between 1 and 10. All models converged with replication of maximum likelihood values using various starting points for the parameters. Among the measures of goodness of fit (Table 9), the *AIC*, *BIC*, and *adjBIC* indices suggested systematic improvement of model fit with increasing number of classes. Entropy indices also improved overall with increasing number of classes – entropy values ranged between .81 and .87, suggesting adequate distinction of the latent classes in all models. The LMR likelihood ratio test suggested significant improvement in fit for the two-latent class model over the one-class model (LR =1483, p <*.001*), the three-class model over the two-class model (LR =632, p =.017), the four-class model over the three-class model (LR =502, p =.012), the seven-class model over the six-class model (LR =232, p =.008), and the ten-class model over the nine-class model (LR =115, p =.017). The LMR likelihood ratio test suggested no significant improvement for models with five versus four, six versus five, eight versus seven, and nine versus eight latent classes (p = .130, .117, .178, and .145, respectively). By contrast, the BP likelihood ratio test suggested significant incremental improvement for all models between 1 and 7 classes (p <.001). The BP likelihood ratio test is not reported for models with 8 classes and beyond due to lack of replication in all bootstrap draws of the best log-likelihood value. The pattern of fit indices suggested here again the presence of a continuum of individual differences rather than the existence of a specific number of groups with differing neurocognitive profiles. Because classes with less than 5% of the population were found in the 9-class solution (one class with < 5% of individuals) and 10-class solution (two latent classes with < 5% of individuals), the 8-class solution was deemed most relevant and representative of the continuum.

Estimated mean neurocognitive profiles are presented in Figure 5a for the 8-class solution. Standard errors of mean estimates and estimated variances are also plotted for each latent class using error bars and linewidth, respectively. The results suggested four pairs of nearly mirroring neurocognitive profiles. The first pair of latent classes encompassed about 40% of the population and was characterized by small to moderate relative variations in neurocognitive profiles (i.e., the maximum amplitude of within-profile variation was about one standard deviation in ability-corrected factor score). This pair consisted of "mildly verbal" individuals, estimated to represent 19.1% of the population based on estimated posterior probabilities, and characterized by slightly better performance, relatively, on verbal compared to perceptual factors; and of "mildly perceptual" individuals, estimated to represent 19.5% of the population and characterized by slightly better performance, relatively, on perceptual compared to verbal factors. All other latent classes presented with larger within profile variations. The second pair of latent classes (within-profile variation of about 3 standard deviations) consisted of "highly verbal" individuals (13.1%), characterized by markedly better relative performance on verbal compared to perceptual factors, and "highly perceptual" individuals (8.9%), characterized by markedly better relative performance on perceptual compared to verbal factors. The third pair of latent classes (within-profile variation of about 3 standard deviations) consisted of "visuospatial cognitive" individuals (6.5%), characterized by markedly better relative performances on the "visuospatial cognition" and "verbal episodic memory" factors compared to the "fluency" factor, and "super fluent" individuals (7.8%), characterized by markedly better relative performance on the "fluency" factor compared to the "visuospatial cognition" and "verbal episodic memory" factors. The fourth pair of latent classes (within-profile variation of about 2.5 standard deviations) consisted of "verbal memorizer" individuals (10.7%), characterized by better relative performance on the "verbal episodic memory" factor compared to the "perceptual attention" and "perceptual speed" factors, and "fast attentive" individuals (14.4%), characterized by better relative performance on the "perceptual attention" and "perceptual speed" factors compared to the "verbal episodic memory" factor.

Post-Hoc Analyses Results

Comparison of Absolute Neurocognitive Profiles. The eight latent classes that were identified based on differences in relative neurocognitive profiles – i.e., demographic- and ability-corrected factor scores (second LPA series) – were also found to differ in absolute neurocognitive profiles – i.e., demographic only-corrected factor scores (Figure 5b). To quantify those differences, a multivariate analysis of variance was carried out on demographic-corrected factor scores with most likely class membership as independent variable (Table 10). Homogeneity assumptions were evaluated and validated using Levene's homogeneity tests (all *p*s > .400). Differences in absolute neurocognitive profiles were found to be significant (omnibus test statistics: Wilk's Λ=.037, F=91.29, p<.001, η^2=.374) with effect sizes varying from small to large depending on the cognitive domain. Notably, "perceptual speed" had the largest between-class variation (univariate test of between-subject effects: $F(7,974)$=49.8, p<.001, η^2=.264), followed by "visuospatial cognition" ($F(7,974)$=36.6, p<.001, η^2=.208), "language" ($F(7,974)$=34.0, p<.001, η^2=.196), "fluency" ($F(7,974)$=30.9, p<.001, η^2=.182), "perceptual attention" ($F(7,974)$=21.6, p<.001, η^2=.135), "verbal episodic memory" ($F(7,974)$=19.7, p<.001, η^2=.124), and "working memory" ($F(7,974)$=5.3, p=.003, η^2=.037). Contrasts are also provided in Table 10 comparing mean demographic-corrected factor scores across classes. Most contrasts were found to be significant, confirming that the latent classes identified in the second LPA series were distinct both in terms of relative and absolute neurocognitive profiles. There was no significant difference across classes, though, in terms of level of general cognitive ability ($F(7,981)$=.528, p=.813, η^2=.004).

For further visualization of within-class variability, relative and absolute neurocognitive profiles were plotted for all participants grouped based on their most likely class membership (Figure 6). Profiles using demographic- and ability-corrected factor scores are provide in the left panels and using demographic only-corrected factor scores in the right panels. To limit overlaps, separate plots are provided for each pair of latent classes with seemingly mirroring estimated neurocognitive profiles (vertically-arranged panels). Averaged factor scores are presented using thicker lines. (The average scores in the left panels of Figure 6 are based on most likely class memberships and may thus be different from the LPA estimated means presented in Figure 5a.) To quantify differences in absolute neurocognitive profile within each pair, univariate analyses of variance were carried out on the demographic-corrected factor scores (Table 11). Differences in absolute neurocognitive profiles were found to be small to negligible between “mildly verbal” and “mildly perceptual” individuals depending on the cognitive domain (η^2=.003 to .120), small to large between “highly verbal” and “highly perceptual” individuals (η^2=.080 to .509), negligible to large between “visuospatial cognitive” and “super fluent” individuals (η^2=.002 to .453), and small to medium between “verbal memorizer” and “fast attentive” individuals (η^2=.024 to .219).

Comparison of Test Scores. For a more detailed comparison of neuropsychological profiles, average test scores were calculated and compared across latent classes for all available eHRB test measures (Figures 7) and Wechsler scales measures (Figure 8). Overall, patterns of differences across latent classes at the factor score level were also found at the test score level.

These differences were quantified using a series of univariate analyses of variance (Table 12). Most eHRB test measures were found to vary significantly across latent classes, with effect sizes that were small to medium depending on the test. The greatest effect sizes were found for the *Letter Fluency*, *Thurstone Word Fluency*, *Story Memory Test-Trial 1*, *Story Memory Test-Learning*, *Figure Memory Test-Learning*, and *TPT-total* test measures (η^2=.20 to .24), followed by the *Grooved Pegboard*, *CVLT-Trials 1-5*, *CVLT-short delay*, *CVLT-long delay*, *Figure Memory Test-Trial 1*, *Category Test*, and *TFR-left hand* test measures (η^2=.14 to .19). The few test measures that did not differ significantly across classes or differed but with a negligible effect size were the *PASAT* (F=.88, p=.525, η^2=.013), *Digit Vigilance-Error* (F=1.04, p=.404, η^2=.013), and *Grip Strength non-dominant* (F=2.37, p=.021, η^2=.018). Among the Wechsler scales, most test measures presented with significant differences across classes but with effect sizes that were small (η^2=.03 to 07). Variations across classes were larger for *Vocabulary* (F=8.62, p<.001, η^2=.095) and *Block Design* (F=7.72, p<.001, η^2=.086); but were negligible or non- statistically significant for *Digit Span* (F=2.37, p=.021, η^2=.018), *Picture Completion* (F=1.79, p=.088, η^2=.021), and *Picture Arrangement* (F=1.32, p=.240, η^2=.017). In terms of within mirroring-class comparison, the demographically-corrected Wechsler scales distinguished well (small to medium effect sizes) between the "highly verbal" and "highly perceptual" groups and between the "visuospatial cognitive" and "super fluent" groups (Table 13). By contrast, the "mildly verbal" and "mildly perceptual" groups and the "verbal memorizer" and "fast attentive" groups differed only by small effect sizes, notably on *Block Design* ("mildly perceptual" >"mildly verbal"), *Vocabulary* ("verbal memorizer" >"fast attentive"), and *Digit-Symbol Coding* ("fast attentive" >"verbal memorizer").

Demographic Corrections of Test Scores. All test scores presented in Figures 7 and 8 were corrected for age, education, and ethnicity using multiple linear regression. Demographic effect sizes, calculated using hierarchical multiple linear regression models incrementally including age, education, and ethnicity, are presented for the eHRB test measures (Tables 14 & 15) and Wechsler scales measures (Table 16). Models including gender and handedness were also run for additional information (see Tables 13 and 14), although no demographic corrections were conducted for these variables. To avoid confounds related to disparities in demographic distributions between the WAIS and WAIS-R data (ethnicity and age), results in Table 16 are presented separately for Caucasian individuals who had been administered the WAIS, Caucasian individuals who had been administered the WAIS-R, and African-American individuals who had been administered the WAIS-R.

Most eHRB test measures (Table 14 & 15) presented with medium to large effects of age (R^2=.134 to .423) and small to negligible effects of education (R^2_{change}=.001 to .065), except for measures related to language – i.e., *Aphasia Screening Test*, *BNT*, and *PIAT Reading Recognition* – which presented with small to negligible effects of age (R^2=.003 to .046) and small to medium effects of education (R^2_{change}=.113 to .203), and for the *Seashore Rhythm Test*, *Spatial Relations*, PASAT, and *Digit Vigilance Test-Error*, which presented with small to negligible effects of age (R^2=.006 to .084) and small to negligible effects of education (R^2_{change}=.012 to .077). Interestingly, slight differences were found across fluency tests, with a greater effect of age but smaller effect of education for the *Category Fluency Test* (age: R^2=.140; education: R^2_{change} =.055) compared to the letter fluency tests – i.e., *Thurstone Word Fluency* and *FAS* (age: R^2=.057 and .062; education: R^2_{change} =.136 and .085). Differences were also found across memory tests, with effects of age that were medium to large for the *CVLT* and *Figure Memory Test* (R^2=.139 to .296), but small to medium for the *Story Memory Test* (R^2=.063 to .160). The effects of education were equivalent across memory tests and were in the small range (R^2_{change} =.020 to .118). The effect of ethnicity was negligible-to-small for all eHRB test measures (R^2_{change} <.001 to .117), except for the BNT, arguably one of the most culture-dependent tests, where the effect was medium (R^2_{change} =.199). The effect of gender was also negligible-to-small for all eHRB test measures except *Grip Strength* where the effect was large (R^2_{change}=.429 and .431). All effects of handedness were negligible (R^2_{change}<.009).

For the Wechsler Scales test measures (Table 16), a contrast was observed between the verbal measures, which for the most part presented with negligible to small age effects (R^2=.006 to .107) and medium to large education effects (R^2_{change}=.105 to .421); and the performance measures, which presented with small to large age effects (R^2=.047 to .279) and small to medium education effects (R^2_{change}=.024 to .138). An exception was found for *Digit Span*, which presented with negligible to small effects for both age and education (age: R^2=.004 to .063; education: R^2_{change}=.006 to .045). The effect of gender was negligible-to-small for all Wechsler Scales test measures (R^2_{change}= <.001 to .078). All effects of handedness were negligible and non-significant.

Demographic Comparison across Latent Classes. The demographic compositions of the latent classes identified using demographic- and ability-corrected factor scores (second LPA series) are provided in Table 17. There were no significant difference in age (F=.68, p=.689, η^2=.005) or education (F=.89, p=.516, η^2=.006) across latent classes. Two series of logistic regression analyses were carried out, comparing gender, ethnicity, and handedness distributions within and across pairs of mirroring latent classes. Significance was tested for each comparison using χ^2-tests, with p-values considered significant using α=.012 (Bonferroni correction). The female proportion was significantly smaller in the “highly perceptual” group (32.2%) compared to the “highly verbal” group (49.6%), with an estimated female to male odds ratio varying by a factor of *exp(b)*=.48 (χ^2=6.542, p=.011). In probing this effect further using contrasts, the female to male odds ratio was found to be significantly smaller in the "highly perceptual" group compared to the other groups combined (*exp(b)*=.52, *Wald*=4.002, *p*=.045), but was not significant different in the "highly verbal" group compared to the other groups combined (*exp(b)*=1.07, *Wald*=.055, *p*=.815).

The proportion of females was not different within any other pair of mirroring latent classes (*ps*=.602 to .920) or across pairs of latent classes (*ps*=.399 to .983). Distributions of African American and Caucasian participants did not differ significantly within mirroring latent classes (*ps*=.318 to .826) or across pairs of mirroring latent classes (*ps*=.028 to .640). There was a sizably smaller African American to Caucasian proportion in the combined "visuospatial cognitive" and "super fluent" classes (54.2%) compared to the other classes combined (64.3%) –odds ratio varying by a factor of *exp(b)*=.66 (χ^2=4.836, *p*=.028) – but this difference was not statistically significant when using α=.012. The proportion of left-handed to right-handed individuals was significantly smaller in the combined "mildly verbal" and "mildly perceptual" classes (6.6%) compared to the other classes (13.6%) – estimated odds ratio of left-handed to right-handed individuals varying by a factor of *exp(b)*=.45 (χ^2=12.425, *p*<.001). By contrast, the proportion of left-handed to right-handed individuals was significantly greater in the combined "highly verbal" and "highly perceptual" classes (15.7%) compared to the other classes combined (9.4%) – estimated odds ratio varying by a factor of *exp(b)*=1.8 (χ^2=6.497, *p*=.011).

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DISCUSSION

The goal of this study was to examine and characterize patterns of individual differences in normal neurocognition. Two series of latent profile analyses were carried out on composite scores representative of absolute and relative performances in seven neurocognitive domains. These domains were identified by factor analysis on the eHRB normative dataset as “working memory”, “fluency”, “language”, “verbal episodic memory”, “visuospatial cognition”, “perceptual speed”, and “perceptual attention”. The first series of LPA revealed a predominant ladder-like continuum of absolute neurocognitive profiles, with some individuals performing better or worse across all cognitive domains, despite corrections for age, education, and ethnicity. Secondary patterns of individual differences were however apparent at average and high-average general cognitive ability, separating individuals who had relatively better or worse performance in verbal versus perceptual cognitive domains. The second series of LPA confirmed the presence of individual differences at every level of general cognitive ability, and revealed mirroring patterns of relative neurocognitive profiles characterized by pairs of relatively competing cognitive abilities: verbal versus perceptual abilities, visuospatial cognition versus fluency abilities, and verbal memory versus perceptual attention and speed abilities.

The remainder of the section is organized in two parts: the first part discusses the eHRB factor analysis results by comparing them to previous factor analyses involving the Halstead Reitan Battery, and the second part discusses the LPA results in the context of available literature on individual differences in neurocognition, including cognitive styles and theories of brain function. Limitations and conclusions drawn from this work are then discussed.

The Cognitive Domains Assessed by the eHRB

Factor Structure and Interpretation. The cognitive constructs underlying the eHRB normative dataset were characterized using a preliminary exploratory factor analysis and iterative series of confirmatory factor analysis. The final retained CFA model suggested seven cognitive domains, defined as “working memory”, “fluency”, “language”, “verbal episodic memory”, “visuospatial cognition”, “perceptual speed”, and “perceptual attention”. The *Finger Tapping Test* and *Grip Strength Test* were not included in the analysis to limit gender differences related to physiological rather than cognitive influences. Based on an additional CFA which provided a good fit of the data, these two tests would have loaded on an 8^{th} “motor” factor.

To confirm the structure and interpretations of these factors, a supplemental EFA was run including the WAIS and WAIS-R variables, initially discarded from the main analyses due to the fewer number of subjects to whom these tests have been administered and to confounding factors related to battery version, age, and ethnicity. Results from the supplemental EFA suggested an 8-factor structure, with 7 of the factors matching those identified in the CFA, and an 8^{th} factor interpreted as “verbal knowledge and reasoning” with primary loadings from the Wechsler Scales’ *Information, Vocabulary, Comprehension,* and *Similarity* subtests, and from the *BNT* (Table 18).

Perhaps surprisingly, the “visuospatial cognition” factor was found to encompass constructs that were both associated with episodic memory (i.e., loadings from the *Figure Memory Test* and from the *TPT-shapes* and *-locations* measures) and with reasoning and abstraction (i.e., loading from the *Category Test*). The supplemental EFA including the WAIS and WAIS-R subtests confirmed this structure, with the finding of a similar “visuospatial cognition” factor encompassing loadings from the *Figure Memory Test, TPT,* and *Category Test,* as well as from subtests from the Wechsler performance subscale, namely *Block Design,* *Object Assembly, Picture Completion*, and *Picture Arrangement*. These findings are consistent with previous factor analytic studies that have examined visuospatial memory tests combined with other neuropsychological tests. Indeed, although a few studies have suggested the loading of visuospatial memory tests on a separate factor (e.g., Bornstein, 1983), most have reported loadings lumped in together with other neurocognitive tests, concluding against separate memory modules (e.g., Leonberger, Nicks, Goldfader, & Munz, 1991). The common association of visuospatial memory measures to a broader visuospatial cognitive construct might suggest that the difficulty of those tasks resides in the visuospatial properties of the stimuli rather than in remembering them. These considerations are consistent with previous studies inferring that figural stimuli employed in most visual memory tasks may be more difficult to encode than stimuli employed in most verbal memory tasks – such studies have proposed matching figural and verbal items for encoding difficulty before assessing recall performance across domains (e.g., Brown, Patt, Sawyer, & Thomas, 2016).

The factor analysis results also indicated the presence of a “perceptual attention” factor, with primary loadings from the *Speech-Sounds Perception Test, Reitan- Kløve Sensory Perceptual Examination, Tactile Form Recognition Test*, and *Seashore Rhythm Test*. The *Speech-Sounds Perception Test* and *Seashore Rhythm Test* were originally designed to measure alertness and attention (Reitan & Wolfson, 2009), suggesting that the central construct underlying performance on this factor is attention-related. Further, the *Reitan- Kløve Sensory Perceptual Examination (SPE)* and *Tactile Form Recognition Test (TFR)* were originally designed to detect unilateral or bilateral sensory-perceptual deficits, but only in brain-lesioned patients. In fact, low performance on these tests has been considered a pathognomonic sign – i.e., a strong indicator of brain damage possibly providing information on lesion lateralization (Reitan & Wolfson, 2004). Cognitively healthy individuals are therefore not typically expected to make errors on these tests (Spree & Sprauss, 1998), and if they do make errors, these are probably more related to lapses in attention rather than to deficits in sensory-perceptual abilities. The results of the supplemental EFA supported this interpretation, by showing a secondary loading of *Digit Span* – a measure of verbal attention and working memory – on the "perceptual attention" factor. A similar attention-related interpretation has also been proposed in previous factor analytic studies (Fowler, Zillmer, & Newman, 1988).

The "working memory" factor, with primary loadings from the *Trail Making Test-Part B* and *PASAT,* and secondary loading from *Digit Vigilance-Error*, is likely also recruiting the brain attentional network, but within the context of its involvement in working memory (D'Esposito, 2007). Indeed, both the *Trail Making Test-Part B* and the *PASAT* have been shown to primarily recruit working memory processes (Gonzalez et al. 2006; Sánchez-Cubillo, 2009). Working memory may also be involved in *Digit Vigilance-Error*, as part of the mechanisms facilitating visual search, presumably contributing to tracking locations already searched (Oh & Kim, 2004). The involvement of working memory was also confirmed in the supplemental EFA by the primary loading of *Digit Span* (combined *forward* and *backward*) on the "working memory" factor (Table 18). A widely accepted working memory model is that of Baddeley and Hitch (1974), encompassing an attentional control system, the "central executive", which is responsible for the manipulation of information, and three independent subordinate systems for the storage and maintenance of verbal, figural, and spatial information (Baddeley, 1986; Della Sala et al. 1999). It is notable that the current "working memory" factor likely involves the "central executive" component of working memory, not simply the subordinate systems. Indeed, as reviewed by Tombaugh (2006), the *PASAT* has been shown to be significantly correlated with *Digit Span-backward*, requiring the mental reordering of numbers ("central executive" process), but not with *Digit Span-forward*, only requiring storage and maintenance of information (subordinate systems). Because tasks involving working memory are somewhat more complex than those requiring simple attention, these tasks are more likely to challenge cognitively healthy individuals at their level of ability, leading to greater variability in performance across individuals (Hambleton, Swaminathan, & Rogers, 1991). Therefore, individual differences on the “working memory” factor are likely dominated by individual differences in working memory abilities rather than attention abilities in healthy cognitive individuals, even though both types of processes are likely simultaneously involved.

Supporting the factor interpretations listed above, differential effects of age, education, and ethnicity were noted depending on the cognitive domain. Notably, large quadratic declines were found with age in “working memory”, “verbal episodic memory”, “visuospatial cognition”, “perceptual attention”, and “perceptual speed”, with the latter cognitive domain suffering the greatest impact. By contrast, medium and very small declines were found in “fluency” and “language”, respectively. These findings are consistent with a large body of research demonstrating age-related cognitive trajectories that differ across cognitive domains (e.g., Hedden & Gabrieli, 2004; Park & Reuter-Lorenz, 2009). Specifically, cognitive domains relatively resistant to aging have been identified as verbal ability, some numerical abilities, and general knowledge; whereas marked declines have been noted in speed of processing, working memory, executive function, and episodic memory. These findings are described well by the theory of fluid and crystallized intelligence, which proposes a division of mental abilities into two separate components: crystallized abilities, which are considered the manifestation of overlearned experiences including education and acculturation and are relatively resistant to aging; and fluid abilities, which are considered the manifestation of biological factors and are more vulnerable to aging, and especially brain pathology often associated with aging (Cattell, 1963; Horn & Cattell, 1966; McArdle et al. 2002). Consistent with these accounts, education and ethnicity, which may arguably be considered representative of amounts of common overlearned experiences, were found to have their greatest impact on the "language" factor – i.e., the only crystallized factor in the present study. Education and ethnicity were also found to have sizeable effects on "verbal episodic memory" and "fluency", perhaps suggesting that amounts of crystallized ability underlie all verbal performances, regardless of the amount of fluid abilities that they may also require.

Anecdotally, for application in human resource departments, it might be worth noting that the effect of education was positive in all cognitive domains, but with quadratic dampening at higher educational levels, suggesting lack of improved cognitive performance between individuals with a Master's and a doctoral degree.

Comparison to Previous Factor Analyses involving the HRB & Wechsler Scales. Although numerous factor analyses (mostly exploratory) have been carried out in the past on combinations of select HRB subtests and other neuropsychological tests, no factor analysis of the full HRB or full eHRB appears to have been published to date (Ross, Dean, & Fischer, 2013 for a review). In synthesizing results from these various studies, Ross et al. (2013) noted that no single and simple agreed-upon structure has emerged for the HRB, perhaps related to a variability in measure selection, heterogeneity in sample selection (often brain-damaged or neuropsychiatric patients), and actual complexity of the HRB measures (leading to complex factor structures). Nonetheless, Ross et al. (2013) concluded that the HRB likely had a four to five factor structure; including four factors corresponding fairly well to those originally proposed by Halstead (1947) with his 13 tests of "biological intelligence" plus a possible language factor.

For example, Fowler et al. (1988) identified five factors, based on an exploratory factor analysis on a modified version of the HRB with addition of subtests from the WAIS, PIAT, Wide Range Achievement Test (WRAT), and Wechsler Verbal and Spatial Memory Tasks. Their sample was composed of 151 neuropsychiatric inpatients. These five factors were: “Verbal Comprehension”, “Perceptual Organization”, “Sensory-Attention”, “Tactile-Spatial”, and “Primary Motor abilities”, which correspond reasonably well to the current “language”, “perceptual speed”, “perceptual attention”, and “visuospatial cognition” factors, and to the motor factor that would have been obtained if *Finger Tapping* and *Grip Strength* had been included in the present CFA analysis. Discrepancies were found, though, in the composition of Fowler’s “Perceptual Organization” and “Tactile-Spatial” factors. Specifically, “Perceptual Organization” essentially lumped together all the tests from the current “perceptual speed” and “visuospatial cognition” factors, while “Tactile-Spatial” remained somewhat undefined with loadings from the *Wechsler Delayed Spatial Memory task, Grooved Pegboard non-dominant hand*, and *Tactile Form Recognition – dominant and non-dominant hands*. These discrepancies may be partially attributed to differences in measure selection, sample size, and sample characteristics, with likely cognitive impairments among neuropsychiatric inpatient participants.

Comparison with the factor structure of Fowler et al.(1988) suggests that at least three domains of cognitive assessment were added with the expansion of the HRB by Heaton et al. (1991, 2004), notably “working memory”, “fluency”, and “verbal episodic memory”. To be exact, the eHRB expansion might also have added or at least solidified the “language” cognitive domain covered by the HRB. Indeed, the “Verbal Comprehension” factor in Fowler et al. (1988) was almost solely composed of subtests added from the WAIS, PIAT, and Wide Range Achievement Test (WRAT), and included only weak loadings from HRB tests, namely *Aphasia Screening, Speech Sounds Perception*, and *Seashore Rhythm*. In other words, it is possible that without the added subtests from the WAIS, PIAT, and WRAT, Fowler et al. would not have found their “Verbal Comprehension” factor. Interestingly, as shown by the additional factor in the supplemental EFA results, the "language" cognitive construct assessed in the eHRB expansion appears to be different from that assessed by the Wechsler subtests. Specifically, while the latter primarily requires accumulated verbal knowledge, the earlier might be representative of less elaborate language skills.

The loading of the *Category Test* on a single and broad visuospatial cognition factor may be surprising for a test suggested to recruit abstraction, problem solving, logical analysis, organized planning, and organized memory skills (Reitan & Wolfson, 2009). Halstead's (1947) initial factor analysis suggested multifactorial contributions of the *Category Test*. Specifically, he reported loadings on a "central integrative field (C)" factor (along with measures of general intelligence and involving integration of various types of perceptual information), and on an "abstraction (A)" factor (along with the *Carl Hollow Square Test* and *TPT-shapes* and *-locations* measures). Other studies have also reported multifactorial contributions of the *Category Test*, for example with loadings on spatial reasoning and visual memory factors (Leonberger et al. 1991), or perceptual organization and attention-concentration factors (Ryan, Prifiteria, and Rosenberg, 1983). Consistent with the present results, though, other studies have also reported single-factor contributions of the *Category Test* on factors often involving either visuospatial cognition (Fowler et al. 1988) or general intelligence (Boyle, 1988).

The *TPT* has been the subject of similar discrepancies (Ross et al. 2013), but with a consensus overall for loading on a single factor together with the *Category Test* and WAIS performance subtests. Further, separate loadings have been sometimes suggested for the *TPT-shapes* and *-locations* components compared to the *TPT* speed components (e.g., Boyle, 1988; Goldstein, & Shelly, 1971). The present findings are rather consistent with this literature. First, the preliminary EFA, which included only one measure per test to avoid instrumental factors, showed a primary loading of the *TPT* speed measure on the "visuospatial cognition" factor (along with the *Category Test* and *Figure Memory Test*). This EFA also indicated the presence of a secondary loading on the "perceptual speed" factor. Then, during the CFA process, which also included same-test measures, a distinction was made between the *TPT-total* speed measure and the *TPT-shapes* and *-locations* components. Notably, *TPT-shapes* and *-locations* presented with single loadings on the "visuospatial cognition" factor, whereas *TPT-total* presented with weak and equivalent loadings on both the "visuospatial cognition" and "perceptual speed" factors. In the end, a choice was made to retain a model with *TPT-total* loading only on "perceptual speed", as this model permitted a stronger factor loading, a slightly better fit of the data compared to the alternate model, and a clearer model interpretation with separation of measures primarily based or not on speed.

Consistent with previous EFAs on the HRB (Ross et al. 2013), the current EFA results suggest an overall complex factor structure for the eHRB, with many tests loading on several factors. Some of the loadings that appear in the EFA solution, however, might have been mathematically driven by small loadings from other factors, and the complementary CFA approach was essential to clarify the cognitive construct underlying the dataset. For example, the EFA results initially suggested loadings of equivalent sizes for the *Story Memory Test* and *CVLT* on both the "verbal episodic memory" and "attention/working memory" factors. The first CFA results proved the loadings on the latter to be non-significant, and they were discarded from subsequent CFA iterations. Finally, although the final CFA results appear solid in that they represent the convergence of many models, these results remain dependent upon the specific eHRB normative sample tested. Indeed, some relationships between variables might not be put forth in the testing of healthy cognitive individuals, and different factor analytic results might be found in patient samples with different diagnoses. In fact, different factor loadings and even factor structures have been occasionally reported in patients with different types of brain dysfunction (e.g., Russell, 1974; Warnock & Mintz, 1979). Nonetheless, the present work does provide some indication of the main cognitive domains that are being assessed by the eHRB, and certainly constitutes a solid basis for examining individual differences in normal neurocognition.

Individual Differences in Normal Neurocognition

Absolute Neurocognitive Profiles. Individual differences in neurocognitive profiles were first characterized by using LPA on absolute performances in seven neurocognitive domains. Results suggested a prevalent ladder-like distribution of profiles, indicating that individual differences in cognition are dominated by levels of general cognitive ability, even after correcting for age, education, and ethnicity. These findings are consistent with previous cluster analyses of neurocognitive batteries, which reported profiles essentially clustered by general cognitive ability (Donders, 1996; Konold et al. 1999; McDermott et al. 1989). These studies, performed on the Wechsler batteries' adult (WAIS-R) and children (WISC-III) normative datasets, have used scores that were corrected for age only, and reported an impact of educational and cultural backgrounds on clustering (e.g., the "high ability" group had an over-representation of Caucasian children and children of parents with higher educational levels, Konold et al. 1999). The present results suggest that a ladder-like distribution continues to dominate individual differences in neurocognitive profiles even after correction for education and ethnicity. That is, within every demographic group, it appears that some individuals simply tend to perform better than others across cognitive domains.

These results support the notion of a unitary factor of general intelligence, or *g*-factor, accounting for most individual differences in all cognitive performance (Spearman, 1904). Findings that *g* accounts for a substantially large amount of variance in cognitive testing regardless of the test's content or modality of administration have been demonstrated in hundreds of studies (e.g., Caroll, 1993). Individual differences in *g* have been shown to be robust and stable throughout the life span (Deary, 2000), with strong predictive influence on life attainments, such as school achievement, socio-economic success, and health (Deary, Strand, Smith, & Fernandes, 2007; Gottfredson, 1997; Strenze, 2007). Individual differences in *g* have also been shown to be robust across test batteries, as long as they include sufficient variety across tests (Johnson, te Nijenhuis, & Bouchard, 2008). Considering the variety and number of tests included in the eHRB, it is not be surprising that the *g*-factor would also dominate latent grouping in the present study.

The LPA results showed systematic improvement in model fit with increasing number of classes. This pattern suggested the presence of a continuum of individual differences rather than the existence of a specific number of qualitatively different groups. In other words, one could probably justify dividing cognitively healthy individuals into various numbers of groups varying in gradation of ability levels– for example, two groups with low versus high ability levels, or five groups with very low, low, medium, high, and very high ability levels.

Interestingly, LPA solutions beyond six classes started revealing a secondary dimension of individual differences. These more subtle profile patterns appeared first at average levels of general cognitive ability (6-class solution) and then at high-average levels of cognitive ability (7-class solution). At both ability levels, the results suggested distinction of individuals based on their relatively better or worse performance on factors involving verbal abilities (i.e., "fluency", "language", and "verbal episodic memory") compared to perceptual abilities (i.e., "visuospatial cognition", "perceptual speed", and "perceptual attention"). These findings are again consistent with the cluster analyses that have been carried out on the WAIS-R and WISC-III normative datasets where minor profile variations in terms of VIQ versus PIQ were reported at various ability levels (Donders, 1996; Konold et al. 1999; McDermott et al. 1989). For example, the eight groups resulting from the multistage cluster analysis of the WISC-III normative dataset were listed as: “High ability”, “Above average”, “Above average and VIQ>PIQ”, “Average and VIQ>PIQ”, “Average and PIQ>VIQ”, “Below average and VIQ>PIQ”, “Below average”, and “Low” (Konold et al. 1999).

Methodological difficulties associated with cluster analysis have been pointed out before for distinguishing subtle profile patterns within data containing large differences in profile elevations (Moses, Pritchard, & Faustman, 1994). The present results, notably the evolution between a ladder-like distribution of profiles at smaller numbers of classes and arising of subtle profile patterns at larger numbers of classes, suggested that these difficulties also apply to LPA techniques. The issue of identifying subtle patterns obscured by larger variation is common in intelligence research, with *g* almost systematically dominating the amount of variance explained in the data and undermining identification of task-specific processes (Deary, Penke, & Johnson, 2010). Controlling for *g* has been suggested before in order to isolate processes unique to single tasks (e.g., Johnson, Jung, Colom, & Haier, 2008; Vernon, 1964). A similar method was applied in the current study to examine subtle patterns of individual differences in relative neurocognitive profiles, independently of general cognitive ability.

Relative Neurocognitive Profiles. The second series of LPAs, carried out on cognitive performances corrected for general cognitive ability, revealed interesting patterns of individual differences in neurocognition. The most representative LPA solution suggested eight groups of cognitively healthy individuals, defined by pairs of seemingly mirroring relative neurocognitive profiles (Figure 5a): “mildly verbal” (19%) versus “mildly perceptual” (20%) individuals, characterized by slightly better relative performance in verbal versus perceptual cognitive domains; “highly verbal” (13%) and “highly perceptual” (9%) individuals, characterized by markedly better relative performance in verbal versus perceptual cognitive domains; “visuospatial cognitive” (6%) versus “super fluent” (8%) individuals, characterized by markedly better relative performances in visuospatial cognition and verbal episodic memory versus fluency; and “verbal memorizer” (11%) versus “fast attentive” (14%) individuals, characterized by better relative performance in “verbal episodic memory” versus “perceptual attention” and “perceptual speed”. The eight groups did not differ in level of general cognitive ability.

These findings support the presence of individual differences in cognition or cognitive styles at every level of general cognitive ability, and the idea that two individuals might reach identical levels of general intelligence by using different cognitive strategies or neuronal routes (Johnson & Bouchard, 2007; Neubauer & Fink, 2009). The resulting pairs of mirroring relative neurocognitive profiles suggested specific compensatory mechanisms to permit attaining similar levels of general cognitive ability. These compensatory cognitive routes were characterized by three main dipoles consisting of: verbal versus perceptual abilities, visuospatial cognition versus fluency abilities, and verbal memory versus perceptual attention and speed abilities. These mechanisms and potential underlying processes are discussed in the following section.

The eight groups of the most representative LPA solution were found to be distinct both in terms of relative and absolute neurocognitive profiles, but with effect sizes varying across groups and neurocognitive domains. For example, “highly verbal” individuals were found to perform markedly better than “highly perceptual” individuals in all verbal cognitive domains in both relative and absolute terms (large effect sizes). By contrast, “mildly verbal” and “mildly perceptual” individuals had large overlaps in absolute neurocognitive profiles (small effect sizes). As a result, many “mildly verbal” individuals were found to have better absolute performances on perceptual tasks compared to "mildly perceptual" individuals (or vice-versa), simply due to higher levels of general cognitive ability. The same was true of "verbal memorizer" versus "fast attentive" individuals.

These considerations likely explain difficulties encountered by previous studies in relating differences in cognitive style to differences in cognitive performance. For example, self-reported preference for using imagery over verbal strategies (c.f. "Verbalizer-Visualizer Questionnaire", Paivio, 1971; Richardson, 1977) was shown to have weak or no correlation with performance on visuospatial tasks (e.g., Alesandrini, 1981; Green & Schroeder, 1990; Lean & Clements, 1981). Further, "verbalizers" in some studies were found to perform at an intermediate level on all visuospatial tasks (Kozhevnikov et al. 2002, 2005). Because these studies did not control for *g*, it is likely that actual relations between cognitive style and specific cognitive performance, if they were present, were masked by larger individual variations in general cognitive ability. In other words, it is possible that the "verbalizers" that were identified using the "Verbalizer-Visualizer Questionnaire" were indeed better at verbal tasks and worse at visuospatial tasks than the "visualizers", but when comparing "verbalizers" and "visualizers" of similar general cognitive ability.

Three-Dimensional Continuum of Individual Differences in Neurocognition. Although the eight-class model provided a good data fit and may arguably offer the most representative description of individual differences in neurocognition, the systematic improvement of model fit with increasing number of classes suggested again the presence of a continuum of individual differences rather than the existence of a specific number of qualitatively different groups. That is, one could probably continue dividing the sample into more classes of fewer and more cognitively similar individuals. Indeed, the ten-class solution resulted in an even better fit of the data with the identification of "very highly verbal" (4.1%)

and “very highly perceptual” (2.9%) classes of individuals in addition to the eight classes previously described. Solutions beyond eight classes were not retained only due to the smaller proportions of individuals represented in the additional classes.

To explore the continuum underlying all LPA solutions, projections of factor scores were calculated onto the three-dimensional vector space corresponding to the three dimensions of greatest variance in the data – i.e., the three eigenvectors with largest eigenvalues in the demographic-corrected factor scores’ covariance matrix. (Eigenvalues: λ=1.907, 0.362, 0.156, 0.054, 0.048, 0.014, 0.006). The dimensions corresponding to the next eigenvalues were considered to represent minimal amounts of variance by comparison and were not plotted. The 7-class solution of the LPA on absolute factor scores was nicely revealed in the plane constituted by the first two eigenvectors (Figure 9 – left upper panel). Notably, the dominant division of individuals by general cognitive ability levels appeared as slices along the first eigenvector dimension; and the verbal/perceptual secondary level of individual differences emerged at average and high average ability levels along the second eigenvector dimension. Unsurprisingly, the 8-class solution of the LPA on relative factor scores did not appear clearly in this plane due to the removal of information pertaining to general cognitive ability (Figure 9 – left lower panel). The LPA relative solution, though, distinctly emerged in the plane constituted by the second and third eigenvectors (Figure 9 – right lower panel).These plots confirm continuity between the latent classes identified in the two LPA series and suggest a mostly three-dimensional continuum of individual differences in normal neurocognition as defined by performance on the eHRB.

Dimension 1: general cognitive ability. As previously mentioned, the first and by far dominant dimension of this continuum (eigenvector 1) may be interpreted as levels of general cognitive ability – i.e., the *g*-factor or psychometric definition of general intelligence (Spearman, 1904). This primary channel of individual differences is visualized in Figure 9 by a dominant stretch of data in this direction and by large positive correlations between factors (Figure 9 – left panels, see also Table 7). The factor most representative of this general direction of variance, or factor with smallest amount of remaining variance after controlling for general cognitive ability, was the "working memory" factor. This is perhaps not surprising as the measures with greatest loadings on this factor (i.e., *Trails Making Test-Part B* and *PASAT*) have been shown to require the simultaneous integration of a wide range of key abilities – including verbal working memory, visual search or imagery strategies, cognitive flexibility, and processing speed – and have been described as non-specific, highly sensitive, and among the best indicators of general brain function (Reitan, 1955b; Reitan & Wolfson, 2009; Sánchez-Cubillo, 2009; Tombaugh, 2006). Further, working memory, the brain system dedicated to the temporary storage and manipulation of information, has been suggested to be one of the best predictors of general intelligence (e.g., Engle, Tuholski, Laughlin, & Conway 1999; Kyllonen, 1996; Jensen, 1998), with a basis for this relationship thought to be mediated by executive-attention control and involvement of the dorsolateral prefrontal cortex (Conway, Kane, & Engle, 2003).

Individual differences in general cognitive ability have been suggested to be related to individual differences in brain structure and activation, white matter integrity, and brain efficiency (e.g., Deary et al. 2010; Jung & Haier, 2007; Neubauer & Fink, 2009). Notably, brain correlates of the *g*-factor have been reported to include brain volume (e.g., Reiss, Abrams, Singer, Ross, & Denckla, 1996) and cortical thickness (e.g., Narr et al. 2007), with more recent studies suggesting that trajectory of change in brain structure may be more closely related to *g* than brain structure itself (Shaw et al. 2006; Schnack et al. 2015). Specifically, Schnack et al. (2015) found an association between higher IQ and greater and faster changes in brain structure during cognitive development (i.e., faster cortical surface area expansion and cortical thinning during childhood, followed by faster surface area reduction and cortical thickening). Specific brain regions have also been associated with individual differences in general cognitive ability. Notably, based on a review of structural and functional neuroimaging studies, Jung & Haier (2007) proposed a parieto-frontal integration theory of intelligence. They suggested that individual differences in intelligence resides in a network of brain regions, involving the occipital and temporal lobes (i.e., the extrastriate cortex, fusiform gyrus, and Wernicke's area for the recognition, imagery, and elaboration of visual and auditory inputs), parietal lobes (i.e., the supramarginal, superior parietal, and angular gyri involved in symbolism, abstraction, and elaboration), and frontal lobes (i.e., the dorsolateral prefrontal cortex, engaged in working memory processes for comparison of possible behavioral responses, and the anterior cingulate cortex responsible for response engagement and inhibition of alternative responses). Most of these brain regions were found to involve predominant activation of the left hemisphere, although some showed dominant involvement of the right hemisphere. White matter integrity but also network organizational efficiency have also been related to greater levels of general intelligence (Deary et al. 2006; Li et al. 2009), presumably contributing to more efficient interactions between the brain regions identified above (Jung & Haier, 2007). Further, higher IQ has been associated with lower cortical activity at rest or during tasks of low to moderate difficulty, but higher cortical activity during more difficult tasks, especially in frontal and parietal regions (Neubauer & Fink, 2009; Song et al. 2008; van den Heuvel, Stam, Kahn, & Hulshoff Pol, 2009). The notion of brain functional efficiency may therefore be key for understanding individual differences in general cognitive ability (Neubauer & Fink, 2009).

Dimension 2: "verbal" vs. "perceptual". The second dominant dimension of individual differences (eigenvector 2), after controlling for general cognitive ability, was found to distinguish individuals based on their verbal versus perceptual abilities. Specifically, individual differences along this dimension were characterized by a tradeoff between relative performances in “language”, “fluency”, and to a lower extent “verbal episodic memory” (negative y-values in Figure 9) and relative performances in “visuospatial cognition”, “perceptual speed”, and “perceptual attention” (positive y-values). In other words, a negative association was found between verbal and perceptual abilities after controlling for general cognition, a finding consistent with previous studies (e.g., Johnson & Bouchard, 2006; Vernon, 1964).

Because general cognitive ability represented a far dominant source of variance, controlling for it was mathematically bound to lead to some negative correlations among residual scores (Vernon, 1964). Nonetheless, as previously debated (e.g., Johnson & Bouchard, 2006; Lynn, 1990), the exact pattern of associations between residual scores is not dictated by the method and is considered representative of actual relationships between underlying cognitive processes. For enhanced interpretation, projections of all available demographic-corrected test scores were also calculated and plotted on the three-dimensional eigenvector space (Figure 10). Almost all tests had projections that were consistent with expectations (Table 1), confirming the interpretation of eigenvector 2 as a “verbal-perceptual” dimension. The only exception was the *PASAT*, a measure primarily considered to assess verbal working memory (Gonzalez et al. 2006), but that unexpectedly projected toward the perceptual direction. Involvement of perceptual processes during *PASAT* administration might be consistent, though, with the complexity and non-specificity of the task (Tombaugh, 2006) and with previous findings suggesting correlations between visual-spatial abilities and performance on the PASAT and other tasks requiring mathematical operations (Hegarty & Kozhevnikov, 1999; Sherman, Strauss, & Spellacy, 1997).

The finding that individual differences in cognition are dominated, after parsing out general cognitive ability, by verbal versus perceptual differences, supports the relevance of the cognitive style literature that has divided and examined individuals along a verbalizer-versus-imager dimension (Binet, 1894; Galton, 1883, Paivio, 1971; Riding & Cheema, 1991). The present results especially confirm the conceptualization of individual differences in verbal versus perceptual cognitive abilities along a continuum rather than as categorical types (Thorndike, 1914). Specifically, consistent with the distribution of VIQ minus PIQ scores presented in Matarazzo & Herman (1985), the frequency distribution of individuals along the verbal-to-perceptual dimension was found to be normal and centered on zero. Individuals with smaller within-profile variations were therefore more common than those with larger variations. Nonetheless, large within-profile variations along the verbal-to-perceptual dimension were not uncommon. For example, 22% of individuals were classified as either "highly verbal" or "highly perceptual" and had within-profile variation of about 1.4 standard deviation, on average, between their language and visuospatial demographic-corrected performances. These results are consistent with the important base rates of statistically significant VIQ/PIQ discrepancies published by Matarazzo & Herman (1984, 1985). An association between greater FSIQ and greater base rates of large VIQ/PIQ differences was also reported in Matarazzo & Herman (1985). That finding, however, was not supported in the present study. In fact, no difference was found in general cognitive ability between "mildly verbal or perceptual" and "highly verbal or perceptual" individuals. The present results suggest similar distributions of relative cognitive strengths and weaknesses at all levels of general cognitive ability.

By highlighting the predominant importance of verbal versus perceptual abilities for understanding individual differences in normal neurocognition, the present study also brings support to theories of information processing that have distinguished between a verbal and non-verbal system of object representations (e.g., Paivio, 1971). Notably, Paivio (1991) suggested in his dual coding theory that the verbal and non-verbal systems had additive effects on cognitive performance and may be activated differentially depending on task demands and on individual differences in verbal versus imagery abilities. The present findings support these ideas, suggesting that similar levels of general cognitive performance may be reached by individuals differing in their verbal versus perceptual abilities, presumably by using information processing strategies differentially involving the verbal or non-verbal systems. Notably, the results suggest amplitude-bound compensation between verbal and perceptual abilities, with greater strengths in one area permitting compensation of greater weaknesses in the other area. Such compensatory relationships were found both in terms of relative and absolute performances, although with large effect sizes only for more extreme profiles. These considerations are consistent with previous reports of a double dissociation between verbal or imagery cognitive styles and performances on tasks involving verbal symbolization or concrete imagery (e.g., Kuhlman, 1960; Luria, 1968). For example, children classified as high imagers were better at recalling concrete visual stimuli but worse at categorizing objects into abstract categories, whereas children classified as low imagers showed the opposite trend (Kuhlman, 1960). Such clean findings are scarcely found in the literature, though, with most studies reporting inconclusive differences in absolute cognitive performance between individuals varying in verbalizer/imager cognitive styles (Alesandrini, 1981; Green & Schroeder, 1990; Kozhevnikov et al. 2002, 2005; Lean & Clements, 1981). As mentioned before, the absence of such findings are likely related to a failure to control for the *g*-factor and the obscuring of subtle individual differences by larger variations in general cognitive ability.

Individual differences along a verbal-to-perceptual dimension maps rather nicely on the demonstrated lateralization of brain functions, with the left hemisphere specializing in language processing and the right in visuospatial and perceptual processing (e.g., Broca, 1861; Milner, 1971; Sperry, 1975; Spring & Deutsch, 2001). The question of individual variations in terms of right-brain versus left-brain processing seems therefore legitimate, with perhaps the idea that individuals might differentially use right versus left hemisphere neuronal routes to reach similar levels of general cognitive ability. There has been no clear evidence so far about the existence of left-brained versus right-brained phenotypes. In fact, a recent fMRI study ruled against it, based on lack of finding for greater left versus right network strength in resting state functioning connectivity across individuals (Nielsen et al. 2013). This study, however, did not have information about their subjects' general cognitive ability and thus could not correct for it. The obscuring by *g* of individual differences in brain activation related to specific tasks has been suggested to greatly impact imaging studies (e.g., Keary et al. 2010). It is therefore possible that individual differences in general cognitive ability, which have been shown to involve a bilateral parieto-frontal network of brain areas (Jung & Haier, 2007), might have masked subtle patterns of individual differences in brain function, notably between the right and left hemisphere. Using magnetic resonance imaging (MRI) and voxel-based morphometry (VBM), Johnson & Bouchard (2008) did examine regional brain structure correlates of verbal versus spatial rotation cognitive abilities independent of *g*, but again did not especially report lateralized effects of one or the other cognitive domain. As they suggested though, their sample size was small for examining individual differences, and their study is pending replication in a larger and broader sample. It is also possible that only a subset of individuals in the population may actually qualify as "right-brainers" or "left-brainers". Indeed, in the present LPA results, only "highly verbal" and "highly perceptual" individuals displayed large effect size differences between their verbal and perceptual absolute performances – and they represented only 22% of the sample population. To have a chance of detecting right-brain versus left-brain phenotypes, imaging studies might have to preliminary sort individuals based on their relative cognitive strengths and weaknesses, and compare only those with larger within-profile variations at equal levels of general cognitive ability.

Dimension 3: "analysis" versus "attention/speed". The third dimension of largest individual variations in normal neurocognition as measured by the eHRB (eigenvector 3) was found to involve a tradeoff between relative performances in "verbal episodic memory", "visuospatial cognition", and "language", and relative performances in "perceptual attention", "fluency", and "perceptual speed" (Figure 9, right panels). As mentioned in the previous section, although some negative correlations between residual scores after correcting for general cognitive ability were mathematically bound to occur, the patterns of associations between residuals are considered representative of underlying cognitive processes (Lynn, 1990; Johnson & Bouchard, 2006; Vernon, 1964). The examination of the factors and tests that projected onto this third dimension (Figure 10) suggested a tradeoff between relative cognitive abilities related to the "analysis" of material content, including learning, memory, and reasoning (dominant projections: *Story Memory Test*, *CVLT*, *Figure Memory Test*, *Category Test*, and *BNT*) and "attention/speed" relative abilities, including sustained attention, behavioral engagement, and speed (dominant projections: *Speech-Sounds Perception Test*, *Seashore Rhythm Test*, *Tactile Form Recognition Test*, *Digit Vigilance Test – Time*, *Trail Making Test – Part A*, *FAS Letter Fluency Test*, *Thurstone Word Fluency Test*, and *Grooved Pegboard Test*).

The comparison of projections of same-test variables supported this "analysis" versus "attention/speed" interpretation. For example, the *TPT* trials' speed measures (i.e., how fast participants were able to place a specific number of shapes onto a wooden board while blind-folded) projected toward "attention/speed" while the *TPT* memory measures (i.e., recall of the shapes and their locations on a wooden board) projected toward the "analysis" direction. In a similar way, the *Digit Vigilance Test*'s speed measure (i.e., time of test completion) projected toward "attention/speed", whereas its accuracy measure (i.e., number of errors committed) projected toward "analysis". Further, the phonemic fluency measures (*FAS Letter Fluency* and *Thurstone Word Fluency Tests*), which have been suggested to bare higher executive loads (e.g., Baldo, Schwartz, Wilkins, & Dronkers, 2006; Gourovitch et al. 2000), had larger projections onto "attention/speed" than the semantic fluency test (*Category Fluency Test*). The projections of the Wechsler scales' test measures, which were not included in the factor analyses and were therefore not involved in the construction of the continuum, were also consistent with the proposed interpretation. Notably, the Wechsler verbal subtests showed increasing projections toward the "analysis" direction with increasing demands, arguably, on reasoning and analytic skills rather than solidified knowledge (in order from least to most analytic: *Vocabulary*, *Information*, *Comprehension*, *Similarities*, and *Arithmetic*). A similar pattern was true for the Wechsler performance subtests which differentially projected toward "analysis" with increasing reasoning and perhaps verbal demands as opposed to perceptual skills (in order: *Object Assembly*, *Block Design*, *Picture Completion*, and *Picture Arrangement*). Strikingly almost all the Wechsler subtests were located in the "analysis" hemi-field, with only *Digit Symbol-Coding* projecting toward "attention/speed". (*Digit Span* projected mostly onto the general cognitive ability dimension, consistent with projections of other measures involving working memory, such as the *PASAT* and *Trail Making Test –Part B*.)

It must be emphasized that the identified tradeoff between "analysis" and "attention/speed" only applies to relative neurocognitive abilities. That is, the results suggest that two individuals with similar general cognitive ability might employ the two following cognitive routes to reach similar scores on most neurocognitive tests: (1) an "analysis" route, which involves in-depth processing of content material including learning, memory, and reasoning; and (2) an "attention/speed" route, which involves sustained attention, behavioral engagement with fast execution, and presumably fast adjustment depending on feedback. These tradeoff mechanisms are well described by the military terms "strategy" versus "tactics", which deal with analyzing, preparing, and planning operations versus observing and reacting to events as they unfold.

Similar accuracy-versus-speed tradeoffs have previously been suggested to describe individual differences in cognition, notably in terms of "reflection" versus "impulsivity" cognitive styles, where "reflection" refers to a tendency to carefully deliberate in uncertain conditions and "impulsivity" to a tendency to make decisions quickly (Messer, 1976 for a review). Perhaps related to a lack of control for general cognitive ability, the studies reviewed by Messer (1976) have often painted a negative picture of "impulsivity". In particular, impulsive children, often identified only in terms of their response speed, have been associated with lower IQ, lower sustained attention, and school failure (Messer, 1976). If IQ had been examined first, though, it might have been found to account for the largest portions of variance in all cognitive performances, including number of accurate answers, speed of decision making, and levels of sustained attention. Then, among individuals of similar IQ, more impulsive children might have shown better attention skills than their IQ counter-parts, and perhaps even outperformed them in tasks other than those requiring pondering and analyzing.

Interestingly, the cognitive mechanisms involved in the "analysis" versus "attention/speed" tradeoff appear remarkably consistent with Luria's theory of brain functioning and his division of the higher cortex into three interacting "blocks" (Luria, 1970). Specifically, the processes corresponding to better performance in the "analysis" direction are consistent with "block 2" processes, encompassing the analysis, coding, and storage of information; and processes leading to better performance in "attention/speed" are consistent with "block 3" processes, encompassing attention regulation and the generation of intentions and behavioral programs. With the close correspondence between Kosslyn's theory of cognitive mode and Luria's theory of brain functioning, the "analysis" versus "attention/speed" tradeoff also maps well onto Kosslyn's "bottom-brain" and "top-brain" systems (Kosslyn & Miller, 2013). Notably, cognitive constructs representative of the "analysis" direction may be subsumed under the "bottom-brain" or ventral pathway functions – i.e., the organization, comparison to memory content, classification, and interpretation of incoming information; and cognitive constructs representative of the "attention/speed" dimension may be classified as "top-brain" or dorsal pathway functions, including the voluntary allocation of attention and executive functions such as planning, monitoring, and adjusting the carrying out of plans (Kosslyn & Miller, 2013; Posner, 1980; Sereno, Pitzalis, & Martinez, 2001).

Despite the correspondence noted above, the tradeoff identified as "analysis" versus "attention/speed" is in no way suggesting a tradeoff between "bottom brain" and "top brain" functions. In fact, most of the individual variance in "bottom brain" and "top brain" functioning is likely related to variance in general cognitive ability, or *g*-factor, just like variance in any brain region related to cognition (Deary et al. 2010). Further, considering that individual differences in *g* have been shown to involve brain regions recruited in information processing (Jung & Haier, 2007), this is probably even truer of Kosslyn's proposed "bottom brain" and "top brain" systems which were identified based on information processing theory (Kosslyn & Miller, 2013). What the present "analysis" and "attention/speed" tradeoff suggests is that at equivalent level of general cognitive ability, two individuals might use their "bottom-brain" or "top-brain" functions differentially to arrive at similar scores on most cognitive tests.

Dimensions 2 × 3. The eight latent classes identified in the second series of LPA on ability-corrected factor scores were distinguished with little overlap in the continuum defined by the verbal-perceptual and “analysis”-“attention/speed” dimensions (Figure 9). Such neat division confirmed discarding dimensions of variance beyond the third eigenvalue for interpreting differences across latent classes. Mirroring pairs of latent classes may be described symmetrically within this two-dimensional continuum. The “highly verbal” class may be described as “verbal” and “slightly analytic”, the “highly perceptual” group as “perceptual” and “slightly executive”, the “super fluent” group as “verbal” and “attentive/fast”, the “visuospatial cognitive” group as “perceptual” and “analytic”, the “verbal memorizer” group as “slightly verbal” and “analytic”, and the “fast attentive” group as “slightly perceptual” and “attentive/fast”. The “mildly verbal” and “mildly perceptual” groups were differentiated only along the verbal-perceptual dimensions. (The qualifier “slightly” represents differences of at least medium effect sizes, verified using univariate analyses of variance). Interestingly, LPA grouping suggests that the “verbal”-“perceptual” and “analysis”-“attention/speed” dimensions might not be completely orthogonal to each other. (That is, the “analysis”-“attention/speed” dimension might not be completely aligned with eigenvector 2.) Indeed, among the six LPA classes with large within-profile variations, four of them showed the associations “verbal”/“analytic” or “perceptual”/“attentive/fast”. A small association between “verbal” and “analytic” relative cognitive skills would be consistent with previous research on cognitive styles, suggesting that individuals identified as having verbal cognitive styles were more analytic, whereas individuals with imagery cognitive styles were more holistic (e.g., Kirby et al. 1988). This association would also be consistent with the dual coding theory of Paivio (1971), who proposed the existence of a verbal system for both language processing and abstraction, permitting the symbolic representation and categorization of objects and experiences. Further evidence is necessary, though, to confirm the “verbal/analytic” association in terms of individual differences in cognition and examine whether the complementary processes – i.e., holistic and concrete information processing – may be related to the "attention/speed" and "perceptual" dimensions.

Two orthogonal tradeoff dimensions have been reported before as part of a study examining cognitive performance corrected for *g* (Johnson & Bouchard, 2006). Although the authors arrived at a different interpretation of these dimensions, the cognitive processes involved in the tradeoffs are strikingly similar to the results of the present study, supporting the possible generalization of the findings to other test batteries and subject samples. Using the twin study sample from the Minnesota Study of Twins Reared Apart (MISTRA, N=436), Johnson & Bouchard (2006) performed a confirmatory factor analysis of *g*-corrected as well as age and sex-corrected scores obtained on 42 tests selected from the Comprehensive Ability Battery, Hawaii Battery, and WAIS. These tests covered a wide range of cognitive abilities, identified in another factor analytic study as verbal, scholastic, fluency, number, content memory, perceptual speed, spatial (or visuospatial), and image rotation abilities (Johnson & Bouchard, 2005). In the third-stratum of their analysis, Johnson & Bouchard (2006) extracted three non-rotated and thus orthogonal factors, consisting of "content memory" and of two tradeoff dimensions termed "rotation-verbal" and "focus-diffusion". (They reported difficulties with the matrix of correlations not being positive definite and used heavy ridge smoothing.) The "rotation-verbal" dimension was characterized by positive loadings from visuospatial, rotation, and perceptual speed, and by negative loadings from verbal, scholastic, and fluency. The "focus-diffusion" dimension was predominantly characterized by positive loadings from perceptual speed and fluency (content memory also loaded positively on this dimension but to a smaller extent), and by negative loadings from scholastic and visuospatial abilities. Based on these primary loadings, the two tradeoff dimensions identified in Johnson & Bouchard (2006) appear rather consistent with the "verbal-perceptual" and "analysis-attention/speed" dimensions identified in the present study. The only major difference was related to "content memory", which Johnson & Bouchard (2006) identified as a third orthogonal residual dimension, and as having a small positive loading on "focus-diffusion". Perhaps related to this difference, the interpretation of the "focus-diffusion" dimension was very different, proposing a tradeoff between relative abilities requiring the application of focused attention (i.e., verbal, scholastic, visuospatial, and image rotation) and those requiring more diffuse attention to a variety of cues simultaneously (i.e., fluency, perceptual speed, and content memory). The reason that abilities such as fluency, perceptual speed, or content memory should require more diffuse attention than language, scholastic, visuospatial, and image rotation abilities, was not justified based on prior literature and may not seem warranted. Nonetheless, the similarities between the orthogonal dimensions of Johnson & Bouchard (2006) and the present results are very encouraging, likely supporting the intrinsic existence of a continuum of individual differences in residual cognitive abilities that is dataset-independent.

Demographic Distributions across Neurocognitive Profiles

The demographic compositions of the identified latent classes indicated no difference in age, education, and ethnicity distributions across groups. These findings suggest the presence of similar patterns of relative cognitive strengths and weaknesses at each age, educational level, and across African American or Caucasian ethnicity, provided that each cognitive domain be previously and separately corrected for these demographics.

Gender. Equivalent distributions of males and females were also found across most latent classes, but with the exception of the "highly perceptual" group, where the proportion of females was significantly smaller. In other words, there was an over-representation of males among individuals with disproportionately greater relative perceptual compared to verbal skills and slightly better attention and executive speed compared to analysis skills. Although the proportion of females was the largest in the "highly verbal" group, that proportion was not significantly different from that of the other groups combined. These rather minimal gender differences in terms of distributions of neurocognitive profiles were also confirmed by minimal differences in average scores on the factors and three-dimensional continuum. Notably, females were found to outperform males in "working memory", "language", "fluency", and "verbal episodic memory", but with negligible effect sizes, and there were no significant gender differences in "visuospatial cognition", "perceptual speed", and "perceptual attention". Further, gender differences were also significant but negligible in effect sizes on the general cognitive ability dimension ($F(1,980)$=4.4, p=.036, η^2=.004, females better than males) and on the "verbal-perceptual" dimension ($F(1,980)$=4.1, p=.042, η^2=.004, females more verbal, males more perceptual, see Figure 11); and there was no significant gender difference on the "analysis-attention/speed" dimension ($F(1,980)$=0.2, p=.665, η^2<.001).

These results overall suggest great similarity across gender in relative neurocognitive profiles, consistent with reviews and meta-analyses suggesting more cognitive similarities than differences between men and women (Hyde, 2005; Zell et al. 2015). The small effects that were nonetheless noted were consistent with previous accounts suggesting that males tend to outperform females on visuospatial tasks and that females tend to outperform males on verbal tasks (Maccoby & Jacklin, 1974), although with differences in verbal skills that have been suggested to be small (Cohen's d = −0.11, Hyde, 2014).

These findings contrast with the large gender differences in relative cognitive abilities reported by Johnson & Bouchard (2006), with males scoring higher towards the "rotation" and "focus" poles, and females scoring higher toward the "verbal" and "diffusion" poles and higher on the "content memory" factor (Cohen's d=0.58, 0.90, and 0.62, respectively). Part of this discrepancy in gender findings might be related to the inclusion in Johnson & Bouchard (2006) of tests assessing mental rotation abilities, with such tests being absent in the present study. Indeed, gender differences in visuospatial skills have been shown to vary depending on the task (Voyer, Voyer, & Bryden, 1995), with robust gender gaps demonstrated in tasks requiring the spatial manipulation of mental images, especially 3D mental rotations (Cohen's d=0.57, Maeda & Yoon, 2013), while gender differences have been shown to be small to negligible in visuospatial perception and visuospatial cognitive tasks (Voyer et al. 1995), and even to benefit women in object-location memory (Voyer, Postma, Brake, & Imperato-McGinley, 2007). It is therefore possible that with the absence of mental rotation tests in the eHRB normative database, gender differences in cognition were underestimated in the present study. That said, the large gender gap reported by Johnson & Bouchard, (2006) along the "focus-diffusion" dimension seems harder to reconcile with the present absence of findings along the "analysis-attention & executive" dimension. Indeed, gender differences suggesting use of more "focused" attention in men and more "diffused" attention in women does not hold strong baring in the literature. In fact, the opposite trend might be expected based on prior studies suggesting information processing that is more analytic in women and more holistic or intuitive in men (e.g., Heil & Jansen-Osmann, 2008; Sadler-Smith, 1999).

Handedness. Considerations of handedness distributions across neurocognitive profiles suggested a disproportionately smaller proportion of left-handers among individuals with smaller within-profile variations (i.e., the "mildly verbal" and "mildly perceptual" groups) and a disproportionately greater proportion of left-handers among individuals with large variations between verbal and perceptual abilities (i.e., the "highly verbal" and "highly perceptual" groups). These results suggest greater intra-individual variability in neurocognition in left-handed compared to right-handed individuals. No significant differences were found between right-handed and left-handed individuals in terms of average scores on the factors or on the three-dimensional continuum, including general cognitive ability ($F(1,980)$=0.6, p=.459, η^2=.001), "verbal-perceptual" dimension ($F(1,980)$=1.1, p=.286, η^2=.001), and "analysis-attention/speed" dimension ($F(1,980)$=0.1, p=.754, η^2<.001). On all three of the continuum dimensions, however, the distributions of scores of left-handers were found to be flatter (kurtosis = -0.41, -0.21, and -0.48 on dimensions 1, 2, and 3, respectively) than those of the right-handers (kurtosis = -0.18, 0.31, and 0.05 – see Figure 11), thus supporting the presence of more cognitive variability in this population.

The effect of handedness on neurocognitive abilities has been the subject of much debate (e.g., Corballis, Hattie, & Fletcher, 2008; McManus, 2002). Notably, left-handedness has been related to a functional reorganization of the brain's usually dominant left-hemisphere, resulting in the relocalization of hand-control and often language functions (Jung, Baumgärtner, Magerl, & Treede, 2008). This re-organization has been suggested to have beneficial effects and lead to enhanced brain functions, with some studies suggesting an over-representation of left-handers among bright and even gifted individuals (Benbow, 1986; Halpern, Haviland, and Killian, 1998). By contrast, other accounts have suggested that left-handedness, unless inherited genetically, might be acquired due to early brain damage to the left cerebral hemisphere and thus be related to general cognitive deficits (Miller, Jayadev, Dodrill, & Ojemann, 2005; Ramadhani, Koomen, Grobbee, van Donselaar, van Furth, & Uiterwaal, 2006; Satz, Orsini, Saslow, & Henry, 1985). This theory has been supported by reports of an association between left-handedness and general deficits in cognitive ability (Johnston, Nicholls, Shah, and Shields, 2009).

The present findings, suggesting greater intra and inter neurocognitive variability in left-handed individuals, are consistent with previous reports of an over-representation of left-handed individuals in both the upper-tail (Benbow, 1986) and lower tail (Johnston et al. 2009) of general cognitive abilities. The greater proportion of left-handers among individuals with large intravariability along the verbal-perceptual dimension is also consistent with previous findings suggesting an over-representation of left-handers among individuals with superior verbal reasoning skills (Halpern et al. 1998) and among individuals with superior perceptual skills, such as creative artists (Preti & Vellante, 2007). The increased intravariability noted along the verbal-perceptual dimension might be related to cerebral functional reorganization associated with left-handedness, previously shown to differentially affect lateralized brain functions (Jung et al. 2008).

The present findings certainly do not support the presence of general or specific cognitive deficits in left-handed compared to right handed individuals. It has been suggested, however, that handedness should be examined not only in terms of dichotomous self-reported hand-preference (as in the present study) but also in terms of strength of handedness, with many studies reporting decreased cognitive performance with weaker hand-lateralization (e.g., Corballis et al. 2008; Crow, Crow, Done, and Leask, 1998). A few studies, however, have also reported the opposite trend. For example, Nicholls et al. (2010) have examined the effect of both hand-preference (using the Annett Handedness Questionnaire; Annett, 1970) and hand-performance (measured as the discrepancy between participants' right- and left-hand finger tapping scores) on general cognitive abilities. They found a quadratic effect of hand-performance on general cognitive ability and concluded that strong left-handers and strong right-handers had a subtle disadvantage compared to individuals with smaller hand-performance disparities.

To test the effect of strength of handedness on general cognitive ability in the present study, a similar method as that of Nichols et al. (2010) was tried out. Specifically, disparities between right-hand and left-hand performance were calculated by using scores on the *Finger Tapping Test*, *Grooved Pegboard Test*, *Grip Strength Test*, *Sensory-Perceptual Examination*, and *Tactile Form Recognition Test*. As suggested in Nicholls et al. (2010), the equation (Right - Left) / (Right + Left) was employed to calculate the lateralization indices of hand-performance. The results obtained were rather mixed. First, although significant effects of self-reported handedness were found on the three motor-based lateralization indices (p<.001), these effects were surprisingly small in effect sizes (η^2 = .041, .053, and .089, for the *Grip Strength Test*, *Finger Tapping Test*, and *Grooved Pegboard Test*, respectively). Further, there was no significant effect of self-reported handedness on the sensory-perceptual-based lateralization indices. Second, the correlations between the three motor-based indices were also surprisingly small, with significant but very small correlations found between the *Grooved Pegboard* lateralization index and *Finger Tapping* (r =.152) and *Grip Strength* (r=.120) indices, and no significant correlation between the *Finger Tapping* and *Grip Strength* indices. These preliminary results suggest that lateralization indices based on hand-performance could be considered, at best, unreliably related to strength of handedness. Using multiple linear regression and a similar quadratic model as that of Nicholls et al. (2010), the effect of the *Grooved Pegboard* lateralization index on general cognitive ability was calculated. The statistical results were almost identical to those of Nicholls et al. (2010), including a significant contribution of the model (p<.001), significant quadratic term (p<.001), significant linear term (p=.034) terms, and a proportion of variance explained by the model that was smaller than 1.5% (R^2=.014). However, unlike the conclusions of Nicholls et al. (2010), it seems that the latter number, which does not even meet criteria for a small effect (Cohen et al., 2003), would suggest a negligible rather than subtle effect of hand-performance on general cognitive ability. As noted earlier, though, with the lack of reliability and construct validity of hand performance as an indicator of strength of handedness, it is unlikely that this result means anything about the effect of handedness on cognition.

Beyond the small differences noted in gender and handedness distributions across patterns of relative neurocognitive profiles, the results overall indicated strong similarities across demographic groups. Such similarities might suggest biological more than environmental contributions to individual differences in relative neurocognition, although both may influence each other and might be hard to parse out (e.g., Noble et al. 2015). All the same, individual differences in brain activation will be worth investigating in relation to individual differences in relative neurocognitive profiles, and should likely focus on investigating patterns of differential activation along the right-left and ventral-dorsal axes.

Limitations and Future Studies

The goal of the present study was to examine heterogeneity in normal neurocognition. This goal was accomplished by using LPA on the eHRB, revealing patterns of individual variations in relative neurocognitive profiles, characterized by relative tradeoffs between specific neurocognitive abilities. The pattern of model fit of the LPAs notably indicated the presence of a continuum of individual differences rather than a specific number of qualitatively different groups. Interestingly, that very finding would suggest the inadequacy of LPA in the present project, a method that specifically assumes a categorical latent construct (i.e., latent class belonging) and tests the presence of specific numbers of groups within a population. In fact, the main conclusions of the current project could have probably been reached by solely using factor analysis and revealing the three-dimensional continuum of individual differences in cognition. LPA was useful, though, as taxonomic tool, providing classifications that, even if somewhat arbitrary, enabled discussions and comparisons of constructs that would have been harder to conceptualize otherwise. In fact, taxonomies have been suggested to be essential for the advancement of most scientific fields, permitting increased accuracy in predictions within organizational categories compared to predictions involving the entire population (Bobko & Russell, 1991). The number of groups to be included in a taxonomy, though, is often subject of debates and compromises, with too few groups leading insufficient differentiation across elements, and too many groups rendering grouping impractical and useless (Gould, 1981). LPA may provide just the perfect tool for guiding such a decision. In fact, in clinical research fields, a combination of factor analysis and LPA may provide an ideal methodological framework for both permitting better understanding of underlying constructs and providing taxonomies for practical application in clinical and research settings.

The present study of individual differences in neurocognition is dependent upon the cognitive domains that were assessed in the eHRB normative project. And although the eHRB represents one of the largest neuropsychological battery with over forty test measures, it does not assess all possible cognitive functions. For example, spatial mental manipulation such as mental image rotation is not assessed in the eHRB. Interestingly, it has been suggested that mental image rotation may represent a separate source of individual differences in cognition compared to verbal or perceptual operations (Bouchard & Johnson, 2005). In fact, in comparing several main psychometric models of intelligence, Johnson & Bouchard (2005) concluded for a subdivision of cognition into verbal, perceptual, and image rotation domains, rather than crystallized and fluid, or only verbal and perceptual. This special importance of spatial operations in human cognition, distinguished from verbal and figural functions, has been also highlighted in the cognitive style (Kozhevnikov et al. 2002, 2005), dorsal versus ventral brain pathway (e.g., Haxby et al. 1991; Ungerleider & Mishkin, 1982; Wilson et al. 1993), and working memory (e.g., Della Sala et al. 1999; Klauer & Zhao) bodies of literature. If tests of spatial mental operations had been included in the present study, it is not clear whether they might have been integrated to the present findings or would have changed the structure of the continuum more deeply. In arguing for the earlier, the interpretations of the continuum's tradeoff dimensions as "verbal-perceptual" and "analysis-attention/speed" were found to be rather robust to test selection. For example, although the continuum was constructed based solely on eHRB test measures, projections of the Wechsler scales' subtests onto the continuum yielded congruent interpretations. In addition, striking similarities were found between the present results and those obtained by Johnson & Bouchard (2006), who used an entirely different participant sample and neuropsychological battery, including assessment of image rotation. If individual differences in spatial operations could be integrated and plotted onto the continuum of relative neurocognitive profiles, it is predicted that they would project toward the "perceptual" and "attention/speed" dimensions. Indeed, the representation and maintenance of spatial information have been shown to recruit the dorsal brain pathway (Haxby et al. 1991; Ungerleider & Mishkin, 1982), and especially the brain's attentional networks (e.g., Awh & Jonides, 2001; Patt et al. 2014; Smyth & Scholey, 1994). Specifically, attentional networks, which involve right hemisphere-dominant fronto-parietal circuitries (Heilman, Watson, & Valenstein, 1985), have been shown to closely overlap with networks governing the planning of eye and body movement, which are key in spatial information processing (Awh, Armstrong, & Moore, 2006; Johnson, 1982). It would therefore not be surprising that a "spatial operations" factor would load in the "perceptual" and "attention/speed" quadrant of the continuum, with other presumed right- and top-brain functions.

Another cognitive domain that might have been under-represented in the present study and yet may be essential for understanding individual differences in neurocognition is executive function. Executive function has been suggested to recruit not one but a variety of higher cognitive abilities, including verbal and nonverbal concept-formation, abstract expression of conceptual relationships, initiation and inhibition of concept-related actions, and flexibility of thinking (Delis, Kaplan, & Kramer, 2001). Some of those constructs are already part of the eHRB assessment – e.g., abstraction (*Category Test*), flexibility of thinking (*Trail Making Test-Part B*), and initiation of concept-related actions (fluency tests, and perhaps the *Trail Making Test* and *Tactual Performance Test*) – but except for the fluency tests, the number of tests in each domain is probably too limited to reveal clear executive factors in the data. In future studies, it would be especially interesting to include additional tests assessing inhibition (e.g., the *Color Word Interference Test*; Delis et al. 2001) and flexibility of thinking (e.g., the *Wisconsin Card Sorting Test*; Heaton, 1981). Based on the discussion earlier in this section, very rough predictions might suggest a projection of the former toward the "perceptual attention" dimension and of the latter toward the "working memory" and thus general cognitive ability dimension.

Other measures that could be useful for validating the present findings in future studies might be the "Verbalizer-Visualizer Questionnaire" (Paivio, 1971; Richardson, 1977) to verify whether self-reported preference for using imagery over verbal representation is indeed related to the present study's "verbal-perceptual" dimension; and a form of assessment of abilities for detailed versus holistic processing, to examine a possible relation with the "analysis-attention/speed" dimension.

Finally, a cognitive domain that is very rarely included in comprehensive clinical neuropsychological batteries but might be essential for fully understanding individual differences in neurocognition, is theory of mind, or the ability to understand others' mental states including their intents, beliefs, desires, and knowledge (Premack & Woodruff, 1978; Wellman & Liu, 2004). Theory of mind has been shown to be impaired in autism spectrum disorder, independently of general cognitive ability (Baron-Cohen, Leslie, & Frith, 1985) and might be involved in a cognitive tradeoff with abilities for mental image mapping and rotation, shown to be enhanced in this population (e.g., Soulières, Zeffiro, Girard, & Mottron, 2011). Interestingly, females have been shown to outperform males in theory of mind abilities (e.g., Bosacki & Astington, 1999). So it seems only fair that if one was to include assessment of mental image rotation in future neurocognitive batteries, a domain where men outperform women with robust effect sizes (Maeda & Yoon, 2013), assessment of theory of mind also be included.

Conclusions

Patterns of individual differences in normal neurocognition were characterized by using LPA on the eHRB normative database. Preliminary factor analyses suggested seven non-motor neurocognitive domains assessed by the eHRB: “working memory”, “fluency”, “language”, “verbal episodic memory”, “visuospatial cognition”, “perceptual speed”, and “perceptual attention”. Individual differences in absolute neurocognitive profiles were characterized by a ladder-like distribution, suggesting dominance by general cognitive ability, or *g*-factor, even after correction for age, education, and ethnicity – that is, some individuals simply tend to perform better than others across all cognitive domains. However, at equivalent levels of general cognitive ability, more subtle patterns of individual differences were revealed, characterized by a continuum of relative tradeoffs along two almost orthogonal dimensions, “verbal-to-perceptual” and “analysis-to-attention/speed”. Higher relative verbal abilities implied lower relative perceptual abilities, and vice-versa; and higher relative “analysis” abilities implied lower relative “attention/speed” abilities, and vice-versa.

By identifying and characterizing individual differences in absolute and relative neuropsychological profiles in a large control population, the present study is providing a new basis of comparison for defining impairment in clinical and research settings. Notably, the present results indicate that within-profile variations are common among cognitively healthy individuals (about 36% of the sample showed medium to large within-profile variations), but only according to specific patterns. For example, a profile with large relative weaknesses in both visuospatial cognition and perceptual speed and relative strengths in both fluency and language might be relatively common and suggest an individual belonging to the “highly verbal” or “super fluent” categories. By contrast, a profile showing large relative weaknesses in both fluency and visuospatial cognition and relative strengths in both perceptual speed and language would probably be very unusual in the cognitively healthy population, and might suggest cognitive impairment.

To make these findings directly applicable in clinical and research settings, subsequent work will focus on constructing base rate tables indicative of how usual or unusual various types of neurocognitive profiles and within-profile variations might be in the cognitively healthy population. A simple formula may also be devised based on a minimal number of tests to help classify healthy participants in other studies into one of the eight LPA groups that were identified and provide a measure of their location on the three-dimensional continuum. Various methodological applications may be envisioned with the availability of such tools. Brain imaging studies might especially benefit from a taxonomy categorizing individuals based on their relative neurocognitive profiles, with the idea of increasing group homogeneity and diminishing signal noise related to between-subject variability.

The present study has implications for validating previous theories of individual differences in cognition and brain function. First, the results support the large body of research showing the existence of one factor underlying performance on all cognitive tests, regardless of test modality and demands (Spearman, 1904). At equivalent levels of general cognitive ability, though, patterns of individual differences were found involving a relative tradeoff between "verbal" and "perceptual" abilities and, to a lesser extent, a relative tradeoff between "analysis" and "attention/speed" abilities. Assuming that individual differences in relative neurocognitive profile may translate into individual differences in brain regional structure and neural activation, the present study brings support to the long tradition of differentiating individuals in terms of right-brain versus left-brain functioning. The results however suggest a continuum of differences in lateralized brain functions rather than clear-cut right-brain versus left-brain phenotypes. Individual variations along the "analysis-attention/speed" dimension also supports theories suggesting individual differences in bottom-brain versus top-brain functions (Kosslyn & Miller, 2013). Incongruent with Kosslyn's suggestion that bottom-versus-top would dominate left-versus-right differences in brain function, individual variations along the "analysis-attention/speed" dimension was found to have a smaller amplitude and be close to orthogonal to "verbal-perceptual" variations. To have a chance of validating the existence of individual differences along the left-right and ventral-dorsal brain axes, imaging studies will have to overcome the dominating influence of general cognitive ability in brain signal, with brain correlates including brain functional efficiency, white matter integrity, trajectories of cortical thickness and surface area, and the differential activation of specific brain regions notably involving the left hemisphere and fronto-parietal networks (Deary et al. 2010; Jung & Haier, 2007; Neubauer & Fink, 2009). These brain correlates are likely to mask subtle patterns of individual differences in relative right/left or dorsal/ventral activation. A possible strategy for these imaging studies might be to maximize individual differences in relative cognitive abilities by preliminarily identifying and selecting individuals at the extremes of the "verbal-perceptual" and "analysis-attention/speed" dimensions.

In conclusion, although individual differences in neurocognition appear to be dominated by one general factor, rich individual differences were revealed at every level of general cognitive ability. These relative variations suggest that two individuals with similar levels of general cognitive ability might employ their pool of mental energy (Spearman, 1904), brain reserve capacity (Satz, 1993), IQ (Wechsler, 1945), or brain functional efficiency (Neubauer & Fink, 2009) via different cognitive strategies and neuronal routes to attain reasonably similar scores on almost all cognitive tests. Notably, to successfully perform the same tasks and solve the same problems, individuals might rely differentially on verbal versus imagery representations, and on in-depth analysis versus efficient observation and reaction. With such strategies likely involving differential use of left versus right and ventral versus dorsal neuronal routes, a better question might be: are you right-dorsal, right-ventral, left-dorsal, or left-ventral brained?

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APPENDIX 1: TABLES

Table 1: Description of the test measures and abilities likely recruited.

TESTS	MEASURES	Verbal modality	Figural modality	Spatial modality	Sensory Perceptual	Motor	Attention/Concentration	Working Memory	Online Executive Skills	Abstraction	Problem Solving	Memory	General Knowledge	Processing Speed
Halstead Reitan Battery (HRB)														
Speech-Sounds Perception	Number of errors													
Seashore Rhythm Test	Number of correct answers													
Reitan-Indiana Aphasia Screening Test	Number of errors													
Spatial Relations	Ratings of complex cross drawing													
Reitan-Kløve Sensory-Perceptual Examination (SPE)	Number of errors (right, left, total)													
Tactile Form Recognition Test (TFR)	Time in seconds (right, left)													
Finger Tapping Test	Number of taps in 10 seconds (dominant & non-dominant hand)													
Grip Strength Test	Kilograms (dominant & non-dominant hand)													
Tactual Performance Test (TPT)	Time of trial completion in seconds (dom., non-dom., both hands, total)													
	Number of shapes remembered (shapes)													
	Number of locations remembered (locations)													
Category Test	Number of errors													
Trail Making Test	Part A – time in seconds													
	Part B – time in seconds													

Table 1: Description of the test measures and abilities likely recruited, continued.

TESTS	MEASURES	Verbal modality	Figural modality	Spatial modality	Sensory Perceptual	Motor	Attention/Concentration	Working Memory	Online Executive Skills	Abstraction	Problem Solving	Memory	General Knowledge	Processing Speed
expanded Halstead Reitan Battery (eHRB)														
Boston Naming Test (BNT)	Correct answers	■											■	
BDAE Complex Ideational Material*	Correct answers	□												
Peabody Individual Achievement Test (PIAT)														
PIAT Reading Recognition	Correct answers	■											■	
PIAT Spelling*	Correct answers	□											□	
PIAT Reading Comprehension *	Correct answers	□										□		
Thurstone Word Fluency	Correct answers	■					■		■					■
Letter Fluency (FAS)	Correct answers	■					■		■					■
Category Fluency (Animal)	Correct answers	■					■		■					■
Paced Auditory Serial Addition Test (PASAT)	Correct answers	■					■	■	■					■
Digit Vigilance Test	Time in seconds	■					■							■
	Number of errors	■					■							
Grooved Pegboard	Time in seconds (dom. & non-dom. hand)					■								■
California Verbal Learning Test (CVLT)	Trials 1-5 – Number of correct answers	■					■	■				■		
	Trial 1 – correct answers	■					■	■				■		
	Trial 5 – correct answers	□					□	□				□		
	Short Delay – correct	■										■		
	Long Delay – correct	■										■		
Story Memory Test	Trial 1 – Correct answers	■					■	■				■		
	Learning – Points per trial	■					■	■				■		
	Delayed recall – correct	■										■		
	Percentage loss	□										□		
Figure Memory Test	Trial 1 – Correct answers		■				■	■				■		
	Learning – Points per trial	■					■	■				■		
	Delayed recall – Correct		■									■		
	Percentage loss		□									□		

Table 1: Description of the test measures and abilities likely recruited, continued.

TESTS	MEASURES	ABILITIES: Verbal modality	Figural modality	Spatial modality	Sensory Perceptual	Motor	Attention/Concentration	Working Memory	Online Executive Skills	Abstraction	Problem Solving	Memory	General Knowledge	Processing Speed
Wechsler Adult Intelligence Scales (WAIS & WAIS-R)														
Information	Correct answers	■											■	
Vocabulary	Correct answers	■											■	
Comprehension	Correct answers	■											■	
Similarities	Correct answers	■					■			■	■		■	
Digit Span	Correct answers	■					■	■						
Arithmetic	Correct answers (timed)	■					■	■					■	■
Picture Completion	Correct answers (timed)		■				■						■	■
Picture Arrangement	Correct answers (timed)		■				■				■		■	■
Block Design	Correct answers (timed)		■	■			■				■			■
Object Assembly	Correct answers (timed)		■	■			■				■			■
Digit-Symbol Coding	Correct answers (timed)		■				■							■

Notes: BDAE stands for Boston Diagnostic Aphasia Examination and “dom.” is an abbreviation of “dominant”. Test measures in gray font with an asterisk refer to variables excluded from the present work due to normative samples that were separately recruited or inadequate in size (*BDAE Complex Ideational Material*, *PIAT spelling*, and *PIAT reading comprehension*). Test Measures in gray font refer to variables excluded from the factor analyses due to: non-normal distributions (*Spatial Relations, Story Memory Percentage Loss,* and *Figure Memory Percentage Loss*), scores combining or included in other measures (*CVLT Trial 5* is included in a combination of *CVLT Trials1-5* and *CVLT Trial 1*, and *TPT dominant, non-dominant,* and *both hands* are included in *TPT total*), and pure motor tests involving physiological differences known to be influenced by gender (*Grip Strength Test* and *Finger Tapping Test*).

Table 2: Sample characteristic and attrition for each test administered as part of the eHRB normative project.

	NUMBER OF PARTICIPANTS						
TESTS	**Total**	**Male**	**Female**	**Caucasian**	**African-American**	**Age M (SD)**	**Education M (SD)**
Halstead Reitan Battery							
Speech-Sounds Perception Test	893	498	395	311	582	47.6 (18.2)	13.8 (2.5)
Seashore Rhythm Test	894	499	395	312	582	47.7 (18.3)	13.8 (2.5)
Reitan-Indiana Aphasia Screening	863	466	397	286	577	47.7 (18.5)	13.8 (2.6)
Spatial Relations	881	485	396	301	580	47.6 (18.3)	13.7 (2.6)
Reitan-Kløve Sensory-Perceptual Examination (SPE)	893	494	399	293	600	46.1 (17.8)	13.7 (2.6)
Tactile Form Recognition (TFR)	837	459	378	257	580	46.9 (18.1)	13.7 (2.6)
Finger Tapping Test	744	428	316	361	383	50.7 (18.1)	13.8 (2.6)
Grip Strength Test	892	489	403	299	593	46.7 (17.9)	13.8 (2.6)
Tactual Performance (TPT)	893	499	394	321	572	47.0 (17.9)	13.8 (2.6)
Category Test	969	529	440	360	609	46.9 (17.9)	13.8 (2.5)
Trail Making Test	982	539	443	364	618	47.2 (18.0)	13.8 (2.5)
Expansion of the Halstead Reitan Battery							
Boston Naming Test (BNT)	844	429	415	227	617	49.0 (18.0)	13.6 (2.4)
BDAE Complex Ideational Material*	0	0	0	0	0	-	-
PIAT Reading Recognition	871	473	398	280	591	47.6 (18.3)	13.7 (2.6)
PIAT Spelling*	125	97	28	125	0	35.5 (12.8)	14.8 (2.9)
PIAT Reading Comprehension*	217	135	82	203	14	48.2 (19.4)	14.4 (2.7)
Thurstone Word Fluency	658	387	271	276	382	39.3 (14.5)	13.9 (2.6)
Letter Fluency (FAS)	806	409	397	203	603	51.8 (18.0)	13.5 (2.5)
Category Fluency (Animal)	801	405	396	200	601	49.0 (18.0)	13.6 (2.4)

Table 2: Sample characteristic and attrition for each test administered as part of the eHRB normative project, continued.

	NUMBER OF PARTICIPANTS						
TESTS	**Total**	**Male**	**Female**	**Caucasian**	**African-American**	**Age M (SD)**	**Education M (SD)**
Expansion of the Halstead Reitan Battery (Continued)							
Paced Auditory Serial Addition Test (PASAT)	479	268	211	104	375	37.8 (12.0)	13.7 (2.5)
Digit Vigilance Test	562	302	260	179	383	42.1 (16.0)	13.7 (2.5)
Grooved Pegboard	950	530	420	361	589	47.1 (17.7)	13.8 (2.5)
California Verbal Learning Test (CVLT)	681	319	362	166	515	51.8 (18.0)	13.5 (2.5)
Story Memory Test	953	519	434	341	612	47.3 (18.1)	13.7 (2.5)
Figure Memory Test	937	510	427	331	606	47.3 (18.0)	13.7 (2.5)
Wechsler Adult Intelligence Scales							
WAIS (11 subtests)	126	98	28	126	0	35.4 (12.8)	14.8 (2.9)
WAIS-R (11 subtests)	459	217	242	97	362	44.9 (16.8)	13.6 (2.5)
					African American:	39.0 (12.6)	13.6 (2.5)
					Caucasian:	67.2 (11.1)	13.7 (2.3)
Individuals administered at least half of the eHRB measures & one memory test							
Total	982	539	443	364	618	47.2 (18.0)	13.7 (2.5)

Notes: BDAE stands for Boston Diagnostic Aphasia Examination, SPE for Sensory Perceptual Examination, and PIAT for Peabody Individual Achievement Test. Test measures in gray with an asterisk were excluded from the present work due to normative samples that were separately recruited or inadequate in size (*BDAE Complex Ideational Material*, *PIAT spelling* and *reading comprehension*).

Table 3: EFA results: Indices of model fit.

NF	*df*	χ^2	*CFI*	Information Criteria (lower=better)			*RMSEA*	*SRMR*
			good>.9	*AIC*	*BIC*	*adjBIC*	good<.05	good<.05
1	189	1939	0.803	80,917	81,225	81,025	0.097	0.079
2	169	958	0.911	79,976	80,382	80,118	0.069	0.043
3	150	587	0.951	79,643	80,142	79,818	0.054	0.031
4	132	411	0.969	79,503	80,089	79,708	0.046	0.026
5	115	299	0.979	79,425	80,095	79,660	0.04	0.023
6	99	211	0.987	79,369	80,117	79,631	0.034	0.017
7	**84**	**138**	**0.994**	**79,326**	**80,147**	**79,613**	**0.025**	**0.014**
8	70	86	0.998	79,302	80,192	79,614	0.015	0.011

Notes: *NF* represents the number of factors included in the model and *df* the number of degrees of freedom. The solution selected is highlighted in bold.

Table 4: EFA results for the 7-factor solution: Geomin-rotated factor loadings and sum of squared structure coefficients after rotation.

TEST MEASURES	Attention / Working Memory	Fluency	Language	Verbal Episodic Memory	Visuospatial Cognition	Perceptual speed	Sensory-Perceptual Processing
Trail Making Test – Part B	**0.502**	0.004	0.031	0.008	-0.014	**0.581**	0.017
PASAT	**0.544**	0.098	-0.046	0.075	0.015	0.314	-0.004
Digit Vigilance (Error)	**0.541**	-0.09	0.152	-0.128	0.061	-0.107	0.044
Thurstone Word Fluency	-0.001	**0.74**	0.036	0.003	0.229	0.069	-0.027
Letter Fluency (FAS)	-0.012	**0.801**	0.009	0.063	-0.028	-0.042	0.167
Category Fluency (Animal)	0.101	0.29	0.023	0.324	0.001	0.142	0.107
Aphasia Screening Test	0.346	0.002	**0.504**	0.140	-0.158	0.079	0.018
BNT	-0.030	0.046	**0.514**	0.309	0.265	-0.009	0.036
PIAT reading recognition	0.029	0.254	**0.618**	-0.004	0.016	-0.083	-0.098
Story Memory (Learning)	0.440	-0.008	0.047	**0.457**	0.169	-0.033	-0.011
CVLT (Trials 1-5)	0.305	0.049	-0.007	0.338	0.192	0.159	-0.002
Figure Memory (Learning)	0.087	0.014	0.024	0.000	**0.789**	-0.017	0.002
Category Test	0.150	0.028	-0.040	0.054	**0.627**	0.075	0.039
TPT (total)	0.011	-0.015	-0.022	0.023	**0.579**	0.27	0.108
Digit Vigilance (Time)	-0.029	0.060	-0.109	0.001	0.021	**0.651**	0.055
Trail Making Test – Part A	0.234	0.023	0.028	-0.060	0.111	**0.625**	-0.020
Grooved Pegboard (dom.)	-0.025	-0.079	0.037	0.069	0.288	0.375	0.262
SPE (right hand)	0.293	0.039	-0.194	0.018	0.033	-0.020	**0.6**
TFR (right hand)	-0.018	-0.018	0.025	0.020	0.012	0.219	**0.528**
Speech-Sounds Perception	0.058	0.192	0.245	-0.068	0.213	0.103	0.271
Seashore Rhythm	0.240	0.169	0.025	-0.141	0.02	0.042	0.254
Sum of squared structure coefficients	*26.1%,*	*22.1%,*	*12.7%,*	*13.5%*	*31.3%,*	*25.0%,*	*23.2%,*

Notes: Numbers in bold indicate loadings >0.45 considered in priority for factor interpretation. Gray-shaded areas indicate loadings >.22, corresponding to parameters included in the starting CFA model before model simplification.

Table 5: EFA results: Correlations between factors.

	Attention / Working Memory	Fluency	Language	Verbal Episodic Memory	Visuospatial Cognition	Perceptual Speed	Sensory-Perceptual Processing
Attention/Working Memory	1						
Fluency	0.442	1					
Language	0.396	0.472	1				
Verbal Episodic Memory	0.274	0.405	0.228	1			
Visuospatial Cognition	0.656	0.319	0.212	0.381	1		
Perceptual Speed	0.319	0.455	*0.085*	0.318	0.562	1	
Sensory-Perceptual Processing	0.407	0.350	*0.120*	0.269	0.642	0.562	1

Notes: Correlations between “language” and “sensory-perceptual processing” and between “language” and “perceptual speed” were negligible in terms of effect size (italicized). All other between-factor correlations were positive with small to medium effect sizes.

Table 6: CFA results: Indices of goodness of fit for a series of models that were iteratively simplified, starting from a factor structure guided by the EFA results (loadings > .22), and progressively keeping only loadings greater than 0.3, and finally 0.4.

CFA models	*df*	χ^2	*CFI*	Information Criteria (lower=better)			*RMSEA*	*SRMR*
			good>.9	*AIC*	*BIC*	*adjBIC*	good<.05	good<.05
Initial	427	647	0.989	120,248	121,065	120,534	0.023	0.026
Interm 1	445	913	0.976	120,478	121,207	120,733	0.033	0.047
Interm 2	451	1092	0.967	120,645	121,344	120,890	0.038	0.050
Interm 3	452	1093	0.967	120,645	121,339	120,888	0.038	0.050
Interm 4	453	1100	0.967	120,649	121,339	120,891	0.038	0.050
Final	454	1135	0.965	120,682	121,366	120,922	0.039	0.050

Notes: *df* represents the number of degrees of freedom. Interm is an abbreviation of intermediate. The solution selected is highlighted in bold.

Table 7: CFA results: Correlations between factors.

	Working Memory	Fluency	Language	Verbal Episodic Memory	Visuospatial Cognition	Perceptual Speed	Perceptual Attention
Working memory	1						
Fluency	0.735	1					
Language	0.595	0.748	1				
Verbal Episodic Memory	0.835	0.741	0.735	1			
Visuospatial Cognition	0.847	0.627	0.542	0.850	1		
Perceptual Speed	0.894	0.646	0.463	0.748	0.910	1	
Perceptual Attention	0.889	0.744	0.552	0.753	0.871	0.913	1

Table 8: Linear Regression Results: Effect of age, education, ethnicity, and gender on each of the CFA factor scores.

	Working Memory	Fluency	Language	Verbal Episodic Memory	Visuospatial Cognition	Perceptual Speed	Perceptual Attention
Regression Model including age							
(Model fit)							
R^2	0.435	0.188	0.041	0.305	0.482	0.539	0.484
F	377.6	113.4	42.3	214.5	454.8	571.7	458.4
p	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Regression Model including age & education							
(Model fit and comparison with previous model)							
R^2	0.529	0.335	0.262	0.458	0.561	0.596	0.557
F	274.1	123.3	115.6	206.3	312.5	359.7	307.0
p	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
R^2_{change}	0.094	0.147	0.221	0.153	0.079	0.057	0.073
F_{change}	96.7	108.3	146.0	138.1	88.7	68.7	80.8
p_{change}	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Regression Model including age, education, & ethnicity							
(Model fit and comparison with previous model)							
R^2	0.630	0.421	0.425	0.592	0.670	0.676	0.639
F	333.0	142.1	180.3	283.4	396.6	408.1	345.8
p	<.001	<.001	<.001	<.001	<.001	<.001	<.001
R^2_{change}	0.101	0.086	0.163	0.134	0.109	0.080	0.082
F_{change}	268.6	144.7	276.7	321.1	322.1	244.0	222.6
p_{change}	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Regression Coefficients							
b_{2a}	$-2.28.10^{-4}$	$-1.76.10^{-4}$		$-1.85.10^{-4}$	$-1.92.10^{-4}$	$-2.63.10^{-4}$	$-2.67.10^{-4}$
b_{1a}	*$-8.11.10^{-3}$*	*$-0.61.10^{-3}$*	$-5.14.10^{-3}$	*$-5.69.10^{-3}$*	$-13.9.10^{-3}$	*$-9.47.10^{-3}$*	*$-6.31.10^{-3}$*
b_{2e}	$-6.78.10^{-3}$	$-8.34.10^{-3}$	$-7.11.10^{-3}$	$-5.90.10^{-3}$	$-4.18.10^{-3}$	$-4.86.10^{-3}$	$-6.71.10^{-3}$
b_{1e}	0.282	0.355	0.340	0.286	0.201	0.207	0.269
b_{eth}	-0.640	-0.575	-0.763	-0.727	-0.668	-0.576	-0.572

Table 8: Linear Regression Results: Effect of age, education, ethnicity, and gender on each of the CFA factor scores, continued.

	Working Memory	Fluency	Language	Verbal Episodic Memory	Visuospatial Cognition	Perceptual Speed	Perceptual Attention
Regression Model including age, education, ethnicity, & gender							
(Model fit and comparison with previous model)							
R^2	0.633	0.425	*0.428*	0.595	0.670	0.677	.640
F	280.1	120.2	*146.3*	238.8	330.2	340.0	289.1
p	<.001	<.001	<.001	<.001	<.001	<.001	<.001
R^2_{change}	0.002	0.004	0.004	0.003	<0.001	<0.001	0.001
F_{change}	6.5	6.4	6.2	7.1	.138	.407	2.7
p_{change}	.011+	.011+	.013+	.008+	.711	.523	.104

Notes: Linear and quadratic terms were included for age and education in all the factors' regression models but that of "language". (The quadratic term for age in the models of "language" was not significant and was removed). R^2 represents the proportion of variance accounted for by each regression model, F and p represent the F-ratio and p-value indicative of model fit. The subscript "change" refers to measures of improvement of one model compared to the previous model in the hierarchy. b_{1a}, b_{2a}, b_{1e}, b_{2e}, and b_{ethn} represent the regression coefficients corresponding to the effects of age (linear and quadratic terms expressed in number of standard deviations per year and per year-squared), education (linear and quadratic terms expressed in number of standard deviations per year and per year-squared), and ethnicity (expressed in units of number of standard deviations using the dummy coding 0 for Caucasian and 1 for African American), respectively. Effect sizes are gauged based on Cohen's criteria (Cohen et al. 2003) – i.e., small ($R^2 \geq .02$), medium ($R^2 \geq .13$), and large ($R^2 \geq .26$) – and are color-coded using very light gray, light gray, and dark gray-shaded areas, respectively. Non-significant regression coefficients are italicized. The signs after the significant p-values of the model including gender indicate whether females performed significantly better (+) or worse (-) than males.

Table 9: Latent Profile Analysis Results: Indices of model fit.

Number Groups	n_p	Information Criteria (lower=better) *AIC*	*BIC*	*adjBIC*	Entropy good>0.8	Likelihood Ratio Tests LMR ratio	LMR p-value	BP p-value
LPAs on demographic-corrected factor scores								
1	14	12449	12518	12473				
2	29	9081	9223	9131	0.894	3365	<.001	NR
3	44	7429	7644	7504	0.909	1666	<.001	NR
4	59	6744	7032	6845	0.896	708	.173	NR
5	74	6372	6734	6499	0.892	398	.173	NR
6	89	6072	6507	6225	0.881	327	.604	NR
7	104	5843	6352	6022	0.884	256	.137	NR
8	119	NR	NR	NR	NR	NR	NR	NR
LPAs on demographic- and ability- corrected factor scores								
1	12	2687	2746	2708				
2	25	1214	1336	1256	0.813	1483	<.001	<.001
3	38	600	786	665	0.809	632	.017	<.001
4	51	119	368	206	0.835	502	.012	<.001
5	64	-230	83	-120	0.835	370	.130	<.001
6	77	-491	-115	-359	0.852	284	.117	<.001
7	90	-700	-260	-546	0.86	232	.008	<.001
8	103	-858	-355	-682	0.861	183	.178	NR
9	*116*	*-980*	*-412*	*-781*	*0.862*	*146*	*.145*	*NR*
10	*129*	*-1070*	*-440*	*-849*	*0.866*	*115*	*.017*	*NR*

Notes: n_p represents the number of model parameters. LMR stands for Lo-Mendell-Rubin adjusted likelihood ratio, and BP for bootstrapped parametric likelihood ratio. NR represents runs for which the maximum likelihood was not replicated despite increase in the number of starts. Numbers italicized represent runs that resulted in one or two latent classes representing less than 5% of the population.

Table 10: Comparison of cognitive performance across latent classes: Multiple analysis of variance on demographic-corrected factor scores, with contrast estimates and univariate tests of between-subject effects for each factor.

Highly verbal (N=129) | *Mildly verbal (N=198)* | *Mildly perceptual (N=194)* | *Highly perceptual (N=87)* | *Visuospatial cognitive (N=60)* | *Verbal memorizer (N=101)* | *Fast attentive (N=142)* | *Super fluent (N=71)*

Univariate Tests & Contrasts		C *p*	*C* *p*	C *p*	C *p*	C *p*	C *p*	C *p*
Working Memory	*F(7,974)=5.3* *p <.001* η^2*=.037*	.060 *.351*	-.180 *.002*	-.086 *.238*	.064 *.502*	.228 *.014*	-.188 *.011*	.137 *.097*
Fluency	*F(7,974)=30.9* *p <.001* η^2*=.182*	.317 *<.001*	.233 *<.001*	.153 *.063*	.253 *.018*	-.315 *.003*	-.431 *<.001*	-.401 *<.001*
Language	*F(7,974)=34.0* *p <.001* η^2*=.196*	.450 *<.001*	.277 *<.001*	.427 *<.001*	-.353 *.001*	-.300 *.003*	.190 *.017*	-.331 *<.001*
Verbal Episodic Memory	*F(7,974)=19.7* *p <.001* η^2*=.124*	.255 *<.001*	-.057 *.310*	.266 *<.001*	-.571 *<.001*	.031 *.733*	.584 *<.001*	-.038 *.640*
Visuospatia l Cognition	*F(7,974)=36.6* *p <.001* η^2*=.208*	-.157 *.005*	-344. *<.001*	-.133 *.035*	-.129 *.117*	.355 *<.001*	.209 *.001*	.318 *<.001*
Perceptual Speed	*F(7,974)=49.8* *p <.001* η^2*=.264*	-.303 *<.001*	-.356 *<.001*	-.318 *<.001*	.303 *<.001*	.397 *<.001*	-.356 *<.001*	.361 *<.001*
Perceptual Attention	*F(7,974)=21.6* *p <.001* η^2*=.135*	-.161 *.007*	-.218 *<.001*	-.254 *<.001*	.362 *<.001*	.289 *.001*	-.525 *<.001*	.196 *.011*
Omnibus Test (Wilk's *Λ*)	*Λ*=.037, *F*=91.3, *p*<.001, η^2*=.374*							

Notes: The multivariate and univariate analyses of variance were carried out on all the demographic-corrected factor scores, simultaneously, with most likely class membership as independent variables. *F*-tests are provided for each analysis with the corresponding *p*-value and effect size (η^2). Contrast estimates (C) compare estimated means of classes from left to right (left minus right). Significance levels of <.005 are highlighted in dark gray and <.05 in light gray.

Table 11: Comparison of absolute cognitive performance across mirroring latent classes: Univariate analyses of variance on the demographic-corrected factor scores.

	Demographic-Corrected Factor Scores						
	Working Memory	Fluency	Language	Verbal Episodic Memory	Visuospatial Cognition	Perceptual Speed	Perceptual Attention
“mildly verbal” vs. “mildly perceptual”							
F(1,390)	9.252	13.382	19.531	0.986	46.627	52.951	15.960
p	.003*	<.001*	<.001*	.321	<.001*	<.001*	<.001*
η^2	.023	.033	.048	.003	.107	.120	.039
“highly verbal” vs. “highly perceptual”							
F(1,214)	18.604	59.351	193.229	36.655	83.957	221.418	73.802
p	<.001*	<.001*	<.001*	<.001*	<.001*	<.001*	<.001*
η^2	.080	.217	.474	.146	.282	.509	.256
“visuospatial cognitive” vs. “super fluent”							
F(1,129)	3.353	101.533	17.477	34.740	107.043	26.131	.200
p	.069	<.001*	<.001*	<.001*	<.001*	<.001*	.655
η^2	.025	.440	.119	.212	.453	.168	.002
“verbal memorizer” vs. “fast attentive”							
F(1,235)	6.604	28.128	5.868	67.417	11.918	38.435	62.253
p	.011*	<.001*	.016	<.001*	.001*	<.001*	<.001*
η^2	.027	.105	.024	.219	.047	.138	.205

Notes: Because four univariate analyses of variance were performed for each factor, effects were considered to be significant (*) only if *p* <.012 (Bonferroni correction). Effect sizes are gauged small ($\eta^2 \geq .02$), medium ($\eta^2 \geq .13$), and large ($\eta^2 \geq .26$) based on Cohen’s criteria (Cohen et al. 2003) and are color-coded using very light gray, light gray, and dark gray-shaded areas, respectively.

Table 12: Comparison of test performance across latent classes: Between subject univariate analyses of variance on demographic-corrected test scores.

Halstead Reitan Battery		**Expansion of the Halstead Reitan Battery**	
Speech-Sounds Perception Test	$F=8.12, p<.001, \eta^2=.060$	Boston Naming Test (BNT)	$F=11.46, p<.001, \eta^2=.088$
Seashore Rhythm Test	$F=4.57, p<.001, \eta^2=.035$	PIAT Reading Recognition	$F=13.04, p<.001, \eta^2=.096$
Aphasia Screening Test	$F=13.18, p<.001, \eta^2=.098$	Thurstone Word Fluency	$F=22.56, p<.001, \eta^2=.195$
Spatial Relations	$F=3.54, p<.001, \eta^2=.028$	Letter Fluency (FAS)	$F=35.12, p<.001, \eta^2=.235$
SPE-total*	$F=17.81, p<.001, \eta^2=.123$	Category Fluency (Animal)	$F=13.50, p<.001, \eta^2=.106$
SPE-right	$F=15.89, p<.001, \eta^2=.112$	PASAT	$F=.88, p=.525, \eta^2=.013$
SPE-left*	$F=15.06, p<.001, \eta^2=.106$	Digit Vigilance Test - Time	$F=7.51, p<.001, \eta^2=.087$
TFR-right	$F=15.49, p<.001, \eta^2=.116$	Digit Vigilance Test - Error	$F=1.04, p=.404, \eta^2=.013$
TFR-left	$F=22.80, p<.001, \eta^2=.162$	Grooved Pegboard - dom	$F=22.09, p<.001, \eta^2=.142$
Finger Tapping Test- dom	$F=2.61, p=.012, \eta^2=.024$	Grooved Peg-board non-dom	$F=30.2, p<.001, \eta^2=.185$
Finger Tapping Test- non-dom*	$F=2.27, p=.028, \eta^2=.021$	CVLT-Trial1	$F=7.40, p<.001, \eta^2=.071$
Grip Strength Test- dom	$F=3.32, p=.002, \eta^2=.026$	CVLT-Trial5	$F=13.52, p<.001, \eta^2=.123$
Grip Strength Test- non-dom	$F=2.37, p=.021, \eta^2=.018$	CVLT-Trials1-5	$F=17.74, p<.001, \eta^2=.156$
TPT-total	$F=33.38, p<.001, \eta^2=.211$	CVLT-Short delay	$F=18.63, p<.001, \eta^2=.163$
TPT-shapes	$F=8.59, p<.001, \eta^2=.063$	CVLT-Long delay	$F=15.94, p<.001, \eta^2=.142$
TPT-locations	$F=7.51, p<.001, \eta^2=.056$	Story Memory Test-Trial 1	$F=33.70, p<.001, \eta^2=.200$
Category Test	$F=26.36, p<.001, \eta^2=.161$	Story Memory Test-Learning	$F=43.34, p<.001, \eta^2=.243$
Trail Making Test - Part A	$F=13.56, p<.001, \eta^2=.089$	Story Memory Test-Free Recall	$F=15.14, p<.001, \eta^2=.101$
- Part B	$F=3.22, p=.002, \eta^2=.023$	Figure Memory Test-Trial 1	$F=27.88, p<.001, \eta^2=.173$
		Figure Memory Test-Learning	$F=34.71, p<.001, \eta^2=.207$
		Figure Memory Test-Free Recall	$F=8.40, p<.001, \eta^2=.059$

Table 12: Comparison of test performance across latent classes: Between subject univariate analyses of variance on demographic-corrected test scores, continued.

Wechsler Adult Intelligence Scales	
Information	F=5.81, p<.001, η^2=.066
Digit Span	F=.903, p=.504, η^2=.011
Vocabulary	F=8.62, p<.001, η^2=.095
Arithmetic	F=2.87, p=.006, η^2=.034
Comprehension	F=3.90, p<.001, η^2=.045
Similarity	F=2.28, p=.027, η^2=.027
Picture Completion	F=1.79, p=.088, η^2=.021
Picture Arrangement	F=1.32, p=.240, η^2=.017
Block Design	F=7.72, p<.001, η^2=.086
Object Assembly	F=5.64, p<.001, η^2=.064
Digit Symbol-Coding	F=2.91, p=.005, η^2=.034

Notes: Univariate analyses of variance were carried out on demographic-corrected test scores with most likely class membership as independent variables. F-tests are provided for each analysis with the corresponding p-value and effect size (η^2). Significant effect sizes are gauged small ($\eta^2 \geq .02$), medium ($\eta^2 \geq .13$), and large ($\eta^2 \geq .26$) based on Cohen's criteria (Cohen et al. 2003) and are color-coded using very light gray, light gray, and dark gray-shaded areas, respectively. (There was no large effect.)

Table 13: Comparison of absolute cognitive performance across mirroring latent classes: Univariate analyses of variance on the demographic-corrected WAIS/WAIS-R test scores.

	Demographic-Corrected WAIS/WAIS-R Test Scores							
	Information	Vocabulary	Arithmetic	Comprehension	Similarity	Block Design	Object Assembly	Digit Symbol Coding
"mildly verbal" vs. "mildly perceptual"								
F(1,222)	.61	.13	1.3	.71	2.06	8.8	1.2	4.8
p	.435	.717	.252	.399	.152	.003	.269	.029
η^2	.003	.001	.006	.003	.009	.038	.006	.021
"highly verbal" vs. "highly perceptual"								
F(1,134)	30.0	41.4	9.7	16.8	4.7	11.5	25.7	7.26
p	<.001	<.001	.002	<.001	.032	.001	<.001	.008
η^2	.183	.236	.067	.112	.034	.078	.161	.051
"visuospatial cognitive" vs. "super fluent"								
F(1,129)	.21	.18	6.6	.49	1.3	27.1	9.8	.17
p	.650	.673	.012	.486	.257	<.001	.002	.684
η^2	.003	.002	.077	.006	.016	.255	.110	.002
"verbal memorizer" vs. "fast attentive"								
F(1,235)	6.0	8.2	.84	3.6	6.1	1.3	.12	7.0
p	.015	.005	.361	.059	.014	.250	.727	.009
η^2	.041	.054	.006	.025	.041	.009	.001	.047

Notes: Comparison across mirroring classes are only provided for the Wechsler tests that had significant omnibus tests (see Table 12). Because four univariate analyses of variance were performed for each test, effects were considered to be significant (*) only if p <.012 (Bonferroni correction). Effect sizes are gauged small ($\eta^2 \geq .02$), medium ($\eta^2 \geq .13$), and large ($\eta^2 \geq .26$) based on Cohen's criteria (Cohen et al. 2003) and are color-coded using very light gray, light gray, and dark gray-shaded areas, respectively.

Table 14: The effects of age and education on eHRB test performance: Results of a series of hierarchical multiple linear regressions, successively taking into account age, education, ethnicity, gender, and handedness.

	Age			Education		
TEST MEASURES	R^2	F	p	R^2_{change}	F_{change}	p
Halstead Reitan Battery						
Speech-Sounds Perception Test	.270	164.4	<.001	.037	23.9	<.001
Seashore Rhythm Test	.084	40.9	<.001	.022	10.8	<.001
Aphasia Screening Test	.003	1.2	.304	.113	54.8	<.001
Spatial Relations	.037	16.7	<.001	.031	14.4	<.001
SPE -total*	.307	197.6	<.001	.009	6.0	.003
-right	.303	193.7	<.001	.011	7.4	.001
-left*	.296	187.4	<.001	.012	7.5	.001
TFR-right	.204	106.7	<.001	.013	7.1	.001
TFR-left	.214	113.5	<.001	.008	4.2	.015
Finger Tapping Test- dom	.260	129.9	<.001	.013	6.4	.002
- non-dom*	.263	132.3	<.001	.020	10.4	<.001
Grip Strength Test- dom	.134	69.1	<.001	.001	.28	.755
- non-dom	.139	71.4	<.001	.001	.37	.692
TPT– total	.423	326.2	<.001	.027	22.0	<.001
TPT-shapes	.268	163.5	<.001	.022	14.0	<.001
TPT-locations	.224	128.6	<.001	.023	13.6	<.001
Category Test	.356	267.4	<.001	.050	40.6	<.001
Trail Making Test - Part A	.295	204.4	<.001	.041	29.8	<.001
- Part B	.326	236.3	<.001	.065	51.9	<.001

Table 14: The effects of age and education on eHRB test performance: Results of a series of hierarchical multiple linear regressions, successively taking into account age, education, ethnicity, gender, and handedness, continued.

	Age			**Education**		
TEST MEASURES	R^2	F	p	R^2_{change}	F_{change}	p
Expansion of the Halstead Reitan Battery						
Boston Naming Test (BNT)	.036	15.6	<.001	.124	62.1	<.001
PIAT Reading Recognition	.046	21.0	<.001	.203	117.3	<.001
Thurstone Word Fluency	.057	19.9	<.001	.136	54.9	<.001
Letter Fluency (FAS)	.062	26.3	<.001	.085	39.8	<.001
Category Fluency (Animal)	.140	64.8	<.001	.055	27.3	<.001
PASAT	.077	20.0	<.001	.077	21.5	<.001
Digit Vigilance Test - Time	.143	46.7	<.001	.019	6.3	.002
- Error	.006	1.7	.191	.012	3.5	.032
Grooved Pegboard - dom	.385	296.1	<.001	.034	27.3	<.001
- non-dom	.373	281.9	<.001	.031	24.8	<.001
CVLT-Trial1	.139	54.6	<.001	.020	8.0	<.001
-Trial5	.214	92.4	<.001	.087	42.2	<.001
-Trials1-5	.227	99.6	<.001	.070	33.8	<.001
-Short delay	.234	103.8	<.001	.062	30.0	<.001
-Long delay	.209	89.8	<.001	.072	34.1	<.001
Story Memory Test-Trial 1	.099	52.2	<.001	.087	50.9	<.001
-Learning	.160	90.7	<.001	.118	77.8	<.001
-Free Recall	.063	32.0	<.001	.080	44.0	<.001
-Loss	.013	6.3	.002	.013	6.5	.002
Figure Memory Test-Trial 1	.258	163.1	<.001	.071	49.2	<.001
-Learning	.296	196.6	<.001	.056	40.2	<.001
-Free Recall	.135	73.1	<.001	.025	13.7	<.001
-Loss	.000	.06	.941	.001	.49	.614

Notes: Hierarchical multiple linear regression were carried out on the eHRB test measures, using models incrementally including quadratic and linear terms for age, quadratic and linear terms for education, dummy coding for ethnicity (Caucasian=0, African American=1), dummy coding for gender (Male=0, Female=1), and dummy coding for handedness (Right=0, Left=1). R^2 represents the proportion of variance accounted for by each regression model, F and p represent the F-ratio and p-value indicative of model fit. The subscript "change" refers to measures of improvement of one model compared to the previous model in the hierarchy. The + or - signs after the p-values for the effects of ethnicity and gender indicate the signs of the corresponding regression coefficients. Effect sizes are gauged small ($\eta^2 \geq .02$), medium ($\eta^2 \geq .13$), and large ($\eta^2 \geq .26$) based on Cohen's criteria (Cohen et al. 2003) and are color-coded using very light gray, light gray, and dark gray-shaded areas, respectively.

Table 15: The effects of ethnicity, gender, and handedness on eHRB test performance: Results of a series of hierarchical multiple linear regressions, successively taking into account age, education, ethnicity, gender, and handedness.

	Ethnicity			Gender		
TEST MEASURES	R^2_{change}	F_{change}	p	R^2_{change}	F_{change}	p
Halstead Reitan Battery						
Speech-Sounds Perception Test	.051	70.2	<.001-	.005	7.4	.007+
Seashore Rhythm Test	.003	2.7	.100	.001	.55	.458
Aphasia Screening Test	.120	134.2	<.001-	.030	35.1	<.001+
Spatial Relations	.014	13.3	<.001-	.001	.839	.360
SPE -total*	.006	7.4	.007-	.002	3.2	.075
-right	.009	11.4	.001-	.000	.347	.556
-left*	.014	17.8	<.001-	.001	1.7	.196
TFR-right	.006	6.0	.014-	.003	3.1	.078
TFR-left	.006	6.4	.012-	.002	2.6	.106
Finger Tapping Test- dom	.019	20.1	<.001-	.113	139.9	<.001-
- non-dom*	.030	32.3	<.001-	.104	131.0	<.001-
Grip Strength Test- dom	.012	12.5	<.001-	.429	896.3	<.001-
- non-dom	.005	5.3	.022-	.431	897.2	<.001-
TPT– total	.055	98.6	<.001-	.000	.05	.171
TPT-shapes	.029	38.4	<.001-	.001	1.2	.281
TPT-locations	.037	46.1	<.001-	.001	.69	.406
Category Test	.086	162.9	<.001-	.006	12.3	<.001-
Trail Making Test - Part A	.046	73.0	<.001-	.003	4.0	.046+
- Part B	.079	144.8	<.001-	.005	10.1	.002+

Table 15: The effects of ethnicity, gender, and handedness on eHRB test performance: Results of a series of hierarchical multiple linear regressions, successively taking into account age, education, ethnicity, gender, and handedness, continued.

	Ethnicity			Gender		
TEST MEASURES	R^2_{change}	F_{change}	p	R^2_{change}	F_{change}	p
Expansion of the Halstead Reitan Battery						
Boston Naming Test (BNT)	.199	259.7	<.001-	.005	6.5	.011-
PIAT Reading Recognition	.035	42.1	<.001-	.001	1.5	.222
Thurstone Word Fluency	.018	14.6	<.001-	.007	5.7	.017+
Letter Fluency (FAS)	.059	59.8	<.001-	.000	.233	.630
Category Fluency (Animal)	.099	111.7	<.001-	.001	1.5	.224
PASAT	.042	24.7	<.001-	.000	.118	.732
Digit Vigilance Test - Time	.000	.043	.837	.023	15.9	<.001+
- Error	.054	32.6	<.001-	.000	.216	.642
Grooved Pegboard - dom	.029	49.9	<.001-	.006	10.0	.002+
- non-dom	.064	113.8	<.001-	.000	.011	.916
CVLT-Trial1	.035	29.4	<.001-	.025	21.4	<.001+
-Trial5	.035	35.6	<.001-	.047	51.8	<.001+
-Trials1-5	.052	53.8	<.001-	.052	59.1	<.001+
-Short delay	.037	37.3	<.001-	.038	40.8	<.001+
-Long delay	.032	32.0	<.001-	.033	34.0	<.001+
Story Memory Test-Trial 1	.072	91.9	<.001-	.003	3.9	.050
-Learning	.094	141.8	<.001-	.000	.34	.561
-Free Recall	.065	77.2	<.001-	.002	2.7	.099
-Loss	.031	31.1	<.001-	.008	8.1	.004+
Figure Memory Test-Trial 1	.102	167.0	<.001-	.003	4.6	.033-
-Learning	.117	205.2	<.001-	.002	2.9	.088
-Free Recall	.027	31.6	<.001-	.000	.12	.733
-Loss	.000	.15	.697	.000	.04	.844

Notes: Hierarchical multiple linear regression were carried out on the eHRB test measures, using models incrementally including quadratic and linear terms for age, quadratic and linear terms for education, dummy coding for ethnicity (Caucasian=0, African American=1), dummy coding for gender (Male=0, Female=1), and dummy coding for handedness (Right=0, Left=1). R^2 represents the proportion of variance accounted for by each regression model, F and p represent the F-ratio and p-value indicative of model fit. The subscript "change" refers to measures of improvement of one model compared to the previous model in the hierarchy. The + or - signs after the p-values for the effects of ethnicity and gender indicate the signs of the corresponding regression coefficients. Effect sizes are gauged small ($\eta^2 \geq .02$), medium ($\eta^2 \geq .13$), and large ($\eta^2 \geq .26$) based on Cohen's criteria (Cohen et al. 2003) and are color-coded using very light gray, light gray, and dark gray-shaded areas, respectively. The effect of handedness was negligible in effect size for all the test measures and was not included in the table. The only measures (indicated by asterisks) for which there was a significant effect of handedness, although still negligible in effect size, were: SPE-total (R^2_{change}=.003, F_{change}=4.5, p =.035-), SPE-left: R^2_{change}=.006, F_{change}=8.2, p =.004-), Finger Tapping-non-dominant (R^2_{change} =.008, F_{change}=10.2, p =.001+), Grooved Pegboard-dominant (R^2_{change} =.003, F_{change}=5.7, p =.017-), and Figure Memory Test–Trial 1 (R^2_{change} =.003, F_{change}=4.5, p =.0.035-). The abbreviations "dom" and "non-dom" stand for dominant and non-dominant hand, respectively.

Table 16: The effects of age, education, ethnicity, gender, and handedness on the Wechsler Adult Intelligence Scales: Hierarchical multiple linear regression results.

	Age			Education			Gender		
	R^2	F	p	R^2_{change}	F_{change}	p	R^2_{change}	F_{change}	p
Wechsler Adult Intelligence Scales (verbal scales)									
Information									
WAIS/C	.032	2.0	.137	.421	46.6	<.001	.025	5.75	.018-
WAIS-R/C-old	.025	1.2	.314	.175	9.9	<.001	.074	9.0	.003-
WAIS-R/AA	.037	6.9	.001	.215	51.4	<.001	.047	23.8	<.001-
Digit Span									
WAIS/C	.037	2.3	.100	.044	2.9	.060	.008	1.1	.299
WAIS-R/C-old	.004	.170	.844	.006	.257	.774	.003	.292	.590
WAIS-R/AA	.063	12.0	<.001	.045	8.9	<.001	.001	.256	.613
Vocabulary									
WAIS/C	.032	2.0	.135	.324	30.5	<.001	.000	.075	.784
WAIS-R/C-old	.015	.694	.502	.142	7.6	.001	.002	.209	.648
WAIS-R/AA	.028	5.2	.006	.228	54.6	<.001	.006	3.0	.085
Arithmetic									
WAIS/C	.107	7.4	.001	.142	11.5	<.001	.062	10.8	.001-
WAIS-R/C-old	.011	.542	.583	.139	7.5	.001	.082	9.7	.002-
WAIS-R/AA	.022	4.1	.018	.150	32.3	<.001	.004	1.9	.173
Comprehension									
WAIS/C	.006	.384	.682	.197	15.0	<.001	.005	.695	.406
WAIS-R/C-old	.006	.261	.771	.158	8.5	<.001	.<001	.014	.906
WAIS-R/AA	.033	6.1	.002	.182	41.3	<.001	.017	7.9	.005-
Similarity									
WAIS/C	.045	2.9	.059	.324	31.1	<.001	.002	.369	.545
WAIS-R/C-old	.006	.273	.762	.105	5.3	.006	.042	4.4	.039-
WAIS-R/AA	.023	4.1	.017	.228	54.4	<.001	.002	.83	.364

Table 16: The effects of age, education, ethnicity, gender, and handedness on the Wechsler Adult Intelligence Scales: Hierarchical multiple linear regression results, continued.

	Age			Education			Gender		
	R^2	F	p	R^2_{change}	F_{change}	p	R^2_{change}	F_{change}	p
Wechsler Adult Intelligence Scales (performance subtests)									
Picture Completion									
WAIS/C	.086	5.8	.004	.065	4.6	.012	.009	1.2	.269
WAIS-R/C-old	.018	.854	.429	.076	3.8	.027	.011	1.05	.308
WAIS-R/AA	.047	8.8	<.001	.092	19.0	<.001	.025	10.7	.001-
Picture Arrangement									
WAIS/C	.141	10.1	<.001	.037	2.7	.070	.011	1.6	.231
WAIS-R/C-old	.138	6.2	.003	.084	4.1	.021	.020	2.0	.163
WAIS-R/AA	.081	15.3	<.001	.062	12.5	<.001	.027	11.4	.001-
Block Design									
WAIS/C	.091	6.2	.003	.054	3.8	.025	.001	.20	.653
WAIS-R/C-old	.131	7.1	.001	.033	1.8	.164	.057	6.6	.012-
WAIS-R/AA	.115	23.4	<.001	.059	12.7	<.001	.019	8.31	.004-
Object Assembly									
WAIS/C	.073	4.86	.009	.024	1.6	.200	.003	.451	.503
WAIS-R/C-old	.189	10.7	<.001	.039	2.3	.110	.002	.241	.625
WAIS-R/AA	.104	20.8	<.001	.049	10.4	<.001	.002	.818	.366
Digit Symbol-Coding									
WAIS/C	.204	15.8	<.001	.138	12.7	<.001	.070	14.4	<.001+
WAIS-R/C-old	.279	18.2	<.001	.029	1.9	.155	.014	1.9	.171
WAIS-R/AA	.220	50.6	<.001	.071	17.8	<.001	.078	43.7	<.001+

Notes: Hierarchical multiple linear regressions were carried out on the Wechsler scales' measures, using models incrementally including quadratic and linear terms for age, quadratic and linear terms for education, dummy coding for gender (Male=0, Female=1), and dummy coding for handedness (Right=0, Left=1). To avoid confounds related to WAIS-version, ethnicity, and age, separate models were run for Caucasian individuals who had been administered the WAIS (WAIS/C, *N*=126, age: *M*=35.4, *SD*=12.8), Caucasian individuals who had been administered the WAIS-R (WAIS-R/C-old, *N*=97, age: *M*=67.2, *SD*=11.1), and African-American individuals who had been administered the WAIS-R (WAIS-R/AA, *N*=362, age: *M*=39.0, *SD*=12.6). R^2 represents the proportion of variance accounted for by each regression model, *F* and *p* represent the *F*-ratio and *p*-value indicative of model fit. The subscript "change" refers to measures of improvement of one model compared to the previous model in the hierarchy. The + or - signs after the *p*-values for the effect of gender indicate the signs of the corresponding regression coefficients. Effect sizes are gauged small ($\eta^2 \geq .02$), medium ($\eta^2 \geq .13$), and large ($\eta^2 \geq .26$) based on Cohen's criteria (Cohen et al. 2003) and are color-coded using very light gray, light gray, and dark gray-shaded areas, respectively. The effect of handedness was negligible in effect size and significance for all the test measures and was not included in the table.

Table 17: Demographic composition of the latent classes.

		TOTAL	*Mildly verbal (N=198)*	*Mildly perceptual (N=194)*	*Highly verbal (N=129)*	*Highly perceptual (N=87)*	*Super fluent (N=71)*	*Visuospatial Cognitive (N=60)*	*Verbal memorizer (N=101)*	*Fast attentive (N=142)*
Age Mean (SD)		*47.2 (18.0)*	49.0 (17.1)	46.7 (18.3)	45.9 (17.9)	47.6 (17.1)	46.4 (18.1)	44.9 (18.7)	48.7 (18.5)	46.7 (18.9)
Education Mean (SD)		*13.7 (2.5)*	13.7 (2.5)	13.8 (2.5)	13.8 (2.5)	13.6 (2.4)	14.2 (2.4)	14.2 (2.9)	13.5 (2.5)	13.7 (2.7)
Gen-der Fe-male Ratio		*45.1%*	43.9%	46.4%	49.6%	**32.2%**	47.9%	43.3%	46.5%	47.2%
	Log. Reg. within pair		χ^2=.238 *p*=.626 *exp(B)*=1.10		χ^2=6.542 *p*=.011 *exp(B)*=.48		χ^2=.272 *p*=.602 *exp(B)*=.83		χ^2=.010 *p*=.920 *exp(B)*=1.03	
	Log. Reg. across pairs		χ^2<.001 *p*=.983 *exp(B)*=1.00		χ^2=.712 *p*=.399 *exp(B)*=.88		χ^2=.029 *p*=.865 *exp(B)*=1.03		χ^2=.423 *p*=.516 *exp(B)*=1.10	
Ethnicity: African-American Ratio		*62.9%*	68.2%	63.4%	60.5%	63.2%	53.5%	55.0%	62.4%	65.5%
	Log. Reg. within pair		χ^2=.995 *p*=.318 *exp(B)*=.81		χ^2=.167 *p*=.683 *exp(B)*=1.12		χ^2=.029 *p*=.866 *exp(B)*=1.06		χ^2=.249 *p*=.618 *exp(B)*=1.15	
	Log. Reg. across pairs		χ^2=2.335 *p*=.126 *exp(B)*=1.23		χ^2=.218 *p*=.640 *exp(B)*=92.6		χ^2=4.836 *p*=.028 *exp(B)*=.66		χ^2=.222 *p*=.637 *exp(B)*=1.08	
Han-ded-ness: Left-Hander Ratio		*10.8%*	**8.1%**	**5.2%**	**16.3%**	**14.9%**	9.9%	13.3%	13.9%	12.0%
	Log. Reg. within pair		χ^2=1.367 *p*=.242 *exp(B)*=.62		χ^2=.070 *p*=.791 *exp(B)*=.90		χ^2=.386 *p*=.535 *exp(B)*=1.41		χ^2=.188 *p*=.664 *exp(B)*=.85	
	Log. Reg. across pairs		χ^2=12.425 *p*<.001 *exp(B)*=.45		χ^2=6.497 *p*=.011 *exp(B)*=1.80		χ^2=.067 *p*=.796 *exp(B)*=1.08		χ^2=1.250 *p*=.263 *exp(B)*=1.30	

Notes: Two series of logistic regression analyses (Log.Reg.) were carried out, comparing gender, ethnicity, and handedness distributions (1) within pairs of mirroring latent classes – *exp(B)* represents the estimated difference in odds ratios between the latent class to the right minus that to the left – and (2) across pairs of mirroring latent classes – *exp(B)* represents the estimated difference in odds ratios between the latent class of interest minus that of all other classes combined. Significance was tested for each comparison using χ^2-tests, with *p*-values <.001 highlighted in dark gray and *p*-values <.0125 highlighted in light gray (considered significant using a Bonferroni correction 0.05/4). Proportions that were notable are highlighted in bold.

Table 18: Supplemental EFA on the eHRB and WAIS/WAIS-R test performances: Geomin-rotated factor loadings corresponding to the 8-factor solution.

TEST MEASURES	Working memory	Fluency	Language	Verbal Episodic Memory	Visuospatial Cognition	Perceptual Speed	Perceptual Attention	Verbal Knowledge & Reasoning
eHRB measures								
Trail Making – Part B	0.265	0.051	0.091	0.079	0.03	0.574	0.05	0.012
PASAT	0.471	0.092	0.003	0.174	0.003	0.324	0.015	0.047
Digit Vigilance (Error)	0.343	-0.242	0.244	0.204	0.086	-0.018	0.026	-0.008
Thurstone Fluency	-0.004	0.576	0.324	0.097	0.112	0.058	0.02	-0.013
Letter Fluency (FAS)	0.041	0.679	0.212	-0.02	-0.022	-0.006	0.1	0.089
Category F. (Animals)	-0.003	0.409	-0.007	0.124	0.089	0.16	-0.054	0.206
Aphasia Screening	0.194	-0.013	0.425	0.047	-0.03	0.073	-0.07	0.256
BNT	-0.152	0.042	0.264	0.031	0.248	0.032	0.011	0.544
PIAT reading recogn.	0.036	0.08	0.52	-0.137	-0.051	-0.079	-0.019	0.383
Story Mem (Learning)	0.077	0.018	-0.005	0.575	-0.033	0.019	0.036	0.403
CVLT (Trials 1-5)	-0.012	0.099	0.133	0.572	0.056	0.159	-0.046	0.035
Figure Mem(Learning)	0.068	-0.037	-0.008	0.137	0.692	0.024	0.071	0.03
Category Test	0.114	0.014	-0.076	0.171	0.448	0.138	0.139	0.076
TPT (total)	-0.011	0.05	-0.054	0.095	0.533	0.296	0.088	-0.06
TPT (memory)	-0.001	0.146	0.002	0.166	0.576	-0.079	0.118	-0.108
Digit Vigilance (Time)	0.003	0.097	-0.075	-0.151	-0.12	0.835	0.013	-0.032
Trail Making – Part A	0.117	0.048	0.067	-0.018	0.073	0.677	-0.01	-0.044
Grvd Pegboard (dom)	-0.109	-0.066	-0.01	0.017	0.111	0.615	0.208	0.096
SPE (right hand)	0.089	0.047	-0.08	0.14	0.075	0.236	0.387	-0.027
TFR (right hand)	-0.063	0.009	0.017	-0.061	0.006	0.462	0.327	0.035
Speech-Sounds Percep	-0.002	0.009	0.424	0.032	0.088	0.203	0.351	0.016
Seashore Rhythm	0.245	0.066	0.186	-0.005	0.013	0.027	0.393	-0.101
WAIS/WAIS-R measures								
Digit Span	0.524	0.014	0.238	-0.02	0.011	0.004	0.295	0.069
Arithmetic	0.487	-0.017	-0.034	-0.001	0.164	0.026	-0.029	0.425
Information	0.11	0.063	-0.013	-0.039	0.151	-0.134	-0.071	0.771
Vocabulary	0.012	-0.003	0.212	0.027	-0.033	-0.016	0.087	0.783
Comprehension	-0.052	-0.019	0.007	0.056	0.017	0.007	0.203	0.743
Similarity	0.026	0.009	0.02	0.033	0.244	0.052	-0.002	0.592
Picture Completion	0.024	-0.034	0.049	0.007	0.446	0.064	0.056	0.318
Picture Arrangement	-0.012	0.026	0.039	0.249	0.303	0.032	0.1	0.143
Block Design	0.166	-0.011	0.004	-0.066	0.766	0.007	-0.03	0.159
Object Assembly	-0.019	0.014	0.104	-0.077	0.888	0.018	-0.118	0.018
Digit-Symbol Coding	0.165	-0.059	0.084	0.087	0.015	0.750	-0.063	0.01

Notes: The 8-factor solution was considered to provide the best and most interpretable fit of the eHRB and WAIS/WAIS-R data *($\chi^2(292)=556.3$, CFI=.982, AIC=110.087, BIC=111,563, adjBIC=110,604, RMSEA=0.030, SRMR=0.018).* Gray-shaded areas indicate loadings >.22, corresponding to items sharing at least 5% of variance with the factor.

APPENDIX 2: FIGURES

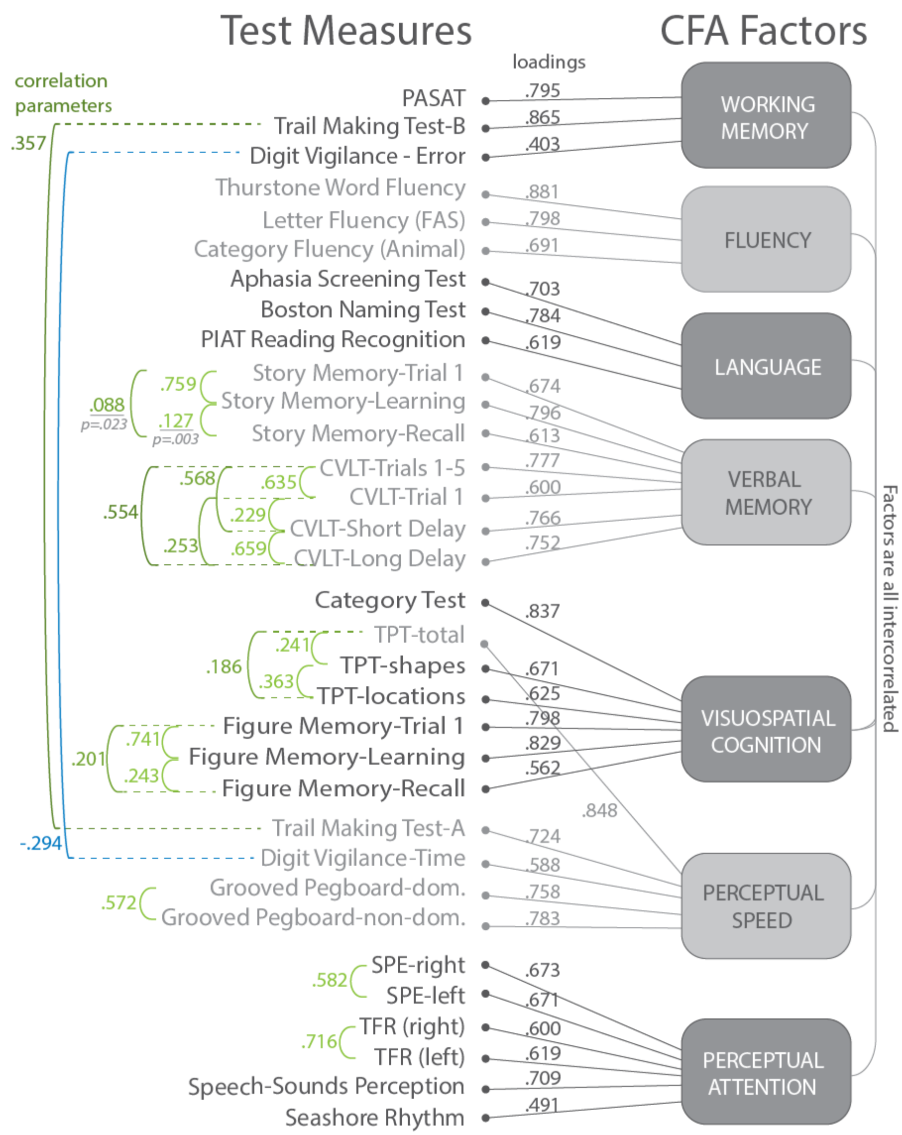

Figure 1: Final CFA model, including factor loadings and correlations between same test measures. All correlations were significant <.001 except those underlined (p-value provided on the graph) and were positive except between Digit Vigilance-Time and -Error (in blue).

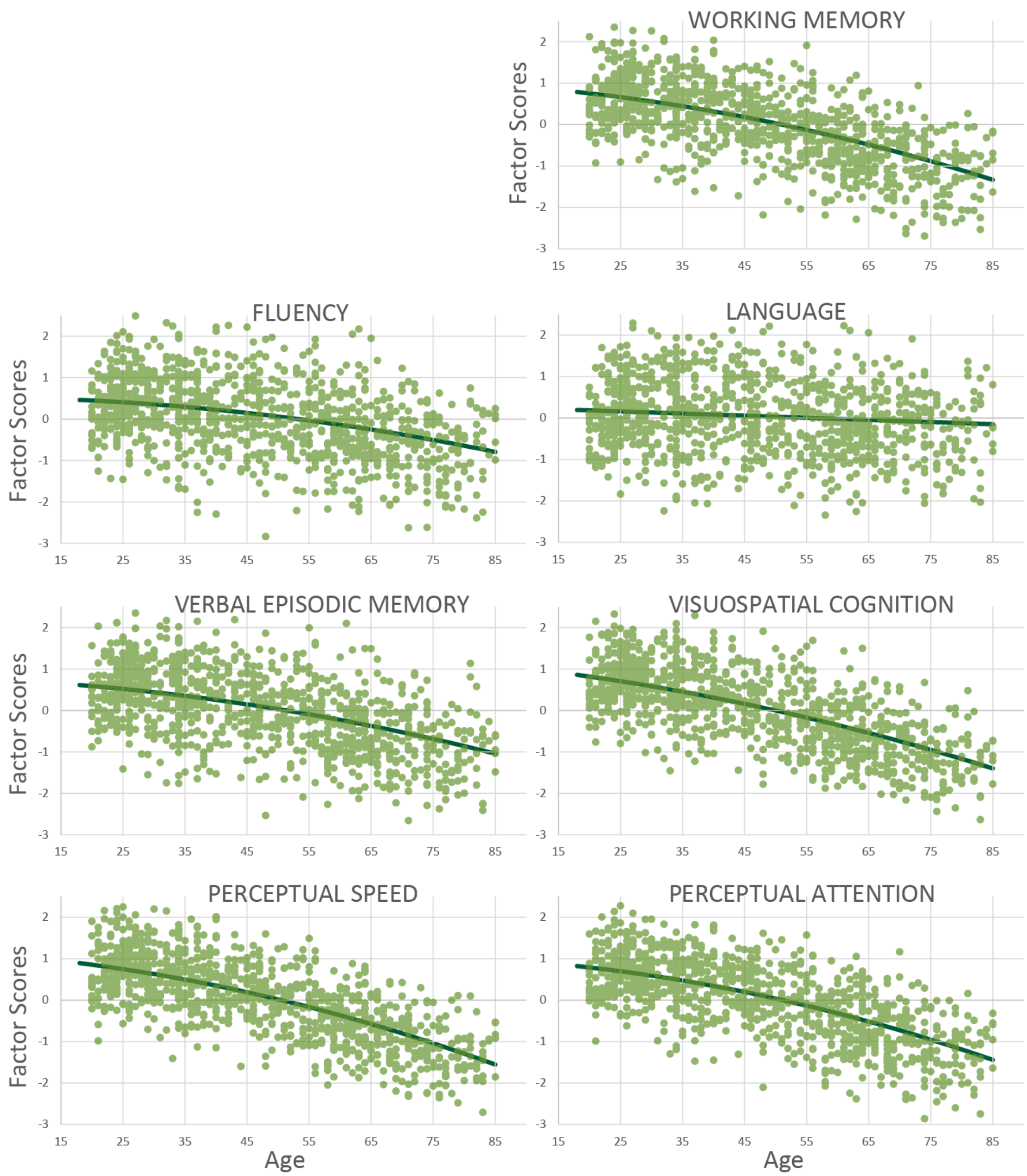

Figure 2: Effect of age on the CFA factor scores.

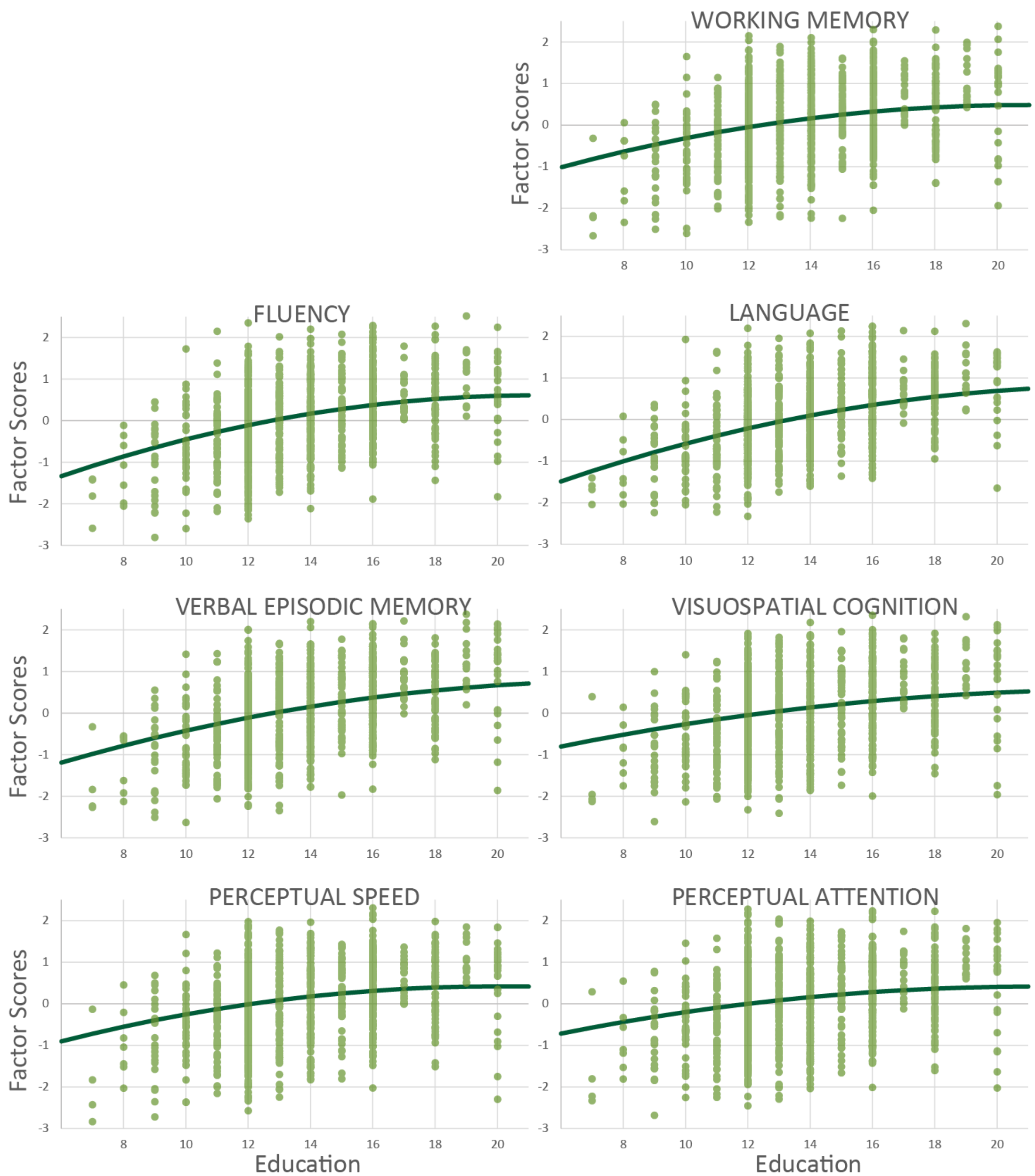

Figure 3: Effect of education on the CFA factor scores.

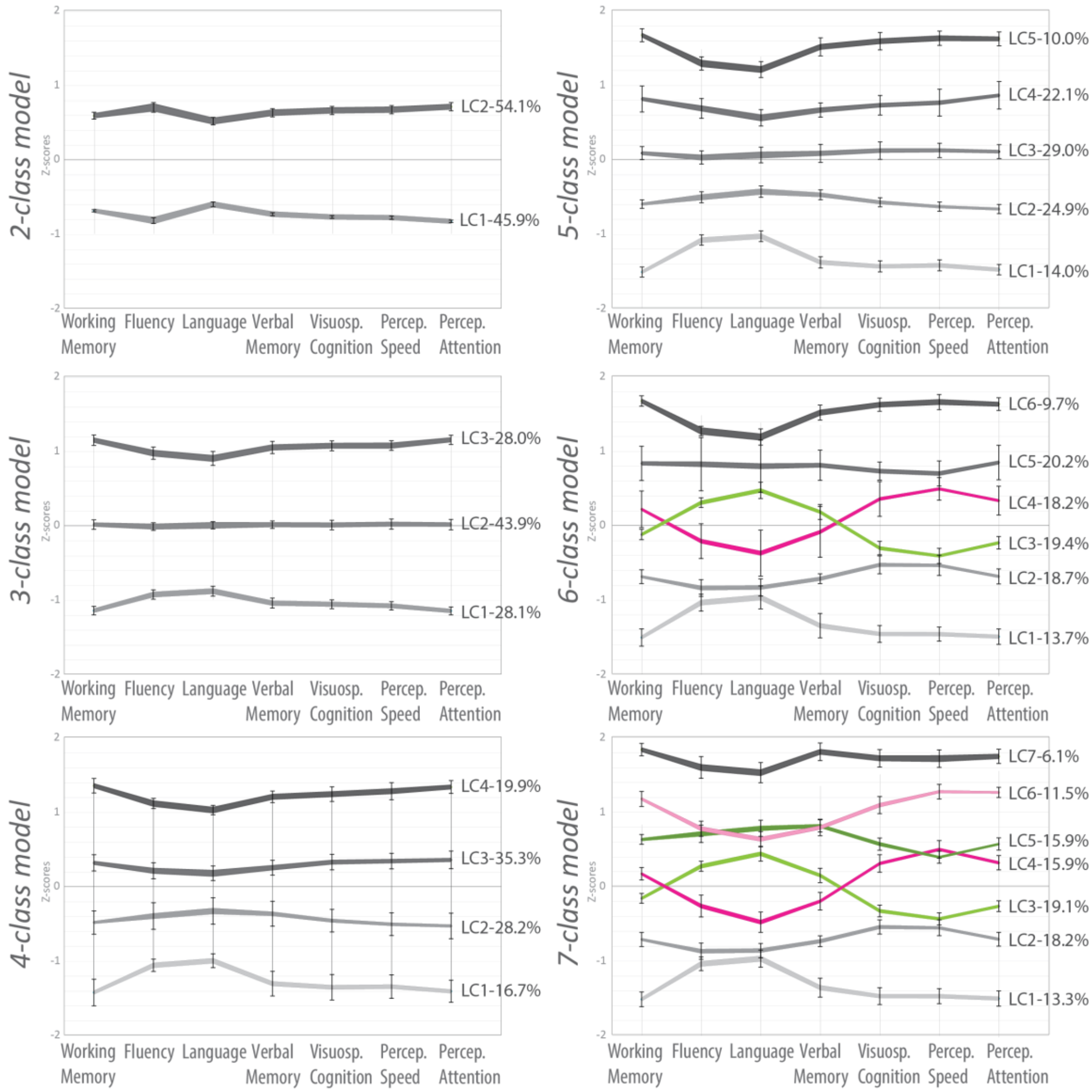

Figure 4: LPA on demographic-corrected factor scores: Absolute average neurocognitive profiles obtained for models with 2 to 7 latent classes. The standard errors of the estimated means are represented using error bars. Estimated variance parameters are represented for each latent class as linewidth. (The band top and bottom are calculated as the estimated mean plus or minus the square root of the estimated variance divided by 2 and divided again by 10 to limit overlap and enhance visualization).

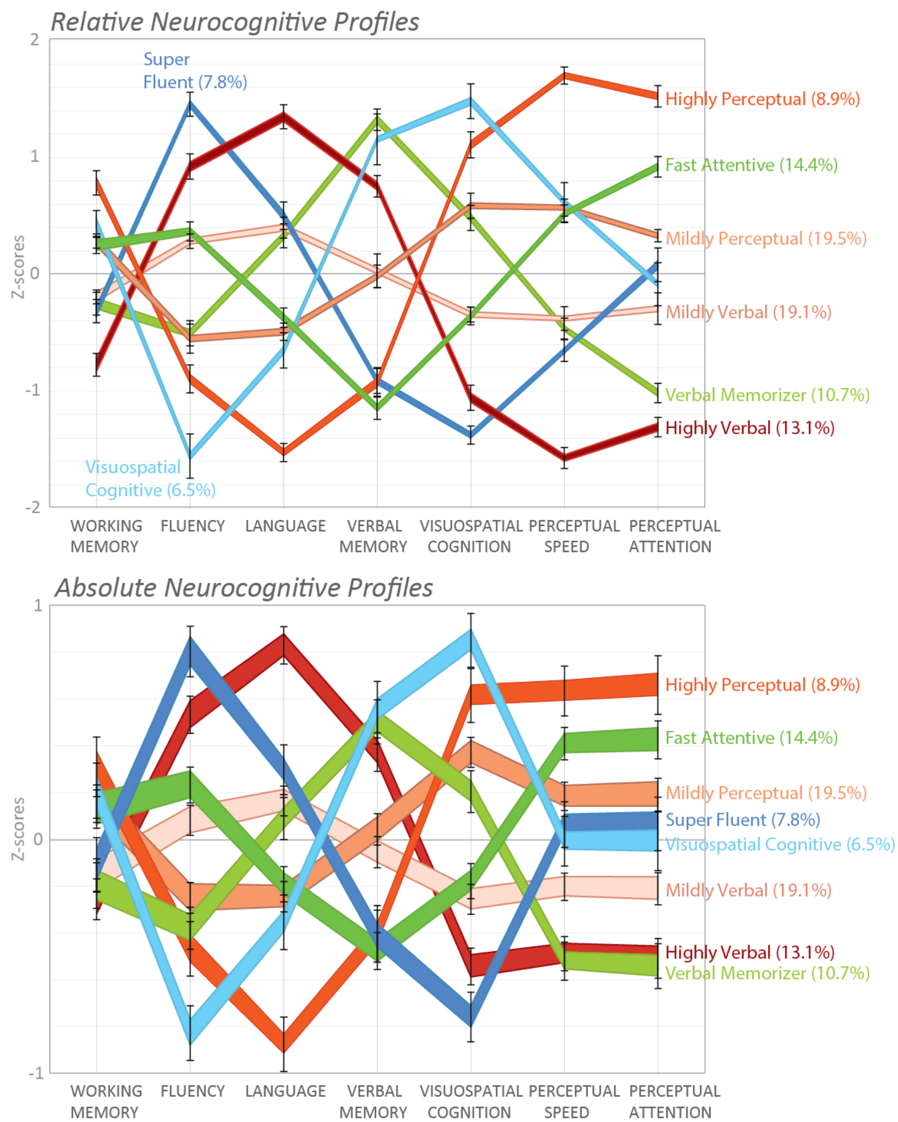

Figure 5: Relative and absolute neurocognitive profiles for the 8 latent class solution (LPA on demographic- and ability-corrected factor scores). Upper Panel: Estimated mean relative neurocognitive profiles. The units on the y-axis are in number of standard deviations of demographic- and ability-corrected factor score. The standard errors of the estimated means are represented using error bars. Estimated variance parameters are represented for each latent class as linewidth. (The band top and bottom are calculated as the estimated mean plus or minus the square root of the estimated variance divided by 2 and divided again by 10 to limit overlap and enhance visualization.) Lower Panel: Average absolute neurocognitive profiles, calculated using most likely class membership. The units on the y-axis are in number of standard deviations of demographic-corrected factor score. The standard errors of the means are represented using error bars. Standard deviation are represented for each latent class as linewidth. (The band top and bottom are calculated as the group average plus or minus the standard deviation divided by 2 and divided again by 10 to limit overlap and enhance visualization.) The percentage of individuals in each latent class are calculated using estimated posterior probabilities.

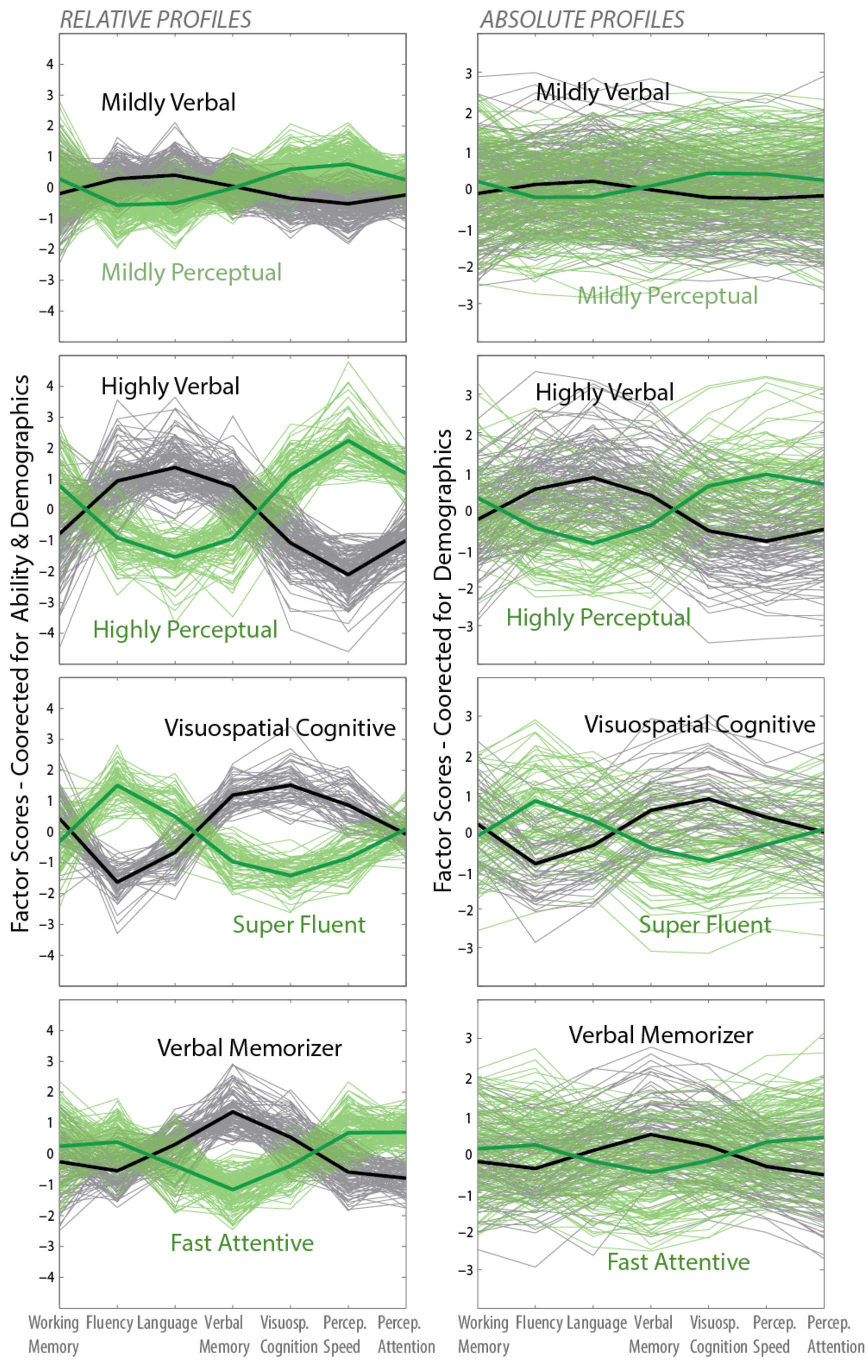

Figure 6: Neurocognitive profiles for all participants grouped by latent class using most likely class memberships in the 8-class LPA on demographic- and ability-corrected factor scores. To limit overlaps, separate plots are provided for each pair of classes with seemingly mirroring neurocognitive profiles (vertically-arranged panels). The units on the y-axis are in number of standard deviations of demographic- and ability-corrected factor score (left panels) and standard deviations of demographic-corrected factor scores (right panels). Average neurocognitive profiles are provided for each group using darker lines.

Figure 7: Comparison across latent classes of the eHRB test scores corrected for age, education, and ethnicity. Scores on the motor tests are provided for information but were not part of the factor analyses. The units on the y-axis are in number of standard deviations of demographic-corrected test score. Error bars are provided corresponding to plus or minus the means' standard errors.

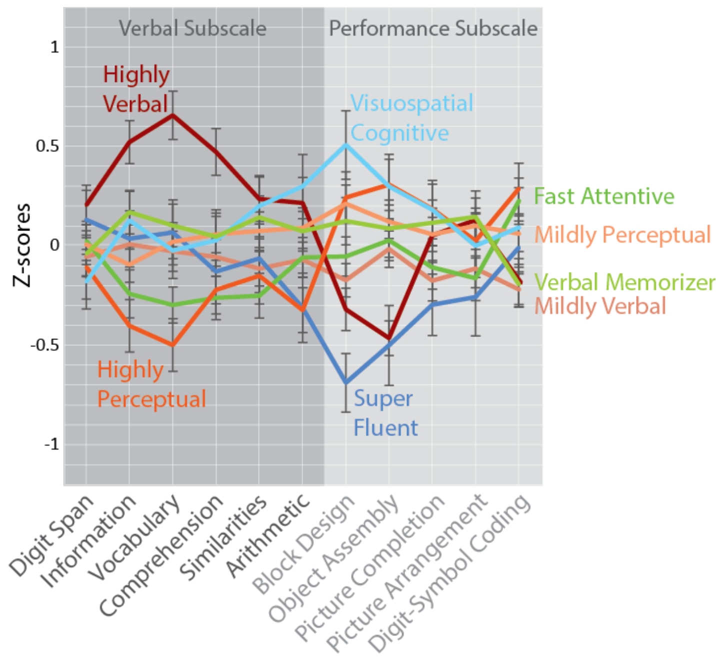

Figure 8: Comparison across latent classes of the combined WAIS/WAIS-R test scores corrected for age, education, and ethnicity. The units on the y-axis are in number of standard deviations of demographic-corrected test score. Error bars are provided corresponding to plus or minus the means' standard errors.

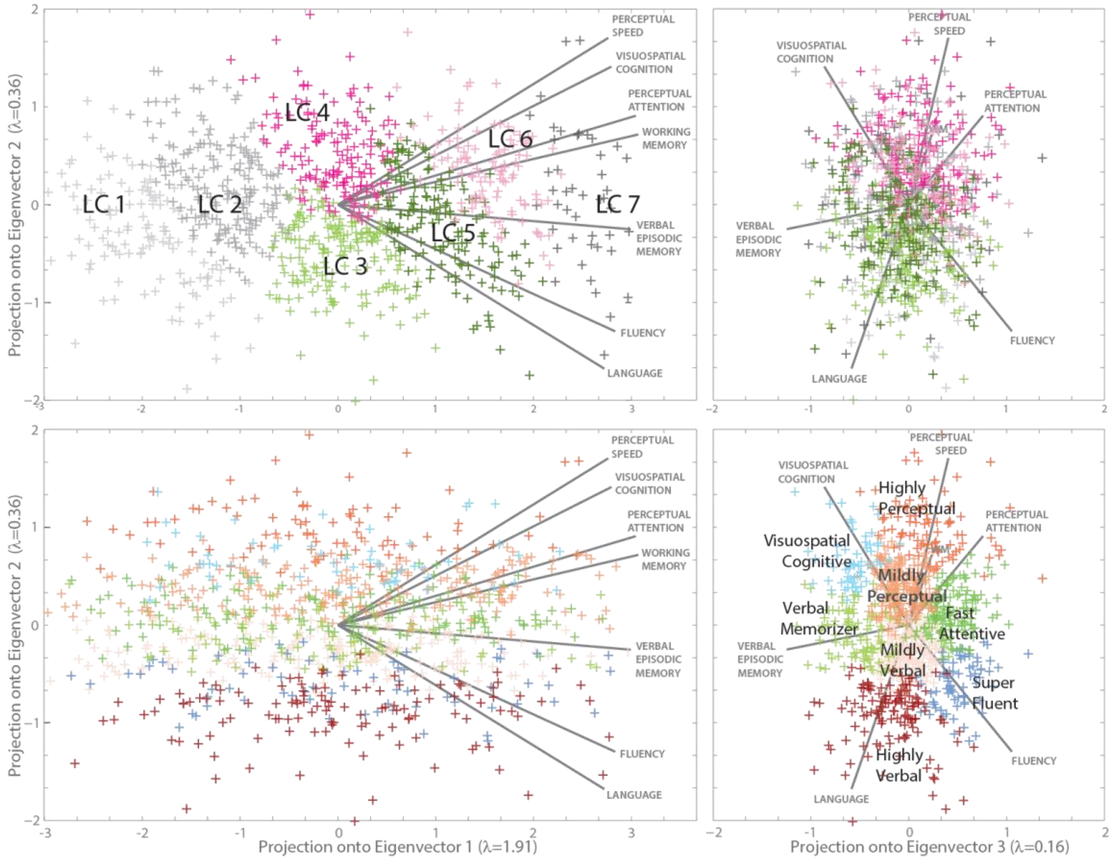

Figure 9: Projections of factor scores in the three-dimensional eigenvector space corresponding to the three largest eigenvalues of the demographic-corrected factor scores' covariance matrix. Projections corresponding to the first and second eigenvectors are plotted in the left panels, and to the second and third eigenvectors in the right panels. Individual performances are represented by crosses and color-coded based on the 7-class solution of the LPA on demographic-corrected factor scores (upper panels) and the 8-class solution of the LPA on general cognitive ability- and demographic-corrected factor scores (lower panels).

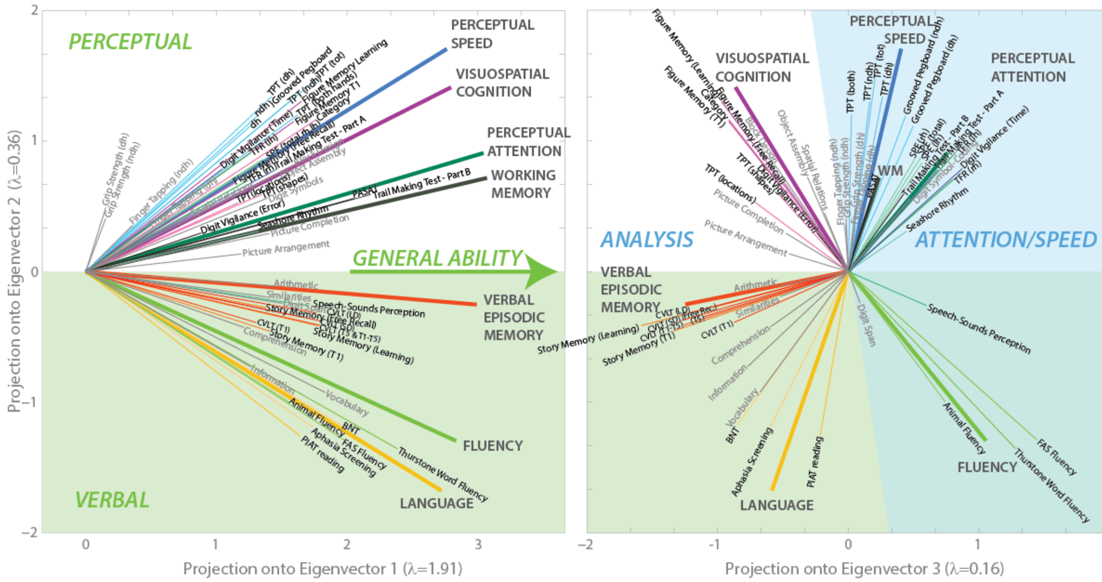

Figure 10: Projections of average demographic-corrected factor scores and test scores in the three-dimensional eigenvector space corresponding to the three largest eigenvalues of the demographic-corrected factor scores' covariance matrix. Projections corresponding to the first and second eigenvectors are plotted in the left panels, and to the second and third eigenvectors in the right panels. Tests presented in gray font were not included in the factor analyses. Tentative interpretations of the overall continuum are provided in larger font.

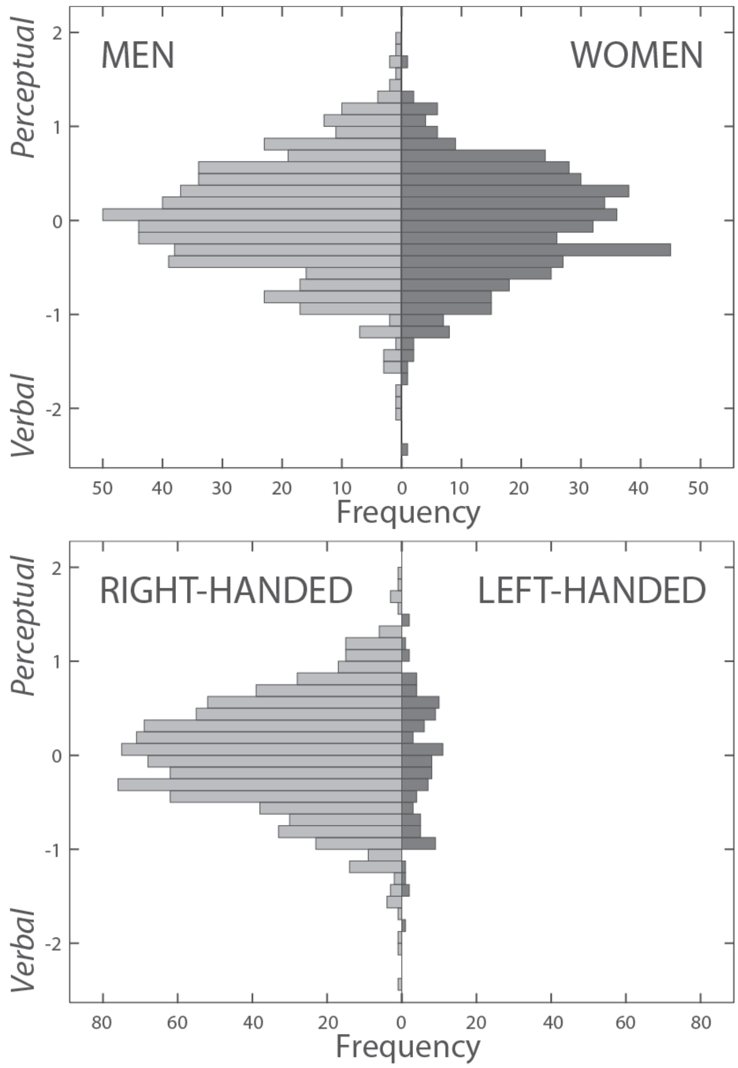

Figure 11: Distributions of gender and handedness along the verbal-perceptual dimension.