Neurocognitive Functioning and Associated Symptoms of Psychosis in Homeless and Precariously Housed Adults with Multimorbidity

by

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Ethics Statement

The author, whose name appears on the title page of this work, has obtained, for the research described in this work, either:

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Abstract

It has been fairly well-established that discrete psychiatric symptoms, such as the positive, negative, and general symptoms of psychosis, are differentially related to distinct deficits in neurocognition. Less well-known are the relationships between symptoms of psychosis and profiles of neurocognitive strengths and weaknesses and no previous study has delineated these relationships in homeless and precariously housed persons living with multimorbidity. Using a unique three-factorial solution on the Positive and Negative Syndrome Scale in a large sample of marginalized persons living in the Downtown Eastside in Vancouver, Canada, we examined the relationships between neurocognitive profiles derived by Latent Profile Analysis and symptoms of psychosis and other psychiatric and psychosocial variables. A three-class solution was found to be of optimal fit, consisting of a comparatively cognitively higher-functioning subgroup, with a relative strength in fluid reasoning (Class 1), and two comparatively cognitively impaired subgroups: one subgroup displaying the same profile of relative strength as Class 1 (Class 2), and a selectively severely cognitively impaired subgroup with a relative strength in attentional control, processing speed, and encoding and retrieval (Class 3). Subsequent between-group comparisons revealed that the two cognitively impaired subgroups overall suffered from more severe symptoms of psychosis and worse psychosocial and adaptive functioning. Our findings contrast the links between cognitive profiles and symptoms of psychosis detected in clinical samples featuring patients with schizophrenia, underscoring the importance of considering the unique interrelationships between neurocognition and psychosis that exist in marginalized persons with multimorbid conditions when implementing targeted intervention strategies.

Keywords: Latent Profile Analysis; neurocognitive assessment; multimorbidity; psychosis; homelessness

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List of Acronyms

AC	Attentional Control
ANOVA	Analysis of variance
AWE	Approximate weight of evidence
BDI	Beck Depression Inventory
BECED	Best Estimate Clinical Evaluation and Diagnosis
BIC	Bayesian information criterion
BL	Baseline
BLRT	Bootstrapped likelihood ratio test
CAIC	Consistent Akaike information criterion
CANTAB	Cambridge Neuropsychological Automated Test Battery
CART	Classification and Regression Trees
CHC	Cattell–Horn–Carroll (model of cognitive functioning)
CNI	Cambridge Neurological Inventory
COWA	Controlled Oral Word Association (test)
DM	Decision Making
DSM-IV	Diagnostic and Statistical Manual for Mental Disorders 4th Edition
DSM-IV-TR	Diagnostic and Statistical Manual for Mental Disorders 4th Edition Text Revision
DTES	Downtown Eastside
E&R	Encoding and Retrieval
ESRS	Extrapyramidal Symptom Rating Scale
Gf	Fluid Reasoning (Problem Solving/Reversal Learning)
HCV	Hepatitis C virus
HIV	Human immunodeficiency virus
HVLT-R	Hopkins Verbal Learning Test – Revised
IED	Intra-Extra Dimensional Set Shift (test)
IGT	Iowa Gambling Task
LL	Log likelihood
LPA	Latent profile analysis
MAR	Missing at random
MCAR	Missing completely at random
MICE	Multiple imputation with chained equations

MINI	Mini-International Neuropsychiatric Interview
MNAR	Missing not at random
npar	Number of parameters
PANSS	Positive and Negative Syndrome Scale
PIQ	Performance Intelligence Quotient
PS	Processing Speed
RFS	Role Functioning Scale
RVP	Rapid Visual Information Processing (test)
SDMT	Symbol Digit Modalities Test
SOFAS	Social and Occupational Functioning Assessment Scale
SRO	Single-Room Occupancy (hotel)
TLFB	Timeline Follow-Back (method)
TMT-A	Trail Making Test part A
TMT-B	Trail Making Test part B
WTAR	Wechsler Test of Adult Reading

Chapter 1.

Introduction

The Downtown Eastside (DTES) in Vancouver, British Columbia is one of the city's oldest neighborhoods, featuring a strong sense of community and a rich cultural heritage (Building Community Society of Greater Vancouver, 2010; Carnegie Community Action Project, 2009). However, it is also an area with complex social issues such as elevated rates of drug use, crime, and unemployment (City of Vancouver, 2019). Many of its residents are considered to be homeless or precariously housed (i.e., without stable, safe, permanent, appropriate housing, or the immediate prospect, means and ability of acquiring it; Gaetz et al., 2012). Among such marginalized individuals in the DTES, polysubstance dependence, psychiatric illness, and viral infections such as human immunodeficiency virus (HIV) and hepatitis C (HCV) are common (Vila-Rodriguez et al., 2013). Furthermore, this population is facing a greater than eightfold increase in mortality rate (Jones et al., 2015) – a rate comparable to what has been reported for homeless populations in other developed nations such as Denmark, Sweden, and the United States (Beijer et al., 2011; Hibbs et al., 1994; Nielsen et al., 2011). The incidence of psychosis (i.e., a loss of touch with reality typically manifested as changes in thought patterns and perceptual experiences) is high among precariously housed persons in the DTES affected by poverty and exposure to polysubstance use (Jones, 2018). Symptoms of psychosis are also associated with increased mortality in this population (Jones et al., 2015).

Psychotic disorders tend to present as heterogeneous phenomena: It has long been recognized that various psychiatric symptom profiles exist and that such profiles have different etiological, pharmacological, and prognostic implications (Kay et al., 1987). For example, extensive research on persons with schizophrenia and other psychotic disorders has revealed that various psychiatric symptoms are differentially related to deficits in cognition (Bejaoui & Pédinielli, 2009; Bozikas et al., 2004; Gisselgård et al., 2014; Müller et al., 2004; Nilsson et al., 2016; O'Leary et al., 2000; Xavier et al., 2018). Such information has important implications for the development of cognitive training programs and medication trials aimed towards improving cognition in persons with psychotic disorders (Bryson et al., 1999), as well as for improving the understanding of the pathophysiology of psychotic disorders in general (Kanchanatawan et al., 2018).

Investigations featuring patients with schizophrenia have revealed a few themes with respect to the relationships between psychosis symptoms and cognition. While the existent literature has not firmly delineated such relationships in homeless and precariously housed adults, research on clinical patient samples nevertheless provide a starting point for comparable investigations in marginalized persons. In general, individuals with schizophrenia who present with predominantly disorganized and/or negative symptoms tend to display poorer cognitive functioning compared to persons with predominantly positive symptoms of psychosis (Bejaoui & Pédinielli, 2009; Bozikas et al., 2004; Bryson et al., 1999; Kanchanatawan et al., 2018; Nilsson et al., 2016; Xavier et al., 2018). More specifically, negative symptoms have been associated with a deficit in select executive functions such as verbal fluency, attentional control (i.e., the ability to manipulate attention flexibly to focus on task-relevant stimuli and ignore task-irrelevant stimuli; Schneider and McGrew, 2018), and speeded tasks involving cognitive flexibility, set shifting, and visual scanning (Bejaoui & Pédinielli, 2009; Berman et al., 1997; Flaum et al., 2000; Kanchanatawan et al., 2018; Müller et al., 2004; Nilsson et al., 2016; Xavier et al., 2018). In contrast, disorganized symptoms have been linked to poor performance on tests of verbal learning and memory (Bejaoui & Pédinielli, 2009; Bozikas et al., 2004; Bryson et al., 1999; Xavier et al., 2018). Furthermore, some reports suggest that the psychosis symptom dimension of lack of judgement and insight is associated with deficits in attentional control, processing speed, and fluid reasoning such as abstract problem solving and reversal learning (Orfei et al., 2010; Schneider and McGrew, 2018; Tiryaki et al., 2018).

Rather than comparing individual relationships on a symptom-by-symptom basis, it is often useful to assess patterns of neurocognition and psychiatric symptoms by taking a profile-based approach, wherein relative strengths and weaknesses across multiple cognitive tests and/or items are assessed. Profile-based approaches thus feature the added advantage of being able to assess study participants based on a pattern of scores rather than individual factor or test scores. Yet, less is known when it comes to cognitive profile patterns of persons with psychotic disorders and conflicting reports exist (Heinrichs & Awad, 1993; Lewandowski et al., 2014). Mirroring the reports of analyses of individual cognitive tests discussed above, patients with more severe negative and/or disorganized symptoms typically are overrepresented in overall lower-functioning cognitive subgroups (Lewandowski et al., 2014; Lewandowski et al., 2018). Further evidence suggests negative symptoms are associated with within-profile relative weaknesses in executive functions such as attentional control, processing speed, cognitive flexibility, and set-shifting (Reser et al., 2015; Suhr & Spitznagel, 2001; Uren et al., 2017) while positive symptoms are associated with within-profile relative weaknesses in verbal memory (Hill et al., 2002). Combining the evidence from single-symptom/item-based and profile-based research thus suggests that a split between verbal memory performance and executive functioning exists in persons with schizophrenia and other psychotic disorders, depending on their psychiatric symptom profile. Furthermore, in individuals with psychotic disorders, neurocognition has been associated with poor functional outcomes such as impaired work performance and independent living (Green et al., 2004). Neurocognition also mediates negative associations that are observed between psychiatric symptoms and functional outcomes (Bowie & Harvey, 2006), underscoring the importance of accurately delineating neurocognitive and psychiatric symptom patterns in persons with psychosis.

In contrast to the extensive literature on symptoms of psychosis in patients with major mental disorders such as schizophrenia, patterns of symptoms and clinical features of psychosis among homeless and precariously housed adults with multimorbidity are less well understood. Indeed, relative to a five- or six-factor structure featuring a negative and a positive symptom factor as the two primary components in psychotic disorders (Emsley et al., 2003; Stefanovics et al., 2014; Van Den Oord et al., 2006; Wallwork et al., 2012), our team has observed a unique three-factorial solution on the Positive and Negative Syndrome Scale (PANSS; Kay et al., 1987) in the vulnerably housed (Giesbrecht et al., 2016). This structure diverged from the typical PANSS factor structures identified in persons with schizophrenia in that the very prominent large factor consisting of primarily positive and disorganized symptoms that Giesbrecht and colleagues found contrast the typical narrower schizophrenia factorial models that split these symptom dimensions across separate factors. Interestingly, two of the three symptom factors (Psychosis/Disorganized and Negative Symptoms/Hostility) were robustly related to daily functioning, suggesting that psychiatric symptoms may be critical to the real-world impairments experienced by marginalized persons. What is uncertain is the extent to which these functional impairments in marginalized persons arise from neurocognitive underpinnings and whether the specific symptom dimensions of marginalized persons reflect distinct neurocognitive impairment patterns. The current study is designed to bridge this gap by evaluating whether patterns of neurocognitive functioning are associated with specific psychosis symptom profiles in a precariously housed sample with high rates of multimorbidity.

Previously our group reported associations between cluster-analytically derived cognitive profiles and psychiatric symptoms in marginalized persons living on the DTES (Gicas et al., 2014). One cluster presented with relatively higher cognitive functioning; a second cluster was characterized by intermediate cognitive functioning with a weakness in executive functioning and decision-making skills; and a third group showed the lowest overall cognitive functioning, with a strength in executive and decision-making skills. In terms of psychiatric symptoms, Gicas et al. found that members of the first cluster had significantly less severe negative symptoms as measured by the PANSS, compared to members of the second and third cluster. No significant differences were found across the clusters with respect to positive symptoms of schizophrenia and general psychopathology (Gicas et al., 2014). Yet, given that the findings reported by Gicas et al. were based on the conventional scales for the PANSS (as opposed to Giesbrecht et al.'s three-factorial PANSS solution that has since been validated for precariously housed and homeless persons with multimorbidity), it is possible that certain linkages between psychiatric symptoms and cognitive functioning would have been obscured from detection. Furthermore, the neurocognitive battery employed by Gicas et al. (2014) did not include measures of executive functioning entailing effortful attentional control and processing speed, such as verbal fluency and divided attention – all domains of cognition that have been associated with symptoms of psychosis in non-marginalized persons with schizophrenia (Berman et al., 1997; Nilsson et al., 2016; Orfei et al., 2010). Finally, cluster analysis as a technique has been criticized on the grounds of being somewhat arbitrary, with the investigator being forced to make important methodological and interpretative decisions (e.g., selecting a distance measure, determining the appropriate amount of clusters) without any reliable statistics to aid them (Alonso-Recio et al., 2018). Therefore, while supporting the feasibility of an analysis linking patterns of neurocognitive functioning and psychiatric symptoms as measured by the PANSS, Gicas et al.'s (2014) study was not designed to address these links in a methodologically rigorous, apriority manner.

The aim of the current research project was therefore two-fold: (1) To investigate patterns of cognitive functioning in marginalized persons by conducting a latent profile analysis (LPA) on performance scores from a comprehensive neuropsychological test battery; and (2) to examine any identified patterns of cognitive functioning by comparing differences across and within the classes on the three factors of psychosis symptoms (i.e., Psychosis/Disorganized, Negative Symptoms/Hostility, and Insight/Awareness) that have been established as valid and reliable for use in this population by Giesbrecht et al. in 2016. Person-centred techniques such as LPA and cluster analysis (in contrast to variable-centered techniques such as factor analysis) have the advantage of describing both similarities and differences among individuals with respect to how a collection of variables relate to each other (Masyn, 2013). Thus, person-centered methods are able to group individuals based on data rather than predetermined criteria (such as psychiatric diagnoses or scores on one particular test), which allows for participants to be classified based on a pattern of traits as opposed to a single variable or factor (Lewandowski et al., 2014). By extension, these approaches permit for homogenous groupings of participants (Lewandowski et al., 2014) and highlight patterns of relative strengths and weaknesses that may go undetected when examining individual test scores in isolation. Person-centered analyses are thus ideally suited for multimorbid samples, as they preserve the heterogeneity of the sample as a whole and permit an investigation of both within- and between-profile patterns of neurocognition (Gicas et al., 2014). Compared to cluster analysis, LPA also has the added advantages as being data-driven in its selection of an optimal model solution, as well as allowing for the computation of posterior membership probabilities, ultimately allowing the resulting classes to be compared statistically (Alonso-Recio et al., 2018). While LPA is considered exploratory (Masyn, 2013), a few general hypotheses were addressed. These hypotheses were derived from the aforementioned schizophrenia literature and our prior work (e.g., Gicas et al., 2014; Gicas et al., 2017).

1.1. Hypothesis 1 – Group 1 and Insight/Awareness Symptoms

We hypothesized that the LPA would reveal a subgroup of participants that presented as overall comparatively higher-functioning, with a relative weakness in executive functions such as attentional control, processing speed, and/or fluid reasoning (i.e., problem solving, reversal learning). We additionally hypothesized such a cognitive profile to be associated with relatively higher scores on the PANSS symptom factor of Insight/Awareness (indicating overall poorer insight into, and lower guilt associated with, any illness), based on reported negative associations between the aforementioned cognitive domains and insight in patients with psychosis (Orfei et al., 2010; Tiryaki et al., 2018). Thus, our first hypothesized subgroup can be summarized as “High-Functioning but Executive-Weak, with Poor Insight/Awareness”.

1.2. Hypothesis 2 – Group 2 and Negative/Hostility Symptoms

We also expected to find a subgroup of cognitive functioning that was relatively low-performing on measures of executive functions such as attentional control, processing speed, and fluid reasoning, in contrast to within-group performance on measures of verbal memory. We hypothesized such a profile to be primarily associated with higher factor scores on the PANSS dimension of Negative Symptoms/Hostility, based on previous reports linking negative symptoms with relative profile weaknesses in executive functions compared to verbal memory in persons with schizophrenia (Liu et al., 1997; Reser et al., 2015; Suhr & Spitznagel, 2001; Uren et al., 2017). Our second hypothesized subgroup can thus be summarized as “Executive-Weak/Memory-Strong, with more severe Negative Symptoms/Hostility”.

1.3. Hypothesis 3 – Group 3 and Psychosis/Disorganized Symptoms

Finally, we expected to find an overall low-performing subgroup with a relative strength in executive functioning (i.e., attentional control, processing speed, problem solving and reversal learning) as compared to verbal memory. As relative strengths in executive functions, as contrasted with verbal memory performance, have been associated with positive and disorganized symptoms (Hill et al., 2002), we hypothesized such a profile to be most impaired with respect to the PANSS symptom dimension of Psychosis/Disorganized. Our final hypothesized subgroup therefore is summarized as "Executive-Strong/Memory-Weak, with more severe Psychosis/Disorganized Symptoms".

Chapter 2.

Method

2.1. Participants

The current study analyzed data collected as part of the Hotel Study: a 10-year prospective longitudinal examination of multimorbidity in precariously housed individuals living in the DTES (for details see Vila-Rodriguez et al., 2013). Study participants were recruited from Single-Room Occupancy (SRO) hotels in the DTES, as well as from a downtown community court. Inclusion criteria consisted of (1) fluency in English; (2) either living, or having lived, in an SRO hotel, alternatively having been involved with the community court, all within the past six months of enrolment; and (3) having completed at least one neurocognitive assessment. The only exclusion criterion consisted of the inability to provide informed consent. A total of 372 participants met all inclusion criteria, with two participants being excluded from analysis due to invalid data, resulting in a final sample of 370 participants. A description of sample characteristics is provided in Table 1.

All study participants provided informed consent prior to study entry and received a minor cash honorarium as compensation. The study received ethics approvals from the Clinical Research Ethics Board of the University of British Columbia and the Simon Fraser University Office of Research Ethics.

2.2. Measures

2.2.1. Neurocognitive Tests

Twelve cognitive test items, spanning various domains such as controlled attention, memory, and processing speed, were combined to create five neurocognitive indicator variables based on the Cattell–Horn–Carroll (CHC) model of cognitive functioning: Attentional Control (AC); Processing Speed (PS); Fluid Reasoning (Problem Solving and Reversal Learning; Gf); Encoding and Retrieval (E&R); and Decision Making (DM). The CHC model is based on factor analysis and describes the major (i.e., broad) and minor (i.e., narrow) individual differences in cognitive performance that are captured by neurocognitive tests (Jewsbury et al., 2017). It was chosen as a basis for the five neurocognitive indicator variables due to its excellent fit as a paradigm for clinical assessment across both healthy and clinical populations (Jewsbury et al., 2017).

AC was assessed by combining scores from the color-word interference trial of the Stroop Color-Word Test, which measures a participant's ability to quickly name the colour of the ink that a list of words are written in (Stroop, 1935); and the A prime (a') score from the Rapid Visual Information Processing (RVP) test of the Cambridge Neuropsychological Automated Test Battery (CANTAB), which is a signal detection measure of the participant's sensitivity to a target sequence of numbers that are presented rapidly on a computer screen (Fray et al., 1996). E&R was assessed by combining the immediate and delayed trial scores from the Hopkins Verbal Learning Test – Revised (HVLT-R), a test of verbal learning and memory that requires the participant to memorize a list of words and recall these after a short and intermediate delay (Benedict et al., 1998). Gf was assessed by the error scores from the reversal stages of the Intra-Extra Dimensional Set Shift (IED) test of the CANTAB (Fray et al., 1996), a task which requires the participant to select the correct visual stimuli presented on a computer screen by updating their current strategy, inhibiting a practiced response, and switching to a more adaptive strategy across nine trials of increasing complexity (Miyake et al., 2000). PS was assessed by combining: (1) the letter fluency and category fluency scores from the Controlled Oral Word Association test (COWA), a test which asks the participant to produce as many words starting with a specific letter, and as many animals, as they can think of in one minute (Benton et al., 1994); (2) the written and oral scores from the Symbol Digit Modalities Test (SDMT), a measure that requires participants to quickly and accurately decode a sequence of symbols using a provided key (Smith, 1982); and (3) the time-to-completion scores from the Trail Making Test parts A and B (TMT-A, TMT-B), a widely-used test of scanning, visuomotor tracking, and cognitive flexibility, originally part of the Army Individual Test Battery in 1944 (Lezak, 2004). Finally, DM was assessed by the net score of the Iowa Gambling Task (IGT), a test that requires participants to maximize their gains and minimize their losses by selecting from four decks of cards containing various simulated monetary values (Bechara et al., 1994). Table 2 provides a summary of the five neurocognitive indicator variables and the individual tests and items that were used for their creation.

2.2.2. Psychosis Measures

Psychosis symptoms and severity was measured by the PANSS (Kay et al., 1987). Traditionally, the PANSS is divided into three different sub-scales: a Positive Syndrome scale containing seven items (representing symptoms that are present in persons with psychosis but not in persons without psychosis, such as hallucinations and delusions); a Negative Syndrome scale containing seven items (representing aspects that are lacking in persons with psychosis but present in persons without psychosis, such as full range of affect); and a General Psychopathology scale containing the remaining 16 items (representing general severity of illness; Kay et al., 1987). For more information on the individual items on the PANSS and the interpretation of scores, see Appendix A. Of note, the current study used the terminology "symptoms of psychosis" as referring to any of the symptoms measured by the PANSS (i.e., not just positive and disorganized symptoms).

The current study used the three-factor solution to the PANSS that has previously been found to be reliable and valid for use in the population under investigation (Giesbrecht et al., 2016). This three-factor PANSS solution consists of a large factor labelled Psychosis/Disorganization; a second factor labelled Negative Symptoms/Hostility; and a third factor labelled Insight/Awareness (with elevated scores representing individuals with low insight or awareness into their psychiatric condition, life situation, and/or transgressions). All of the three PANSS factors discovered by Giesbrecht et al. (2016) contribute significantly to the measurement of a higher-order psychopathology construct. Figure 1 provides additional information about Giesbrecth et al.'s (2016) PANSS factor solution, including the factor loadings for each item. To construct the individual factor scores, weighted sums of the individual items contained within each factor were used, with the weights corresponding to the respective factor loadings of each item (Uluman & Doğan, 2016).

2.2.3. Psychiatric, Psychosocial, and Neurological Measures

To evaluate psychiatric diagnoses, the Best Estimate Clinical Evaluation and Diagnosis (BECED; Endicott, 1988) was used, applying criteria from the Diagnostic and Statistical Manual for Mental Disorders 4th Edition Text Revision (DSM-IV-TR; American Psychiatric Association, 2000). In addition, the Mini-International Neuropsychiatric

Interview (MINI; Amorim et al., 1998) was used to assess psychiatric and substance-use disorder diagnostic status at the time of neurocognitive testing. The Beck Depression Inventory (BDI; Beck et al., 1961) was used to examine depressive symptoms. To assess psychosocial and occupational functioning, the Social and Occupational Functioning Assessment Scale (SOFAS) from the DSM-IV (American Psychiatric Association, 2000) and the Role Functioning Scale (RFS; Goodman et al., 1993) were used. For the BDI and the SOFAS, the raw total score on each measure was used for data analysis. For the RFS, the total raw score, as well as the total dimension scores of work productivity, independent living and self-care, immediate social network relationships, and extended social network relationships were used as outcome measures for between-group comparisons.

In order to examine substance use patterns around the time of neurocognitive testing, information regarding recent alcohol and drug use was collected using the Timeline Follow-Back method (TLFB; Sobell et al., 1986). The amount of days a substance (alcohol, cocaine, methamphetamine, heroin) was reported as being used was averaged across the three months around neurocognitive testing (current month, preceding month, following month) and used as an outcome measure. A modified version of the TLFB method, examining patterns of prescription medication use, was also used to assess antipsychotic usage. Further, in order to assess for symptoms of psychosis immediate to the time of neurocognitive testing, a shortened version of the PANSS was used, applying previously validated psychosis-threshold criteria for a dichotomous outcome indicator of whether the participant currently experienced psychosis (Chen et al., 2010).

Exposure to viral infections including HIV was assessed by serology screening for antibodies evaluated by the British Columbia Centre for Disease Control. Extrapyramidal symptoms were assessed with the Extrapyramidal Symptom Rating Scale (ESRS; Chouinard & Margolese, 2005) and neurological soft signs were assessed by summing the scores from the Cambridge Neurological Inventory (CNI; Chen et al., 1995). For both the ESRS and the CNI, the scores from each inventory dimension (dystonia, dyskinetic movements, and parkinsonism for ESRS; motor coordination, sensory integration, complex sequencing, and disinhibition for CNI) were summed to generate a total score reflective of the degree of impairment.

2.2.4. Demographic Measures

To ensure English language proficiency, the English Language Acculturation Questionnaire – a 12-item tool with scores ranging from 12 (wholly fluent in English) to 60 (not at all fluent in English) – was administered to all participants. Sociodemographic information, including date of birth, gender, and education history was collected via a thorough interview. Premorbid IQ was estimated by the Wechsler Test of Adult Reading (WTAR; Wechsler, 2001), a measure of single-word reading ability.

2.3. Procedure

Data for the current study were collected as part of a longitudinal examination consisting of both annual and monthly follow-up visits for study participants. Given the lack of parameters that time-locked the various testing sessions combined with an aim to minimize the amount of missing data, data from the most complete neurocognitive assessment available were analyzed for each participant. For all other measures, including the psychosis assessments (i.e., the PANSS), data from the assessment that occurred closest in time to the selected neurocognitive assessment were used for between- and within-group comparisons.

The neurocognitive assessments were conducted on an annual basis by trained research assistants under the supervision of a psychologist. Each cognitive measure was rated for validity by the administering research assistant. The PANSS, the ESRS, and the CNI were administered by study psychiatrists at baseline [BL], as well as during the annual follow-up clinical assessments. The serology screening for viral antibodies also took place on an annual schedule. The SOFAS and the RFS were administered biannually, whereas the MINI, the BDI, all versions of the TLFB, and the abbreviated version of the PANSS were administered monthly. Information on demographics, language capacity, and premorbid IQ was collected by research assistants at BL. The BECED was also administered by study psychiatrists at this time.

2.4. Statistical Analysis

To identify subgroups of cognitive functioning, data collected from the neurocognitive assessments were analyzed by LPA. The LPA methodology followed the recommendations set forth by Masyn (2013). The resulting subgroups of cognitive functioning were externally validated by additional between-group analyses examining whether the profiles differed in a meaningful way on sociodemographic, psychosocial/functional, and clinical variables, including the three validated PANSS factors of Psychosis/Disorganization, Negative Symptoms/Hostility, and Insight/Awareness, as well as the general Psychopathology factor discovered by Giesbrecht et al. (2016).

2.4.1. Data Preparation

All data were screened for validity and missingness. Missing neurocognitive data were fairly ubiquitous in the sample, with rates of missing-ness among the raw neurocognitive test variables ranging from 3.8% (HVLT-R immediate recall score) to 22.7% (RVP a' score). Sensitivity analyses were undertaken assessing whether the missing-ness of the data could be predicted from factors suspected to be related to cognition (age, education, having attended special education in school, and self-reports of having been diagnosed with a learning disability or attention deficit disorder). None of the factors examined significantly predicted missing-ness of neurocognitive data. The neurocognitive test data were thus assumed to be missing at random (MAR) and were handled by a two-step imputation process wherein the missing test score was replaced with the applicable score from the preceding or following neurocognitive testing session (whichever occurred closest in time), if available, and imputed using multiple imputation with chained equations (MICE), applying the non-parametric Classification and Regression Trees (CART) machine learning algorithm (Burgette & Reiter, 2010) if no other corresponding neurocognitive test item data were available. Finally, participants with imputed data on at least one neurocognitive item (n=292) were compared with participants with no missing data (n=78) on select demographic and clinical, psychosocial, and physiological variables, using independent-group t-tests and Mann-Whitney tests for continuous variables, as well as chi-square tests of independence for categorical variables. Further details of data screening, assumption checking, and handling of missing data are described in Appendix B. All statistical analyses were completed using IBM® SPSS® Statistics (Version 20) and RStudio (2020), using the tidyLPA package (Rosenberg et al., 2018).

Prior to conducting the LPA, the IED error scores used to create the Gf indicator variable were adjusted for the number of stages completed by examining the score of the participant who made the most errors on a given trial but still completed the trial, and then adding 1 to this score for all participants who did not complete the stage (for more details on this approach see Giesbrecht et al., 2014). The resulting IED reversal-error scores, as well as the time-to-completion scores from TMT-A and TMT-B, were then inverted to allow for higher scores to reflect better performance in accordance with the rest of the neurocognitive measures. Subsequently, all individual test scores were scaled by feature scaling to ensure equal weighting (Alfonso-Recio et al., 2018). The five neurocognitive indicator variables (AC, E&R, Gf, PS, and DM) were created by summing the applicable individual scaled test scores (see Table 2). The five indicator variables were then re-scaled to a common scale of 0 – 100, in order to prevent tests with larger metric values to unduly influence the LPA solution, following the methods of Alfonso-Recio et al. (2018). The resulting scaled five indicator variables were used as input in the LPA. Following the LPA, and in preparation for between- and within-group analyses, the feature-scaled indicator scores were standardized to t-scores[1], in order to control for varying levels of difficulty across the test measure and normalize the data to the sample.

2.4.2. Data Analysis

Four separate within-class variance–covariance matrix structures were explored as possibilities for the specification of the final model solution: a class-invariant diagonal structure (where the covariances between the indicator variables are fixed at zero within class and variances are constrained to be equal across the latent classes); a class-varying diagonal structure (where the variances are freely estimated and allowed to be different across the latent classes, but the covariances are fixed at zero within each class); a class-invariant unrestricted structure (where all the indicator variables are allowed to covary within class, but the variances and covariances are kept equal across the latent classes); and a class-varying unrestricted structure (where all the indicator variables are allowed to covary within class, and the variances and covariances are allowed to be different across the latent classes). Model solutions ranging from two to

[1] The resulting t-scores were unaffected by the type of score used as input for standardization. That is, the resulting individual t-scores and their respective distributions appeared identical regardless whether raw scores or feature scaled indicator scores were used for standardization.

five classes were compared for each of the four within-class variance–covariance matrix structures.

The best model solution was chosen based on an analytic hierarchical process that compared the explored models on measures of relative fit, while simultaneously favouring model simplicity (Akogul & Erisoglu, 2017; Masyn, 2013). Entropy was assessed for each model, allowing for the comparison of the proportion of individuals correctly classified across different model solutions. Bootstrapped likelihood ratio (BLRT) tests assessed for goodness-of-fit, comparing all competing models on the ratio of their log likelihood (LL) of the data.

In order to examine whether the classes conformed to our hypothesized subgroups (i.e., one "High-Functioning but Executive-Weak, with Poor Insight/Awareness" subgroup; a second "Executive-Weak/Memory-Strong, with more severe Negative Symptoms/Hostility" subgroup; and a third "Executive-Strong/Memory-Weak, with more severe Psychosis/Disorganized Symptoms" subgroup), as well as verify the clinical meaningfulness of the finalized class solution, a series of external validation analyses were subsequently performed. The latent classes were compared on demographic variables, as well as psychiatric, psychosocial, and neurological measures, employing analyses of variance (ANOVA) for continuous variables and chi-square tests of independence for categorical variables.

In order to further examine the proposed hypotheses, profiles of cognitive strengths and weaknesses were evaluated with within-group comparisons. The class-specific mean performance on each of the standardized five neurocognitive indicator variables was compared against the respective class-specific predicted performance (based on the class-specific average performance across all neurocognitive predictors; Flanagan & Harrison, 2012) using one-sample t-tests. Within-subjects ANOVAs compared the magnitude of standardized psychosis factor t-scores within each class and hierarchical regression analyses evaluated potential interactions between neurocognitive performance and class on PANSS factor scores.

Chapter 3.

Results

3.1. Latent Profile Analysis

An optimal goodness-of-fit was reached for a three-class class-varying unrestricted model (BLRT=127.86, *p*=.01), indicating that the fit of this model was a significant improvement from the two-class model of identical within-class variance–covariance structure specification. The BLRT statistic was no longer significant for the four-class class-varying unrestricted model (BLRT=33.84, *p*=.70), meaning that the overall model was not further improved by the addition of a fourth class. Table 3 provides details on the model fit indices for the LPA, including the four different within-class variance–covariance structure specifications (Σ_k). Because it is desired to maximize the LL, a higher value is preferable for the LL function. Conversely, for the three indices of relative fit, a lower value is indicative of superior model fit. Entropy provides information on the proportion of the overall sample that is classified correctly under the estimated conditions. The neurocognitive indicator of Gf (Problem Solving/Reversal Learning) appeared to hold the most weight in terms of uniquely defining the three classes (see Appendix C for a discussion of the contribution of each neurocognitive indicator variable to class homogeneity and class separation).

Class 1 included a little over half of the participants from the overall sample (*n*=207, 55.9%); Class 2 included just under a third of the participants from the overall sample (*n*=109, 29.5%); and Class 3 featured the smallest proportion of participants (*n*=54, 14.6%). Examining the average posterior class probabilities by modal latent class assignment revealed that participants had an average probability of 0.94 to be classified into the correct class under the selected model conditions (see Table 4).

3.1.1. Neurocognitive Class Characteristics

The overall neurocognitive profiles for each of the three classes are illustrated in Figure 2. As illustrated in Table 5, overall, the cognitive profiles displayed an exceptional divergence across the class-specific means, standard deviations, and within-group item correlations of the five neurocognitive indicators. It should be noted that all three classes performed well below established norms with respect to their demographically corrected performance on select measures of executive functioning (AC) and verbal memory (E&R).

Members of Class 1 generally exhibited stronger cognitive performance compared to members of both Class 2 and Class 3, with superior performance compared to both classes on the neurocognitive indicators of Gf, PS, and DM, as well as superior AC performance compared to members of Class 2 and superior E&R performance compared to members of Class 3. For members of Class 1, increasing performance on all cognitive domains except Gf had a positive valence – that is, when performance within one domain increased, so did the performance within the others (i.e., a positive correlation). Finally, Class 1 featured a relative strength in Gf, compared to the other intra-profile neurocognitive domains.

Members of Class 2 exhibited significantly inferior cognitive performance across all five neurocognitive indicator variables except E&R compared to members of Class 1, and significantly superior Gf performance compared to members of Class 3. Class 2 also displayed similar positive correlational patterns to Class 1 across the domains of AC, E&R, and PS, with a small positive correlation between DM and AC. However, in contrast to the patterns observed for Class 1, increased DM performance for members of Class 2 was associated with a decrease in Gf performance (and vice versa, i.e., a negative correlation). In regards to relative strengths and weaknesses, members of Class 2 presented with a similar within-group neurocognitive profile as members of Class 1, with a relative strength in Gf.

Members of Class 3 displayed a comparably impaired cognitive profile to members of Class 2 with the exception of their performance on the neurocognitive indicator of Gf, which was remarkably weak for members of this class compared to that of Class 1 and Class 2. Class 3 further displayed moderate-to-large positive within-class correlations between AC, E&R and PS. In terms of within-group patterns, Class 3 presented with relative strengths in AC, PS, and E&R, as well as with a severe relative weakness in Gf.

Figures C1-C5 (Appendix C) further allow for the visualization of the within-group item correlations among the five neurocognitive indicators across the three classes. Table 6 displays the within-group mean differences for the five neurocognitive indicators across the three classes.

3.2. Clinical Comparisons

3.2.1. Group Comparisons

Significant group differences for the external validation variables are summarized in Table 7. Specifically, members of Class 1 displayed the least severe psychiatric and physical symptoms and the best psychosocial and occupational functioning. Compared to members of Class 3, members of Class 1 were also of significantly younger age.

Members of Class 2 appeared to display the most severe symptoms of psychosis, with significantly higher scores on all of Giesbrecht et al.'s (2016) PANSS factors except Negative Symptoms/Hostility (i.e., Positive/Disorganized, Insight/Awareness, and General Psychopathology), as well higher total PANSS score when compared to members of Class 1. In terms of psychosocial and occupational functioning, members of Class 2 displayed significantly lower work productivity, as well as significantly lower levels of independent living and self-care, compared to members of Class 1. Members of Class 2 also had significantly lower total scores on the RFS compared to members of Class 1, indicating an overall lower level of adaptive functioning. In terms of neurological symptoms, members of Class 2 displayed significantly higher levels of extrapyramidal symptoms compared to members of Class 1.

Members of Class 3 were characterized by significantly older age when compared to members of Class 1, as well as by significantly more severe Insight/Awareness deficits. Further, similar to Class 2, members of Class 3 displayed significantly lower work productivity and overall adaptive functioning compared to members of Class 1.

No differences were found between the three classes on the Giesbrecht et al. (2016) PANSS factor of Negative Symptoms/Hostility, nor on other demographic variables (gender, ethnic background, levels of education, estimated premorbid IQ); psychiatric diagnoses (schizophrenia, schizoaffective disorder, major depressive disorder, bipolar I and bipolar II disorder, substance-induced disorders); diagnoses of substance dependence (stimulant dependence, opioid dependence, alcohol dependence, cocaine dependence, methamphetamine dependence, heroin dependence, cannabis dependence); psychiatric diagnostic criteria met at time of testing; depressive symptoms around the time of testing; substance use around the time of testing; antipsychotic medication usage around the time of testing; neurological soft signs; or HIV diagnostic status. Further, the amount of previous exposure to the neurocognitive tests was not found to impact cognitive performance for any of the three classes[2].

3.2.2. Neurocognition and Psychosis Symptom Profiles

In order to test the hypotheses that one "High-Functioning but Executive-Weak" subgroup of cognitive functioning would exhibit more severe Insight/Awareness symptoms; a second "Executive-Weak/Memory-Strong" subgroup would display more severe Negative/Hostility symptoms; and a third "Executive-Strong/Memory-Weak" subgroup would display more severe Positive/Disorganized symptoms, fluctuations in symptom severity based upon symptom type was examined within each class by conducting three within-subjects ANOVAs, i.e., one analysis for each class. The dependent variable, Symptom Severity, was standardized for each symptom type to the entire sample's corresponding raw psychopathology scores. Symptom Type (Positive/Disorganized, Negative/Hostility, Insight/Awareness) served as the within-subjects factor. Symptom Severity did not vary based upon Symptom Type for any of the three classes (Class 1 [$F(2, 404) = .43$; $p > .05$]; Class 2 [$F(2, 208) = .65$; $p > .05$]; Class 3 [$F(2, 100) = .20$; $p > .05$]), indicating that all three classes had relatively consistent within-group psychosis symptom profiles (see Figure 3).

Given the lack of within-group differences in psychosis symptom severity, we felt it would be additionally informative to examine the relationships between the interaction of class membership and cognitive performance with symptoms of psychosis across the three classes. A series of exploratory hierarchical regression analyses were subsequently conducted, using age as a covariate and psychosis symptom domain (i.e.,

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[2] While members of Class 1 were found to having been exposed to the IED from the CANTAB at a significantly higher rate than members from Class 2 [$F(2, 367)=3.89$, $p<.05$], test exposure was not found to significantly predict neurocognitive performance for any of the three classes.

Psychosis/Disorganization; Negative Symptoms/Hostility; and Insight/Awareness) as outcome variables. All three regression models included age in the first block, then added cognitive performance on all five indicator variables (AC, PS, Gf, E&R, and DM) in the second block, class membership in the third block, and interactions between class membership and cognitive performance in the fourth block.

Main effects of age, cognitive performance, and class membership were revealed on Psychosis/Disorganization; main effects of age and cognitive performance on Insight/Awareness; and only a main effect for cognitive performance on Negative Symptoms/Hostility. No significant interactions were detected between class and neurocognitive performance on the severity of any of the three psychosis symptom factors, indicating a comparable association between neurocognition and symptom severity across all three classes. For additional information on the regression analyses, as well as tables of statistics, see Appendix D).

An overall summary of the results organized by LPA class can be found in Table 8.

Chapter 4.

Discussion

Three subgroups of cognitive functioning were detected in a sample of homeless and precariously housed persons. The largest subgroup (Class 1; 55.9% of the overall sample) had the highest neurocognitive capacity, as well as the least psychopathology. In contrast, the two other subgroups had considerably lower neurocognitive capacity. One of these two groups (Class 3; 14.6% of the overall sample) possessed a remarkable weakness in the executive domain of Fluid Reasoning (Problem Solving/Reversal Learning; Gf). Relative to the highest-capacity group, these persons also lacked insight and awareness into their psychiatric symptoms. The second cognitively impaired subgroup (Class 2; 29.5 % of overall sample) exhibited higher rates of a variety of psychosis symptoms as well as more severe extrapyramidal symptoms. Both of the cognitively impaired subgroups displayed impairments in various areas of adaptive psychosocial functioning, compared to the members of the highest-capacity group.

With respect to profile patterns of cognitive functioning (i.e., relative cognitive strengths and weaknesses within each subgroup) and their respective links to psychosis symptoms, we had hypothesized to find a divergence between select executive functions (AC, PS, Gf) and verbal memory performance (E&R) within the subgroups with the most severe symptoms of psychosis (based on similar patterns having been described previously in persons with schizophrenia; Hill et al., 2002). Specifically, as summarized in Table 9, we had expected to find a “High-Functioning but Executive-Weak, with Poor Insight/Awareness” subgroup; a cognitively “Executive-Weak/Memory-Strong, with more severe Negative Symptoms/Hostility” subgroup; and a cognitively “Executive-Strong/Memory-Weak, with more severe Psychosis/Disorganized Symptoms” subgroup. In support of our hypotheses regarding patterns of cognitive functioning within each subgroup, members of one of the most cognitively impaired subgroups (Class 3) displayed relative strengths in the executive domains of attentional control (that is, the ability to manipulate attention flexibly to focus on task-relevant stimuli and ignore task-irrelevant stimuli; Schneider and McGrew, 2018) and processing speed (that is, the ability to quickly and accurately perform tasks involving initiation, switching, and scanning/visuomotor tracking). Yet, the hypothesized links between profiles of cognition and patterns of psychosis received little-to-no support, as both of the other two subgroups displayed relative strengths in the domain of Gf (Problem Solving/Reversal Learning). Additionally, no within-class differences across the standardized PANSS scores could be detected for any of the three classes. Similarly, no associations were detected for any interactions between cognition and class membership and psychosis symptom severity. This suggests that, while overall presenting as more or less psychotic, most members of our sample have fairly consistent psychosis-symptom profiles (wherein all symptom domains display a similar degree of severity). Ultimately, it thus appears that the different patterns of cognitive functioning and their respective links to specific symptoms of psychosis that have previously documented in clinical samples with schizophrenia (Hill et al., 2002; Uren et al., 2017) do not extend to include precariously housed and homeless individuals with high levels of psychosis.

Several additional findings worth noting emerged from our analyses. Firstly, the executive functions tested in the current study (i.e., AC, Gf, and PS) did not behave as a unitary construct, with Gf (Problem Solving/Reversal Learning) behaving differently from AC and PS across all three classes. Indeed, performance with respect to the neurocognitive domain of Gf appeared to be a robust cognitive differentiator for the three classes. Members of both the highest-capacity Class 1 and the comparatively cognitively impaired Class 2 performed well on this indicator, whereas members of the cognitively impaired Class 3 performed exceptionally poorly within the same domain. This suggests that the test underlying this cognitive indicator – the IED from the CANTAB (Fray et al., 1996) – may serve as a uniquely polarizing task for marginalized homeless and precariously housed adults with multimorbidity. Interestingly, despite the two better-performing subgroups (i.e., Class 1 and Class 2) displaying ceiling effects within this neurocognitive domain (that is, these classes included members that achieved the maximum scores possible on the underlying test), the group difference with Class 3 was enormous, suggesting that the true difference between Class 3 and Class 1 and 2 on this domain is even greater than what was detected in the current study. This would suggest that members of Class 3 suffer from a significant impairment in fluid reasoning and/or inhibition and switching (Miyake et al., 2000). It is worth noting that the three latent classes did not differ in respect to their Performance Intelligence Quotient (PIQ) as estimated by the WTAR (Wechsler, 2001). While the WTAR admittedly is not an adequate substitute for a more comprehensive measure of current fluid reasoning performance, this finding nevertheless opens up for speculation that the Gf deficit displayed by Class 3 may be more related to perseveration. Further research examining the three latent classes on more expansive measures of fluid reasoning (e.g., Matrix Reasoning) and perseveration is warranted in order to evaluate this possibility.

Another finding worth highlighting is the fact that members of the most psychotic subgroup (i.e., Class 2) displayed an inverse relationship between their Gf (Problem Solving/Reversal Learning) performance and their DM performance. A similar trend was observed for members of the second comparatively cognitively impaired subgroup (i.e., Class 3). This suggests that, in our sample, the more cognitively impaired individuals who suffer from more severe psychosis may have applied similar strategies across the two tests underlying the domains of Gf and DM (with DM being assessed by the IGT). Specifically, the cognitively impaired participants with the most severe symptoms of psychosis appear to have benefitted from applying a persistent strategy on the IGT (where it “pays off” to stick with the more rewarding decks of cards) while simultaneously been penalized for such perseveration during their IED trials (which demands that the test-taker quickly and flexibly recognizes that a previously successful strategy is no longer the correct way to go). This suggestion raises the question of whether such an inflexible application of maladaptive strategies when faced with a task that has previously been rewarded extends to the “real world”. That is, is it possible that members of the more cognitively impaired subgroups may be so entrenched in maladaptive patterns of behaviour that have previously been associated with rewarding properties that these individuals become unable to “break out” of such patterns when no longer rewarding? Such a suggestion would have important implications for clinical interventions targeting the most cognitive impaired persons within the marginalized population under investigation, as it would underscore the need to prioritize such individuals for any efforts aimed towards recognizing where this type of entrenchment may impede adaptive functioning.

Comparing the three LPA classes that were obtained in the current study with the three clusters of neurocognitive functioning previously uncovered by our research team (Gicas et al., 2014) reveals both resemblances and contrasts. Similar to what Gicas and colleagues discovered, three subgroups of cognitive functioning were detected in the current study, with verbal memory abilities differentiating two of the three LPA classes well. Yet, the current class solution contrasted with the cluster solution found by Gicas et al. on measures of executive functioning, and Gicas and colleagues did not detect as dramatic of a difference across their clusters in respect to Gf performance as was found in the current study. Additionally, Gicas et al. (2014) did not detect as many psychosis symptom differences across their clusters, whereas the current study found that the LPA classes differed on symptoms of psychosis involving psychosis/disorganization and deficits in insight and awareness.

The majority of the aforementioned differences between the results from the current study and the clusters detected by Gicas et al. (2014) likely stem from different approaches in selection of a study sample and/or analytical techniques. Gicas and colleagues analyzed a smaller sample of precariously housed persons and applied complete case analysis, whereas the current study attempted to minimize any potential selection bias when dealing with missing data (see Appendix B). It is also likely that, considering the dynamic flux a precariously housed and/or homeless person on the DTE experiences with respect to their day-to-day living environment, the time difference between the two studies may have impacted the findings. Importantly, the current study used LPA, rather than cluster analysis, in deriving subgroups of cognitive functioning. LPA is a type of finite mixture modelling, and thus derives subgroups (i.e., classes) using a probabilistic model that describes the distribution of the data at hand. That is, instead of finding clusters using a distance measure chosen by the investigator, a model describes the distribution of your data and uses this as a basis for assessing the probabilities that certain cases are members of certain latent classes (Oberski, 2016). In doing so, LPA is able to compare multiple models that classify participants across aspects such as the standardized mean difference, as well as differences in within-class variance and correlation-patterns across indicator variables, ultimately providing an overall statistical evaluation of multi-dimensional similarities and differences across classes. The underlying assumption of LPA is that there exists some latent aspect that is captured by the indicator variables and that is able to separate the overall sample into sub-classes (Masyn, 2013). This assumption has important implications, as it guides the selection of suitable indicator variables and subsequently the “criteria” that the LPA algorithm uses to classify study participants. To illustrate this concept, one can consider how it is possible to classify a group of people by either their gender, hair-colour, or favourite food. The resulting subgroups will likely differ based on the classification indicator(s) that is/are selected. When considering the differences between the latent classes detected in the current study and the clusters of cognitive functioning detected by Gicas et al. (2014) in light of such an illustration, these differences become less puzzling.

4.1. Implications

The results from the current study bring several implications, some more theoretical in nature and other more practical in nature. As for the theoretical aspects, the finding that the executive functions examined (AC, PS, and Gf) displayed divergent performance patterns across all three classes may inform the debate as to whether it might be advantageous to consider these “frontal lobe” related functions as diverse, rather than unitary constructs (Jewsbury et al., 2017; Miyake et al., 2000). In their study on the appropriateness of the CHC model for clinical assessment, Jewsbury and colleagues concluded that there was no distinct general executive function factor and that the hypothesized executive function indicators did not individually measure specific executive functions separate from any of the CHC constructs. On a similar note, Miyake and colleagues have proposed that three separate functions – mental set shifting, information updating and monitoring, and inhibition of prepotent responses – contribute differentially to performance on complex executive tasks. The results from the current study strongly suggests that executive functioning is better assessed as individual validated cognitive domains within this population, a notion that echoes existing criticism of the use of a unitary construct of executive functioning (Jewsbury et al., 2017; Miyake et al., 2000).

There are several practical implications stemming from the current findings as well. To begin, it is important to recognize that, since our results differed quite a bit from what was hypothesized based on research on clinical patient samples with schizophrenia, one needs to consider precariously housed/homeless persons with psychosis as a unique population that cannot necessarily be considered within the same clinical framework as “cleaner” and less multimorbid populations. That is, echoing empirically supported recommendations previously stated by our research group (Honer et al., 2017), care for marginalized persons with multimorbidity requires urgent attention and more empirically supported clinical instruments developed specifically for this population are sorely needed.

Further, in the population under investigation, specific cognitive impairments appear in distinct, psychosocially and adaptively impaired subgroups that each display unique within-group relative cognitive strengths and weaknesses. This finding opens up the possibility of developing targeted clinical intervention efforts that target such subgroup-specific cognitive weaknesses while simultaneously capitalizing on subgroup-specific cognitive strengths – similar to how one would target treatment recommendations based on the results from a recent neuropsychological assessment for an individual. By taking such an approach and targeting the specific needs of distinct subgroups, the efficacy and cost-effectiveness of clinical intervention efforts are likely to be maximized. Potential areas to focus on could be to improve treatment adherence, general psychosocial wellbeing, and independent living in precariously housed persons experiencing cognitive impairments.

4.2. Limitations and Future Study

The results from the current study suggest that a subgroup of precariously housed and homeless persons living with multimorbidity experience severe impairments in fluid reasoning. However, we only used one measure of fluid reasoning which involved reversal learning (reversal error scores from the IED from the CANTAB). Thus, it would be useful for future research efforts to include more comprehensive measures of fluid reasoning such as Matrix Reasoning and Wisconsin Card Sorting Test paradigms in order to disentangle the specifics of these fluid impairments (i.e., whether they are more related to deficits in abstract problem solving alternatively perseveration). Further, there are cognitive abilities that were not examined in the current study (e.g., visuospatial memory). Additional research would be necessary to establish how these abilities are affected in marginalized individuals.

Furthermore, the complexity and heterogeneity of the sample under investigation also brings a limitation in the form of uncertain levels of generalizability of our findings to other populations. Thus, it would be helpful for future studies to attempt to replicate some of our findings in both precariously and stably housed persons. Nevertheless, the current study provides compelling evidence for the existence of unique relationships between neurocognitive functioning, symptoms of psychosis, and adaptive psychosocial functioning in marginalized persons living with high levels of multimorbidity. This underscores the importance of augmenting our current understanding of psychotic illness with community-based research findings involving homeless and precariously housed persons.

Tables

Table 1: Overall Sample Characteristics (n=370)

Characteristic	%	*M*(SD)	*Mdn*	*Range*
Age (years)		44.60 (12.94)	46.51	20.22 – 75.07
Education (years)		10.56 (2.27)	10.00	2.00 – 17.00
Gender (% male)[a]	74.05			
Ethnicity[b]				
White	56.49			
Indigenous	27.3			
West Asian	1.62			
Black	1.35			
Latin American	0.54			
South Asian	0.27			
Middle East and North Africa	0.27			
Other/Unknown	12.16			
Premorbid IQ (WTAR)[c]		99.13 (8.91)	100.00	73.00 – 122.00
Symptoms of Psychosis (PANSS)				
Positive/Disorganized[d]		22.70 (5.79)	21.50	10.84 – 39.99
Negative/Hostility[e]		10.76 (3.05)	10.26	5.81 – 22.31
Insight/Awareness[f]		2.39 (1.10)	2.23	-0.58 – 4.57
Psychopathology[g]		29.79 (6.81)	28.39	16.56 – 50.28
Depressive symptoms (BDI)[h]		11.11 (10.89)	8.00	0.00 – 58.00
Social Functioning (SOFAS)[b]		42.66 (10.10)	40.00	18.00 – 85.00
Role Functioning (RFS)[b]		12.68 (3.11)	12.00	5.00 – 25.00
Psychiatric Diagnosis at Recruitment				
Schizophrenia[i]	11.08			
Schizoaffective Disorder[a]	9.73			
Psychosis NOS[a]	12.16			
Substance-Induced Psychosis[a]	16.49			
Major Depressive Disorder or Depression NOS[a]	12.70			
Bipolar Disorder I or Bipolar NOS[a]	7.57			
Bipolar Disorder II[a]	5.14			
Active Psychosis at Testing[j]	45.68			
Substance Usage at Testing (average days of monthly use)[a]				
Alcohol		4.29 (8.16)	0.50	0.00 – 28.00
Cocaine		5.15 (9.29)	0.00	0.00 – 28.00
Methamphetamine		5.78 (9.42)	0.00	0.00 – 28.00
Heroin		5.34 (9.81)	0.00	0.00 – 28.00
HIV infection (% positive)	10.54			
Medication Usage at Testing (average days of monthly use)[k]				
Antipsychotic		17.01 (11.90)	22.00	0.00 – 28.00
Extrapyramidal Symptoms (ESRS score)[l]		27.70 (14.40)	27.00	0.00 – 76.00
Neurological Soft Signs (CNI score)[m]		5.74 (5.39)	4.00	0.00 – 35.00

Note. WTAR = Wechsler Test of Adult Reading; PANSS = Positive and Negative Syndrome Scale; BDI = Beck Depression Inventory; SOFAS = Social and Occupational Functioning Assessment Scale; RFS = Role Functioning Scale; ESRS = Extrapyramidal Symptom Rating Scale; CNI = The Cambridge Neurological Inventory
[a] n=369; [b] n=367; [c] n=320; [d] n=360; [e] n=361; [f] n=362; [g] n=359; [h] n=366; [i] n=368; [j] n=365; [k] n=135; [l] n=356; [m] n=311.

Table 2: Neuropsychological Indicators, Processes, Tasks, and Input Variables for Latent Profile Analysis

Neurocognitive Indicator	Process	Task	Variable(s)
Attentional Control (AC)	Inhibitory control; Divided attention	Stroop Color-Word Test	Color-word interference trial raw score
	Sustained attention	RVP (CANTAB)	A prime (a') score
Encoding & Retrieval (E&R)	Verbal learning and memory	HVLT-R	Total immediate recall raw score Delayed recall raw score
Fluid Reasoning (Problem Solving/Reversal Learning) (Gf)	Perception of conceptual relationships; Visuospatial reasoning; Switching; Inhibition	IED (CANTAB)	Total number of errors made on reversal stages, adjusted for the number of stages completed
Processing Speed (PS)	Word fluency and initiation	COWA	Word fluency raw score Category fluency raw score
	Scanning and visual tracking	SDMT	Written raw score Oral raw score
	Scanning, visuomotor tracking	TMT-A	Time-to-completion raw score
	Scanning, visuomotor tracking, cognitive flexibility	TMT-B	Time-to-completion raw score
Decision Making (DM)	Decision making, response to reward	IGT	Net score

Note. RVP = Rapid Visual Information Processing; CANTAB = Cambridge Neuropsychological Automated Test Battery; HVLT-R = Hopkins Verbal Learning Test – Revised; IED = Intra-Extra Dimensional Set Shift; COWA = Controlled Oral Word Association; SDMT = Symbol Digit Modalities Test; TMT-A = Trail Making Test part A; TMT-B = Trail Making Test part B; IGT = Iowa Gambling Task.

Table 3: Model Fit Indices for Latent Profile Analysis Using Four Different Within-Class Variance–Covariance Structure Specifications

Σ_k	# of classes	*LL*	*npar*	BIC	CAIC	AWE	Entropy	BLRT	BLRT *p*-value
Class-invariant diagonal	2	-7863.21	20	15821.03	15837.03	15962.19	0.73	297.01	0.01
	3	-7714.51	30	15559.12	15581.12	15753.56	0.82	297.40	0.01
	4	-7680.90	40	15527.37	15555.37	15775.36	0.80	67.22	0.01
	5	-7670.26	50	15541.57	15575.57	15843.22	0.71	21.28	0.01
Class-varying diagonal	2	-7721.15	20	15566.47	15587.47	15752.16	0.75	581.14	0.01
	3	-7626.33	30	15441.90	15473.90	15725.61	0.76	189.62	0.01
	4	-7592.92	40	15440.11	15483.11	15821.85	0.77	66.83	0.01
	5	-7512.26	50	15343.85	15397.85	15823.57	0.81	161.31	0.01
Class-invariant unrestricted	2	-7790.67	30	15735.09	15761.09	15965.61	0.62	21.14	0.02
	3	-7621.33	40	15431.90	15463.90	15715.74	0.70	338.67	0.01
	4	-7613.60	50	15451.91	15489.91	15789.31	0.66	15.48	0.13
	5	-7603.84	60	15467.87	15511.87	15858.78	0.64	19.51	0.02
Class-varying unrestricted	2	-7525.23	40	15292.91	15333.91	15656.78	0.79	552.03	0.01
	3	**-7461.30**	**60**	**15289.23**	**15351.23**	**15840.24**	**0.81**	**127.86**	**0.01**
	4	-7444.38	80	15379.58	15462.58	16117.76	0.82	33.84	0.70
	5	-7396.36	100	15407.73	15511.73	16333.10	0.82	96.03	0.01

Note. Σk = Class *k* variance-covariance matrix for the five indicator variables; LL= log likelihood of the data, given the model; npar = number of parameters estimated, given the model; BIC = Bayesian information criterion, based on -2 log-likelihood, and penalized by the number of parameters adjusted by sample size; CAIC = consistent Akaike information criterion, based on -2 log-likelihood, and penalized by the number of parameters adjusted by sample size; AWE = approximate weight of evidence, combining information on model fit and on classification errors; BLRT = bootstrapped likelihood ratio test. Because it is desired to maximize the log-likelihood, a higher value is preferable for LL. Conversely, for all three indices of relative fit (BIC, CAIC, AWE), a lower value is indicative of superior model fit. Entropy provides information on the proportion of the overall sample that is classified correctly under the estimated conditions.

Table 4: Average Posterior Class Probabilities by Modal Latent Class Assignment

Class assignment	$M_{\hat{p}_{\text{Class 1}}}$(SD)	$M_{\hat{p}_{\text{Class 2}}}$(SD)	$M_{\hat{p}_{\text{Class 3}}}$(SD)
Class 1 (*n*=207)	0.92 (0.10)	0.07 (0.10)	0.00 (0.01)
Class 2 (*n*=109)	0.05 (0.09)	0.90 (0.11)	0.05 (0.09)
Class 3 (*n*=54)	0.00 (0.00)	0.01 (0.05)	0.99 (0.05)

Note. The posterior class probabilities display the average probability of a participant from class *k* being assigned to either Class 1, Class 2, or Class 3.

Table 5: Observed Class-Specific Means, SDs, and Correlations Based on the Three-Class Latent Profile Analysis with Class-Varying, Unrestricted Σ_k (*n*=370)

						Correlations (ρ)				
Class	**Variable**	***M*(SD)**	**Test statistic**	**Effect Size**	**Contrasts**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Class 1 *n*=207 (55.9%)	(1) AC	51.39 (9.62)	*F*(2, 367)= 4.66, *p*<.05	*d*=0.33	$1 > 2^{*}$	1.00				
	(2) PS	52.07 (8.96)	*F*(2, 367)= 10.65, *p*<.001	*d*=0.47 *d*=0.49	$1 > 2^{***}$ $1 > 3^{**}$	$.64^{***}$	1.00			
	(3) Gf	55.69 (0.94)	*F*(2, 97.48)= 389.75, *p*<.001	*d*=2.35 *d*=4.20	$1 > 2^{***}$ $1 > 3^{***}$	.10	-.04	1.00		
	(4) E&R	51.33 (9.94)	*F*(2, 367)= 4.84, *p*<.01	*d*= 0.43	$1 > 3^{*}$	$.52^{***}$	$.59^{***}$	.04	1.00	
	(5) DM	51.87 (10.23)	*F*(2, 137.81)= 10.16, *p*<.01	*d*=0.32 *d*=0.65	$1 > 2^{*}$ $1 > 3^{***}$	$.16^{*}$	$.24^{***}$	.04	$.15^{*}$	1.00
Class 2 *n*=109 (29.5%)	(1) AC	48.11 (10.24)	*F*(2, 367)= 4.66, *p*<.05	*d*=0.33	$2 < 1^{**}$	1.00				
	(2) PS	47.27 (11.22)	*F*(2, 367)= 10.65, *p*<.001	*d*=0.47	$2 < 1^{***}$	$.73^{***}$	1.00			
	(3) Gf	49.74 (3.45)	*F*(2, 97.48)= 389.75, *p*<.001	*d*=2.35 *d*=3.08	$2 < 1^{***}$ $2 > 3^{***}$	-.06	-.14	1.00		
	(4) E&R	48.89 (9.99)	*F*(2, 367)= 4.84, *p*<.01	N/A	N/A	$.38^{***}$	$.48^{***}$	.10	1.00	
	(5) DM	48.89 (8.14)	*F*(2, 137.81)= 10.16, *p*<.01	*d*=0.32	$2 < 1^{*}$	$.30^{**}$	.09	$-.30^{**}$	$.19^{*}$	1.00

Class	Variable	*M*(SD)	Test statistic	Effect Size	Contrasts	Correlations (ρ) (1)	(2)	(3)	(4)	(5)
Class 3 *n*=54 (14.6%)	(1) AC	48.49 (10.30)	$F(2, 367)= 4.66$, $p<.05$	N/A	N/A	1.00				
	(2) PS	47.57 (9.47)	$F(2, 367)= 10.65$, $p<.001$	d=0.49	3 < 1**	.69***	1.00			
	(3) Gf	28.73 (9.10)	$F(2, 97.48)= 389.75$, $p<.001$	d=4.20 d=3.08	3 < 1*** 3 < 2***	-.11	-.21	1.00		
	(4) E&R	47.13 (9.56)	$F(2, 367)= 4.84$, $p<.01$	d=0.43	3 < 1*	.57***	.67***	-.11	1.00	
	(5) DM	45.08 (10.64)	$F(2, 137.81)= 10.16$, $p<.01$	d=0.65	3 < 1***	.00	.24	-.15	-.01	1.00

* Significant at $p<.05$
** Significant at $p < .01$
*** Significant at $p < .001$
Note. d = Cohen's d (0.20 = small effect; 0.50 = medium effect; 0.80 = large effect); ρ = Spearman rank-order correlation coefficient (|.00-.19| = very weak correlation; |.20-.39| = weak correlation; |.40-.59| = moderate correlation; |.60-.79| = strong correlation; |.80-1.0| = very strong correlation); AC = Attentional Control; PS = Processing Speed; Gf = Fluid Reasoning (Problem Solving/Reversal Learning); E&R = Encoding and Retrieval; DM = Decision Making.

Table 6: Within-Class Cognitive Indicator Mean Differences Based on the Three-Class Latent Profile Analysis with Class-Varying, Unrestricted Σ_k (n=370)

Class	Indicator Variable	Tot Neurocog. Score Mean	Mean Difference	Statistic	95% CI	
					Lower	Upper
Class 1	AC	52.47	-1.08	$t(206) = -1.61$	-2.40	0.24
n=207	PS		-0.40	$t(206) = -0.64$	-1.62	0.83
(55.9%)	**Gf**		**3.22**	**$t(206) = 49.40^{***}$**	**3.09**	**3.34**
	E&R		-1.14	$t(206) = -1.65$	-2.50	0.22
	DM		-0.60	$t(206) = -0.85$	-2.00	0.80
Class 2	AC	48.58	-0.47	$t(108) = -0.48$	-2.41	1.47
n=109	PS		-1.31	$t(108) = -1.22$	-3.44	0.82
(29.5%)	**Gf**		**1.16**	**$t(108) = 3.51^{**}$**	**0.50**	**1.81**
	E&R		0.31	$t(108) = 0.33$	-1.58	2.21
	DM		0.31	$t(108) = 0.40$	-1.24	1.86
Class 3	**AC**	43.40	**5.09**	**$t(53) = 3.63^{**}$**	**2.27**	**7.90**
n=54	**PS**		**4.17**	**$t(53) = 3.24^{**}$**	**1.59**	**6.75**
(14.6%)	**Gf**		**-14.66**	**$t(53) = -11.95^{***}$**	**-17.13**	**-12.20**
	E&R		**3.73**	**$t(53) = 2.87^{**}$**	**1.12**	**6.34**
	DM		1.68	$t(53) = 1.16$	-1.22	4.59

* Significant at p <.05
** Significant at p < .01
*** Significant at p < .001
Note. AC = Attentional Control; PS = Processing Speed; Gf = Fluid Reasoning (Problem Solving/Reversal Learning); E&R = Encoding and Retrieval; DM = Decision Making; CI = Confidence Interval. Values representing within-group relative strengths and weaknesses are bolded.

Table 7: Significant Between-Group Mean Score and Standard Deviation (SD) Differences for External Validation Variables

Variable; *M*(SD)	Class Membership: Class 1, *n*=207 (55.9%)	Class 2, *n*=109 (29.5%)	Class 3, *n*=54 (14.6%)	Test statistic	Effect Size	Contrasts
Age (years)	42.88 (12.99)	45.77 (13.16)	48.83 (11.10)	$F(2, 367)= 5.29$ ($p<.01$)	d=0.49	3 > 1**
Symptoms of Psychosis (PANSS)						
Positive/Disorganized[a]	22.10 (5.60)	23.85 (6.24)	22.69 (5.32)	$F(2, 357)= 3.18$ ($p<.05$)	d=0.29	2 > 1*
Insight/Awareness[b]	2.23 (1.09)	2.55 (1.12)	2.69 (1.02)	$F(2, 359)= 5.19$ ($p<.01$)	d=0.29 d=0.43	2 > 1* 3 > 1*
Psychopathology[c]	29.00 (6.63)	31.10 (7.35)	30.24 (5.97)	$F(2, 356)= 3.49$ ($p<.05$)	d=0.30	2 > 1*
Total PANSS score[d]	69.74 (13.96)	74.26 (15.53)	72.37 (13.79)	$F(2, 359)= 3.57$ ($p<.05$)	d=0.31	2 > 1*
Role Functioning (RFS)						
Total score[e]	13.23 (3.26)	11.93 (2.75)	12.07 (2.83)	$F(2, 364)= 7.71$ ($p<.01$)	d=0.43 d=0.38	1 > 2** 1 > 3*
Work productivity[f]	2.02 (1.31)	1.56 (0.97)	1.50 (0.93)	$F(2, 156.96)=8.34$ ($p<.001$)	d=0.40 d=0.46	1 > 2** 1 > 3*
Independent living, self-care[e]	3.60 (0.95)	3.24 (0.99)	3.35 (0.95)	$F(2, 364)= 5.47$ ($p<.01$)	d=0.38	1 > 2**

Variable; *M*(SD)	Class Membership			Test statistic	Effect Size	Contrasts
	Class 1, *n*=207 (55.9%)	Class 2, *n*=109 (29.5%)	Class 3, *n*=54 (14.6%)			
SOFAS/RFS General Functioning[g]	56.74 (13.40)	53.10 (11.12)	54.28 (11.34)	$F(2, 144.60)=3.38$ ($p<.05$)	$d=0.30$	1 > 2[*]
Extrapyramidal symptoms (ESRS)[h]	25.92 (13.6)	30.02 (16.16)	29.75 (12.92)	$F(2, 353)= 3.46$ ($p<.05$)	$d=0.27$	2 > 1[*]

[*] Significant at $p < .05$
[**] Significant at $p < .01$
[***] Significant at $p < .001$
[a] Class 1 (C1) *n*=204, Class 2 (C2) *n*=105, Class 3 (C3) *n*=51; [b] C1 *n*=204, C2 *n*=106, C3 *n*=52; [c] C1 *n*=203, C2 *n*=105, C3 *n*=51; [d] C1 *n*=204, C2 *n*=106, C3 *n*=52; [e] C1 *n*=205, C2 *n*=108, C3 *n*=54; [f] C1 *n*=204, C2 *n*=108, C3 *n*=54; [g] C1 *n*=205, C2 *n*=108, C3 *n*=54;[h] C1 *n*=198, C2 *n*=106, C3 *n*=52.
Note: *d* = Cohen's *d* (0.20 = small effect; 0.50 = medium effect; 0.80 = large effect); PANSS = Positive and Negative Syndrome Scale; SOFAS = Social and Occupational Functioning Assessment Scale; RFS = Role Functioning Scale; ESRS = Extrapyramidal Symptom Rating Scale.

Table 8: Summary of Results for the Three Latent Classes Based on the Latent Profile Analysis with Class-Varying, Unrestricted Σ_k (n=370)

Descriptor	Class 1	Class 2	Class 3
Neurocognition	• Overall cognitively highest performing.	• Inferior cognitive performance across all five neurocognitive indicators except E&R compared to Class 1. • Superior Gf performance compared to Class 3.	• Inferior cognitive performance across all five neurocognitive indicators except AC compared to Class 1. • Inferior Gf performance compared to Class 2.
	• Relative strength in Gf.	• Relative strength in Gf.	• Relative strength in AC, PS, and E&R. • Severe relative weakness in Gf.
	• Moderate-to-large positive within-class correlations between the domains of AC, E&R, and PS. • Small positive correlations between DM and AC, E&R, and PS.	• Moderate-to-large positive within-class correlations between the domains of AC, E&R, and PS. • Small positive correlation between DM and AC. • Small negative correlation between DM and Gf.	• Moderate-to-large positive within-class correlations between AC, E&R and PS.
External Validation Variables*	○ Lower age compared to Class 3. ○ Less severe symptoms of psychosis (Positive/Disorganized, Insight/Awareness, General Psychopathology, PANSS total score).	○ Higher symptoms of psychosis (Positive/Disorganized, Insight/Awareness, General Psychopathology, PANSS total score) compared to Class 1.	○ Higher age compared to Class 1. ○ Lower Insight/Awareness compared to Class 1.

Descriptor	Class 1	Class 2	Class 3
	○ Higher work productivity and degree of independent living and self-care. ○ Less extrapyramidal symptoms.	○ Lower overall adaptive functioning as well as lower work productivity and degree of independent living and self-care compared to Class 1. ○ More extrapyramidal symptoms compared to Class 1.	○ Lower overall adaptive functioning as well as lower work productivity compared to Class 1.
Psychosis and Neurocognition	▪ No within-class difference in severity across standardized PANSS scores. ▪ No interaction between Class and neurocognition on PANSS scores.	▪ No within-class difference in severity across standardized PANSS scores. ▪ No interaction between Class and neurocognition on PANSS scores.	▪ No within-class difference in severity across standardized PANSS scores. ▪ No interaction between Class and neurocognition on PANSS scores.

*Including between-group psychosis/PANSS comparisons.
Note. PANSS = Positive and Negative Syndrome Scale; AC = Attentional Control; E&R = Encoding & Retrieval; Gf = Fluid Reasoning (Problem Solving/Reversal Learning); PS = Processing Speed; DM = Decision Making.

Table 9: Summary of Evidence Supporting and Refuting our Hypotheses for the Three Latent Classes

Hypothesized	Supporting Evidence	Refuting Evidence/Non-Support
Hypothesis 1 – Subgroup 1 ("High-Functioning but Executive-Weak, with Poor Insight/Awareness") Overall higher-functioning; Relative weakness in executive functions (AC, Gf, PS) Higher Insight/Awareness symptoms	• Overall higher-functioning compared to Class 2 and Class 3.	○ Relative strength in Gf detected. ○ No within-class difference in severity across standardized PANSS scores. ○ No interaction between Class and neurocognition on PANSS scores.
Hypothesis 2 – Subgroup 2 ("Executive-Weak/Memory-Strong, with more severe Negative Symptoms/Hostility") Poor executive functions (AC, Gf, PS) in contrast to verbal memory (E&R) Higher Negative/Hostility symptoms		○ Relative strength in Gf detected. ○ No within-class relative strength in E&R detected. ○ No difference in Negative/Hostility symptoms compared to Class 1 and 3. ○ More severe Psychosis/Disorganized Symptoms and Insight/Awareness Symptoms compared to members of Class 1. ○ No within-class difference in severity across standardized PANSS scores. ○ No interaction between Class and neurocognition on PANSS scores.
Hypothesis 3 – Subgroup 3 ("Executive-Strong/Memory-Weak, with more severe Psychosis/Disorganized Symptoms")	• Relative strength in AC and PS detected.	○ Relative weakness in Gf detected. ○ Relative strength in E&R detected.

Hypothesized	Supporting Evidence	Refuting Evidence/Non-Support
Overall low-performing; Relative strength in executive functioning (AC, Gf, PS) compared to verbal memory (E&R) Higher Psychosis/Disorganized symptoms		○ No difference with respect to Psychosis/Disorganized factor scores compared to Class 1 and/or Class 2. ○ No within-class difference in severity across standardized PANSS scores. ○ No interaction between Class and neurocognition on PANSS scores.

Note. PANSS = Positive and Negative Syndrome Scale; AC = Attentional Control; E&R = Encoding & Retrieval; Gf = Fluid Reasoning (Problem Solving/Reversal Learning); PS = Processing Speed; DM = Decision Making.

Figures

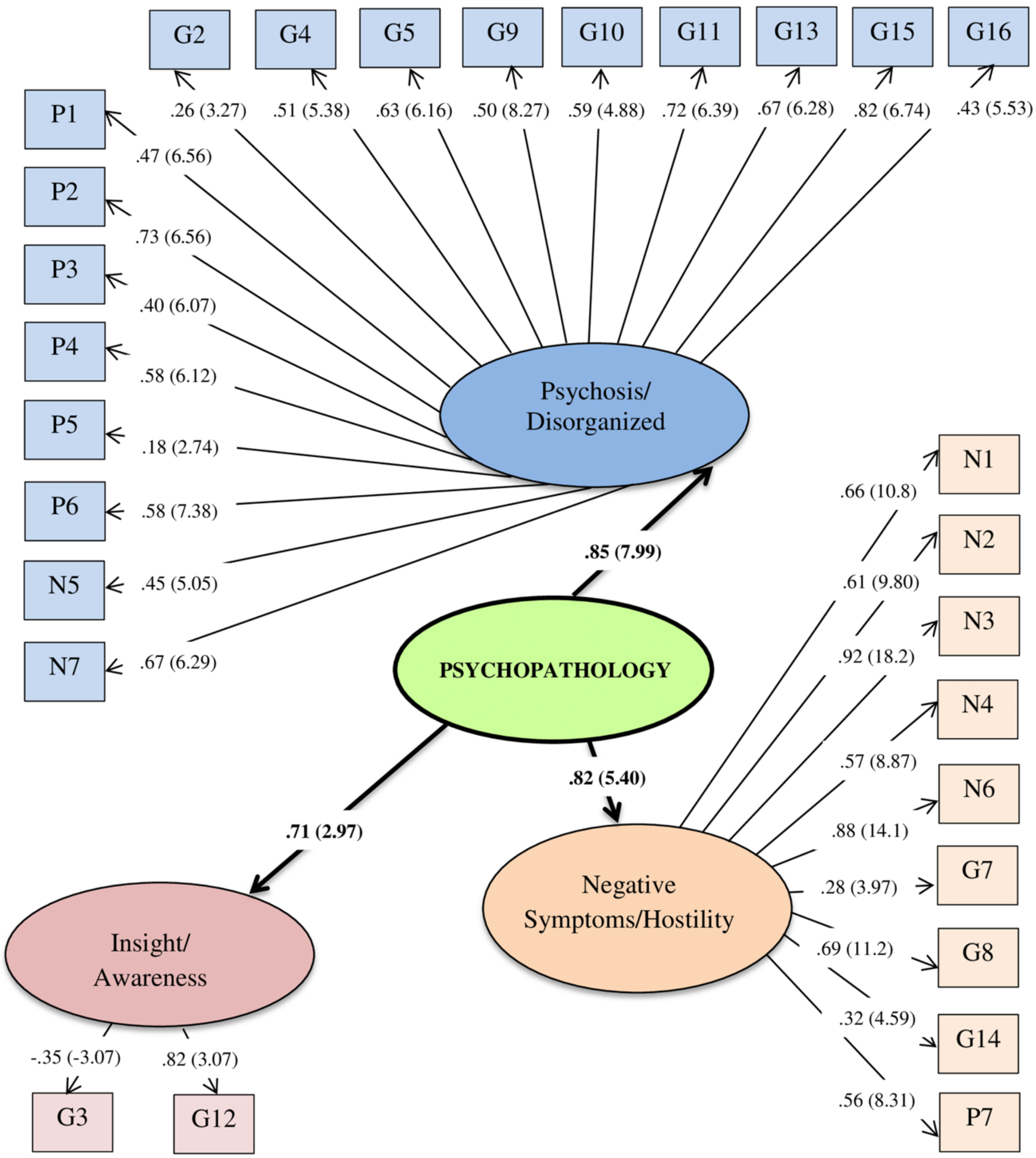

Figure 1: Giesbrecht et al.'s (2016) Three-Factor Model of Psychopathology Based on the Positive and Negative Syndrome Scale (PANSS).

Note. Maximum likelihood estimates, standardized solution and significance levels. Parenthetical numbers indicate significance levels for parameter estimates (statistically significant t values >|1.96|). Creating factor loading-based composite scores using weighted sums resulted in three individual PANSS factor scores and one higher-order psychopathology construct score with possible ranges of 9.19-64.33 (Psychosis/Disorganization); 5.49-38.43 (Negative Symptoms/Hostility); -1.63-5.39 (Insight/Awareness); and 11.156-90.02 (General Psychopathology). For all four composites, higher scores represented higher levels of psychopathology. Figure used by permission of the author.

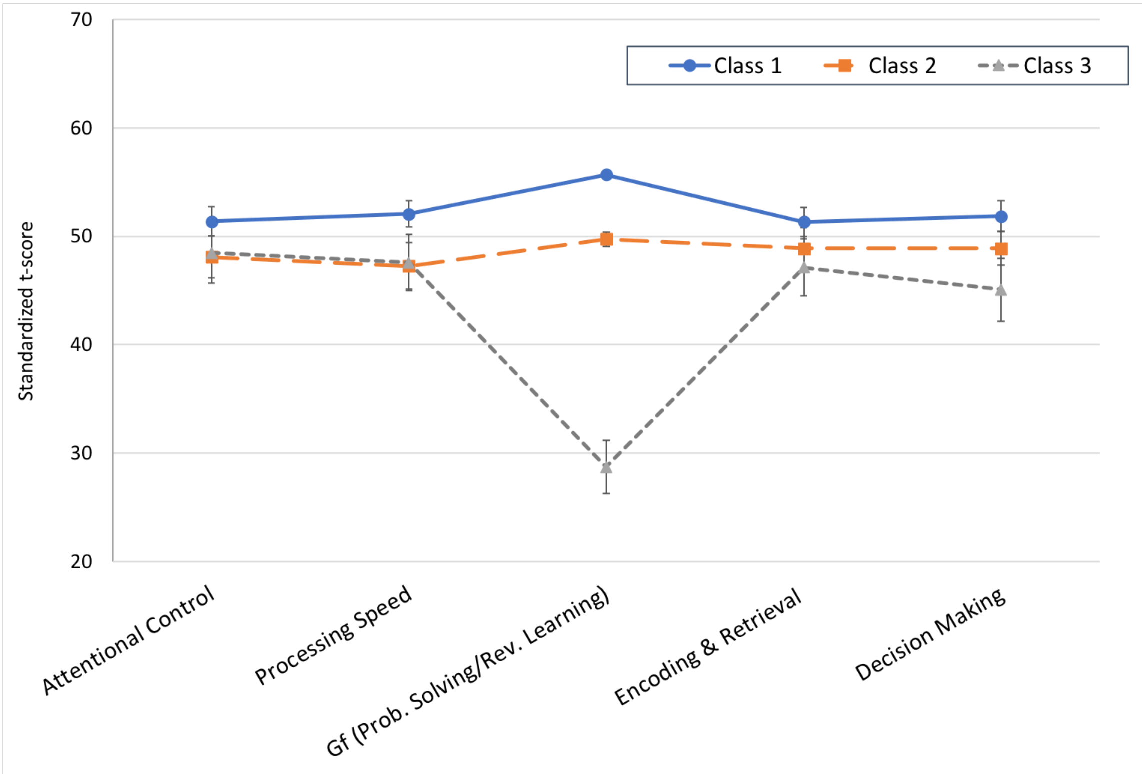

Figure 2: Neurocognitive Profiles of the Three Latent Profile Analysis Classes
Note. Neurocognitive profiles featuring the mean score of each standardized indicator variable for each of the three classes based on the latent profile analysis with class-varying, unrestricted within-class variance–covariance structure. Error bars represent 95% confidence intervals.

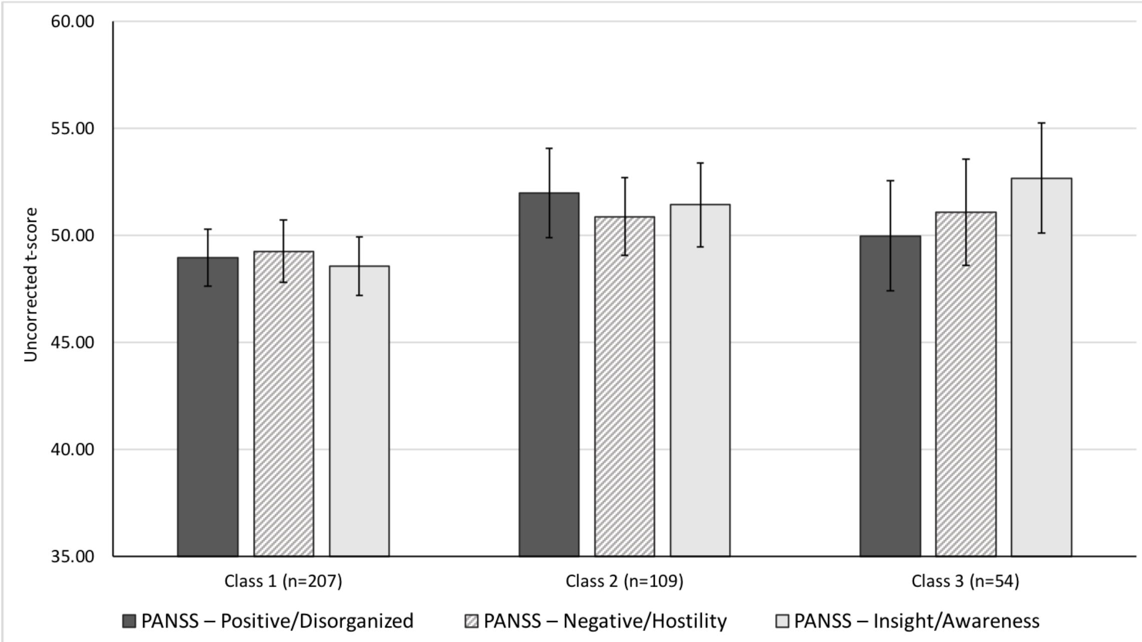

Figure 3: Profiles of Symptoms of Psychosis for Each of the Three Latent Profile Analysis Classes

Note. Mean uncorrected t-scores of severities of symptoms of psychosis within each of the three LPA classes, as measured by the three PANSS factors discovered by Giesbrecht et al. (2016). For each class, within the class there was no significant difference in severity across the three PANSS factors, indicating that all three classes had relatively consistent within-group psychosis symptom profiles. Error bars represent 95% confidence intervals. PANSS = The Positive and Negative Syndrome Scale.

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Appendix A.

Description of Each of the 30 Individual Items on the PANSS

P1	Delusions
P2	Conceptual disorganization
P3	Hallucinatory behavior
P4	Excitement
P5	Grandiosity
P6	Suspiciousness/persecution
P7	Hostility
N1	Blunted affect
N2	Emotional withdrawal
N3	Poor rapport
N4	Passive/apathetic social withdrawal
N5	Difficulty in abstract thinking
N6	Lack of spontaneity & flow of conversation
N7	Stereotyped thinking
G1	Somatic concern
G2	Anxiety
G3	Guilt feelings
G4	Tension
G5	Mannerisms & posturing
G6	Depression
G7	Motor retardation
G8	Uncooperativeness
G9	Unusual thought content
G10	Disorientation
G11	Poor attention
G12	Lack of judgement & insight
G13	Disturbance of volition
G14	Poor impulse control
G15	Preoccupation
G16	Active social avoidance

Note. PANSS = Positive and Negative Syndrome Scale. Table adapted from Kay et al. (1987). For the PANSS, all individual items are scored on a scale from 1 (i.e., "absent") to 7 (i.e., "extreme"). Scores for each subscale (Positive Syndrome Scale, Negative Syndrome Scale, General Psychopathology Scale) are obtained by summing the score of each individual item from the relevant subscale, resulting in max scores of 49 for each of the Positive and Negative subscales and a max score of 112 for the General Psychopathology subscale. At the time of development, the PANSS was tested on a sample of patients with schizophrenia who obtained a mean score of M=18.20, M=21.01, and M=37.74 on the Positive, Negative, and General subscales, respectively (Kay et al., 1987), providing a reference for interpretation.

Appendix B.

Supplemental Methods

Variable Screening and Assumption Checking

All variables were screened for validity prior to analysis. Neurocognitive item values with an administrator-provided validity rating of three or less were removed and temporarily replaced with missing values during this process. All neurocognitive dates of assessment were screened and the cognitive test session containing the most complete data for each participant was selected for further analysis.

Next, variables from all external validation assessments, with the exception of those only occurring at BL (i.e., sociodemographic interview, BECED) were locked in time to the selected neurocognitive assessment, in order to minimize the interval of time between cognitive testing and all other types of assessments. For all annual and bi-annual external validation variables, at least 70% of participants had completed their assessments within 60 days of their neurocognitive testing session. For all monthly external validation variables, at least 90% of participants had completed their assessments within 30 days of their neurocognitive testing session. Table B1 contains additional information about the time intervals between the neurocognitive testing and additional assessments.

As joint-distributional normality is not a necessary assumption of LPA (Masyn, 2013), all neurocognitive indicator variables were included for analysis as is (i.e., no transformations were applied), following the inversion of reverse-coded items and the feature scaling of indicator variables discussed previously. All external validation variables were visually inspected for normality and standardized residuals were evaluated for homoscedasticity, as well as for univariate and multivariate outliers. All TLFB variables (average days of use for alcohol, cocaine, methamphetamine, and heroin) were found to be positively skewed in the joint distribution, signifying the heterogeneity in substance-use patterns within the overall sample. The variable assessing average antipsychotic medication usage was found to be bimodally jointly distributed, indicating that a large proportion of the participants either reported not using any antipsychotic medication, alternatively reported using it close to daily. Ultimately, considering the large sample size and the high tolerance of ANOVA to violations of assumptions of normality (Lund Research Ltd., 2018), all external validation variables were included for between-group comparison analyses.

Missing Data

Missing data can either be considered missing not at random (MNAR; i.e., when the missing-ness is related to the values of the missing data), missing at random (MAR; i.e., when the missing-ness is related to the available data), or missing completely at random (MCAR; i.e., when the missing-ness is not related to either the missing or observed data; White et al., 2011). As previously briefly discussed, in order to examine patterns of missing data and provide guidance as to whether it would be appropriate to make either a MCAR or MAR assumption, sensitivity analyses were undertaken assessing whether the missing-ness of the data could be predicted from factors suspected to be related to cognition (age, education, having attended special education in school, and self-reports of having been diagnosed with a learning disability or attention deficit disorder). None of these factors were found to significantly predict missing-ness of neurocognitive data (see Table B2).

Based on the results from these sensitivity analyses, the neurocognitive test data were assumed to be MAR. Subsequently, a two-step imputation process was applied wherein the missing test score was replaced with the applicable score from the preceding or following neurocognitive testing session, if available, and imputed using multiple imputation with chained equations (MICE), applying the non-parametric Classification and Regression Trees (CART) machine learning algorithm (Burgette & Reiter, 2010) otherwise. The CART algorithm was selected due to its ability to capture complex relations among the data, ultimately leading to more plausible imputations compared to traditional parametric imputation algorithms (Burgette & Reiter, 2010). All imputed data were inspected prior to the LPA and deemed to fall within reasonable test score limits when compared to the non-imputed data. For a summary of the number of participants with imputed data (and respective imputation method), see Table B3.

As a final post-imputation sensitivity analysis, participants with imputed data on at least one neurocognitive item (n=292) were compared with participants with no missing/imputed data (n=78) on select demographic and clinical, psychosocial, and physiological variables, using independent-group t-tests and Mann-Whitney tests for continuous variables, as well as chi-square tests of independence for categorical variables. The participants with imputed neurocognitive data had significantly lower estimated premorbid IQ (*M* = 98.5, SD = 8.81) compared to the participants who did not have any missing neurocognitive data (*M* =101.41, SD = 8.97), $t(318) = 2.44$, $p = .02$, as well as significantly higher PANSS Total scores (*M* = 72.44, SD = 14.80) compared to the participants who did not have any missing neurocognitive data (*M* = 67.73, SD = 12.82), $t(360) = -2.55$, $p = .01$. Further, PANSS Negative Symptoms/Hostility factor scores were significantly higher for the participants with imputed data than for the participants who did not have any missing neurocognitive data, U = 8215.00, $p = .001$. No significant differences were detected between participants with imputed data and participants with no missing data on any demographic variables (age, education, gender, ethnicity) nor on any other clinical, psychosocial/occupational, or physiological variables (i.e., other PANSS factor scores, psychiatric diagnoses, depressive symptoms, substance use, social/occupational and role functioning, extrapyramidal symptoms and neurological soft signs, or HIV status).

Table B1: Time Intervals in Days between Neurocognitive Assessment Dates and Clinical Assessment Dates

Assessment Type	Administration Schedule	Time interval (days) from neurocognitive assessment		% of sample completed assessment within specified day-interval		
		M (SD)	Range	30	60	90
PANSS[a]	Annual	68.4 (179.7)	0 – 1877	63.5	76.2	84.3
PANSS (short)[b]	Monthly	11.2 (21.5)	0 – 327	93.8	98.6	99.2
MINI[c]	Annual	83.6 (186.2)	0 – 1995	49.7	70.7	79.3
BDI[b]	Monthly	14.3 (29.3)	0 – 327	90.5	97.0	98.6
TLFB-Drug[b]	Monthly	11.9 (22.9)	0 – 327	92.4	98.4	98.9
TLFB-Alcohol[b]	Monthly	11.7 (21.8)	0 – 327	92.7	98.6	99.9
SOFAS[b]	Bi-annual	53.8 (76.0)	0 – 534	50.9	72.9	83.5
RFS[b]	Bi-annual	54.8 (77.0)	0 – 534	49.3	72.9	82.9
TLFB-Prescription[b]	Monthly	12.1 (22.2)	0 – 327	92.1	98.4	99.9
ESRS[d]	Annual	70.2 (189.2)	0 – 1877	65.4	77.4	84.6
CNI[e]	Annual	73.0 (195.0)	0 – 1877	65.3	77.3	84.3
Viral serology[f]	Annual	63.1 (134.1)	0 – 1454	52.7	71.2	82.3

Note. PANSS = Positive and Negative Syndrome Scale; MINI = Mini-International Neuropsychiatric Interview; BDI = Beck Depression Inventory; TLFB = Timeline Follow-Back; SOFAS = Social and Occupational Functioning Assessment Scale; RFS = Role Functioning Scale; ESRS = Extrapyramidal Symptom Rating Scale; CNI = Cambridge Neurological Inventory.
[a] *n*=362; [b] *n*=369; [c] *n*=368; [d] *n*=358; [e] *n*=357; [f] *n*=260.

Table B2: Associations Between Factors Reflective of Cognitive Aspects and Missingness of Data

Factor	*B*	*SE B*	β	*p*-value
Age (years)	0.001	0.002	0.036	0.49
Education (years)	-0.005	0.009	-0.030	0.56
Attended special education	0.028	0.044	0.033	0.53
Self-reported learning disability	0.025	0.046	0.029	0.58
Self-reported history of Attention Deficit Disorder	0.065	0.049	0.069	0.19

Note. B = Unstandardized regression coefficients; *SE B* = Standard error of unstandardized regression coefficients; β = Standardized regression coefficients.

Table B3: Number of Participants (*n*) with Available and Imputed Data

Test variable	Available data (*n*)	Imputed (score replacement; *n*)	Imputed (MICE; *n*)
Stroop CW score	349	7	16
RVP a' score	286	9	77
HVLT-R immediate score	356	8	8
HVLT-R delayed score	353	8	11
IED adjusted error score	301	5	66
COWA letter fluency score	348	9	64
COWA animal fluency	348	10	14
SDMT written score	335	10	14
SDMT oral score	333	12	25
TMT-A time-to-completion	354	13	26
TMT-B time-to-completion	319	7	11
IGT net score	299	5	66

Note. RVP = Rapid Visual Information Processing; HVLT-R = Hopkins Verbal Learning Test – Revised; IED = Intra-Extra Dimensional Set Shift; COWA = Controlled Oral Word Association; SDMT = Symbol Digit Modalities Test; TMT-A = Trail Making Test part A; TMT-B = Trail Making Test part B; IGT = Iowa Gambling Task; MICE = Multiple Imputation by Chained Equations.

Appendix C.

Evaluation of Class Homogeneity and Class Separation

Class homogeneity refers to the expectation that study participants belonging to the same class should be more similar to each other in regards to their scores on the indicator variables than they are to participants in other classes (Masyn, 2013). On the other hand, class separation refers to the expectation that values on indicator variables should yield between-class differences in terms of standardized mean differences and/or differential correlational patterns (Masyn, 2013). For a display of the correlational patterns between the neurocognitive indicator variables within each LPA class, see Table 5 and Figures C1-C5.

In assessing class homogeneity, as well as class separation as per standardized mean difference and differential within-class correlation-patterns across indicators, all three aforementioned aspects should be considered when determining the relative "importance" of a particular indicator to the overall model interpretation (Masyn, 2013). That is, an indicator may for example not yield significant standardized mean differences across classes, yet contribute to class separation as it covaries with other indicators in a distinct manner for each class. In terms of interpretation, a large absolute standardized mean difference (> 2.0) indicates that there is less than 20% overlap in the finite mixture distributions of the three classes on the indicator in question, whereas a small absolute standardized mean difference (< 0.85) corresponds to more than 50% distributional overlap and a low degree of separation between the classes on the indicator (Masyn, 2013). A summary of the class homogeneity and class separation in respect to each neurocognitive indicator variable for all three classes is provided in Table C1.

All five neurocognitive indicator variables were deemed to contribute to class homogeneity and class separation, based on comparisons of within-class variances to the variance of the overall sample, as well as standardized mean differences across classes and/or differential correlational patterns among the indicator variables across classes. Overall, Gf appeared to be the indicator variable allowing for the strongest class homogeneity and separation, with all three classes displaying lower within-class variance when compared to the overall sample, and having a large degree of class separation in terms of the standardized mean difference ($|\hat{d}_{\text{Gf Class 1, Class 2}}| = 2.35$; $|\hat{d}_{\text{Gf Class 1, Class 3}}| = 3.21$; $|\hat{d}_{\text{Gf Class 2, Class 3}}| = 3.09$). Further, Class 2 was well-separated from both Class 1 and Class 3 in respect to distinct within-class correlational patterns between Gf and other indicator variables.

As for the other four neurocognitive indicator variables, AC appeared to define Class 1 well, as indicated by a smaller within-class variance for Class 1 on AC ($s^2_{\text{Class 1}}$=255.64) compared to the overall sample (s^2_{Overall}=274.00). Class 2 also displayed a smaller within-class variance on AC ($s^2_{\text{Class 2}}$=270.10) compared to the overall sample, whereas Class 3 did not, indicating high class homogeneity in respect to AC for Class 1 and Class 2 and low class homogeneity in respect to AC for Class 3. Further, while AC did not separate Class 1, Class 2, or Class 3 well from each other in terms of standardized mean difference ($|\hat{d}_{\text{AC}}| < 0.85$ for all between-class comparisons), it did separate the three classes fairly well from each other in terms of correlations (with different patterns across the three classes, indicating a high degree of class separation on this indicator in this regard).

Class 2 and 3 were homogenous on the indicator of E&R, as evidenced by lower class specific variances compared to the variance of the overall sample ($s^2_{\text{Class 2}}$=490.57; $s^2_{\text{Class 3}}$= 298.58; s^2_{Overall}= 515.84), whereas Class 1 was not ($s^2_{\text{Class 1}}$= 515.94). Further, E&R served to separate Class 1 and Class 3 from each other moderately well in respect to both the standardized mean difference ($|\hat{d}_{\text{E\&R}}$ Class 1, Class 3$| = 1.27$) and different correlational patterns across the two classes. E&R separated Class 2 from Class 3 in terms of dissimilar correlation patterns across classes, but not in terms of the standardized mean difference. Finally, E&R did not separate Class 1 and Class 2 well from each other on either the standardized mean difference nor correlational patterns (which were similar across the two classes).

In respect to the neurocognitive indicator variable of PS, Class 1 and Class 3 appeared homogeneous ($s^2_{\text{Class 1}}$=226.27; $s^2_{\text{Class 3}}$=253.31; s^2_{Overall}=276.01), while Class 2 did not ($s^2_{\text{Class 2}}$= 323.82). PS did not separate the three classes well in terms of the standardized mean difference ($|\hat{d}_{\text{PS}}| < 0.85$ for all between-class comparisons), however, it did separate Class 1 well from both Class 2 and Class 3 in respect to correlational patterns. Class 2 and Class 3 were not well-separated on PS on either their standardized mean differences or their correlational patterns.

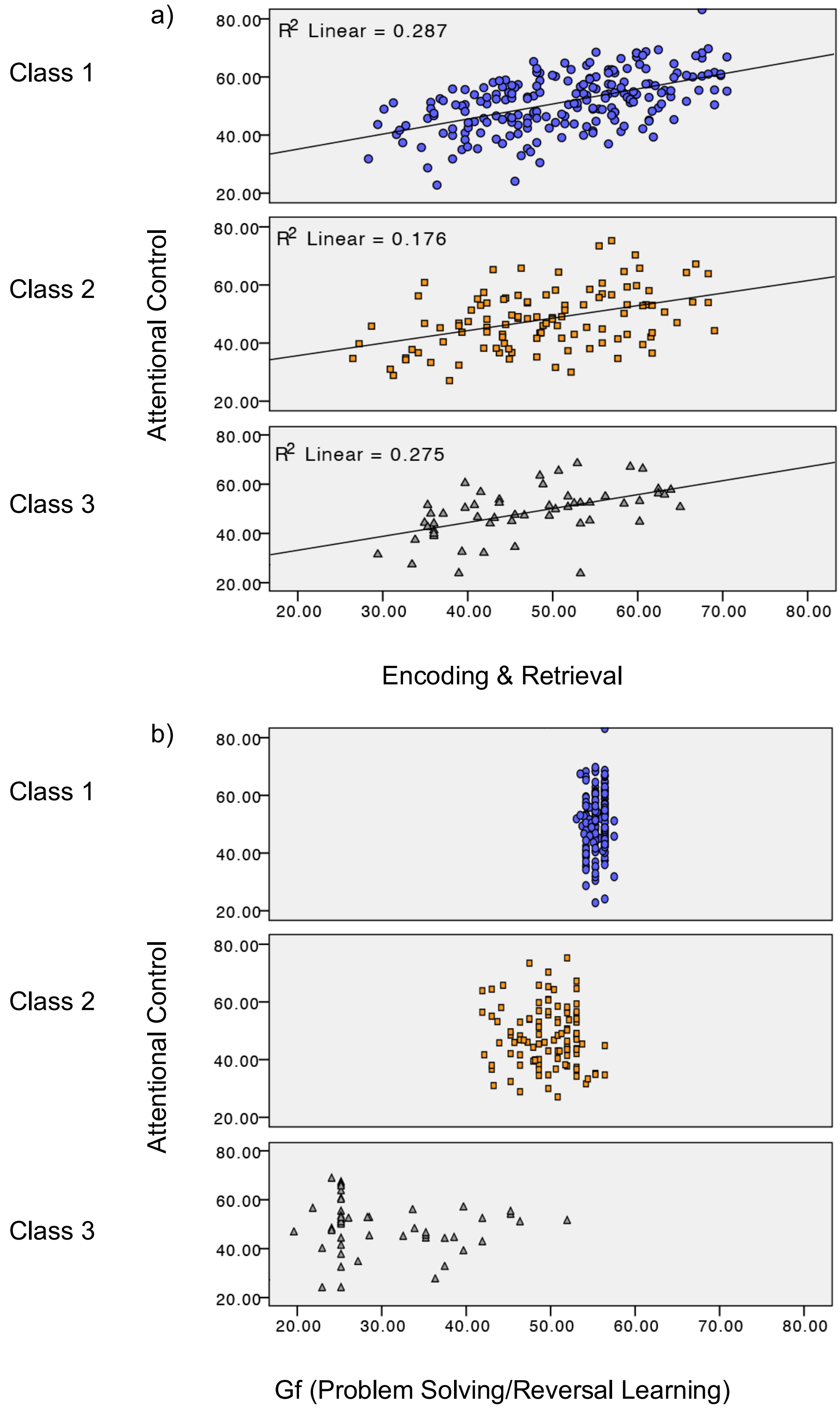
Finally, the neurocognitive indicator variable of DM displayed good class homogeneity for Class 2 ($s^2_{\text{Class 2}}$=182.68; s^2_{Overall}= 264.72), but not for Class 1 or Class 3. None of the three classes were well-separated from each other in respect to their standardized mean differences on DM, however all three classes were very well separated with respect to distinct correlational patterns (or lack thereof) between DM and the other neurocognitive indicator variables.

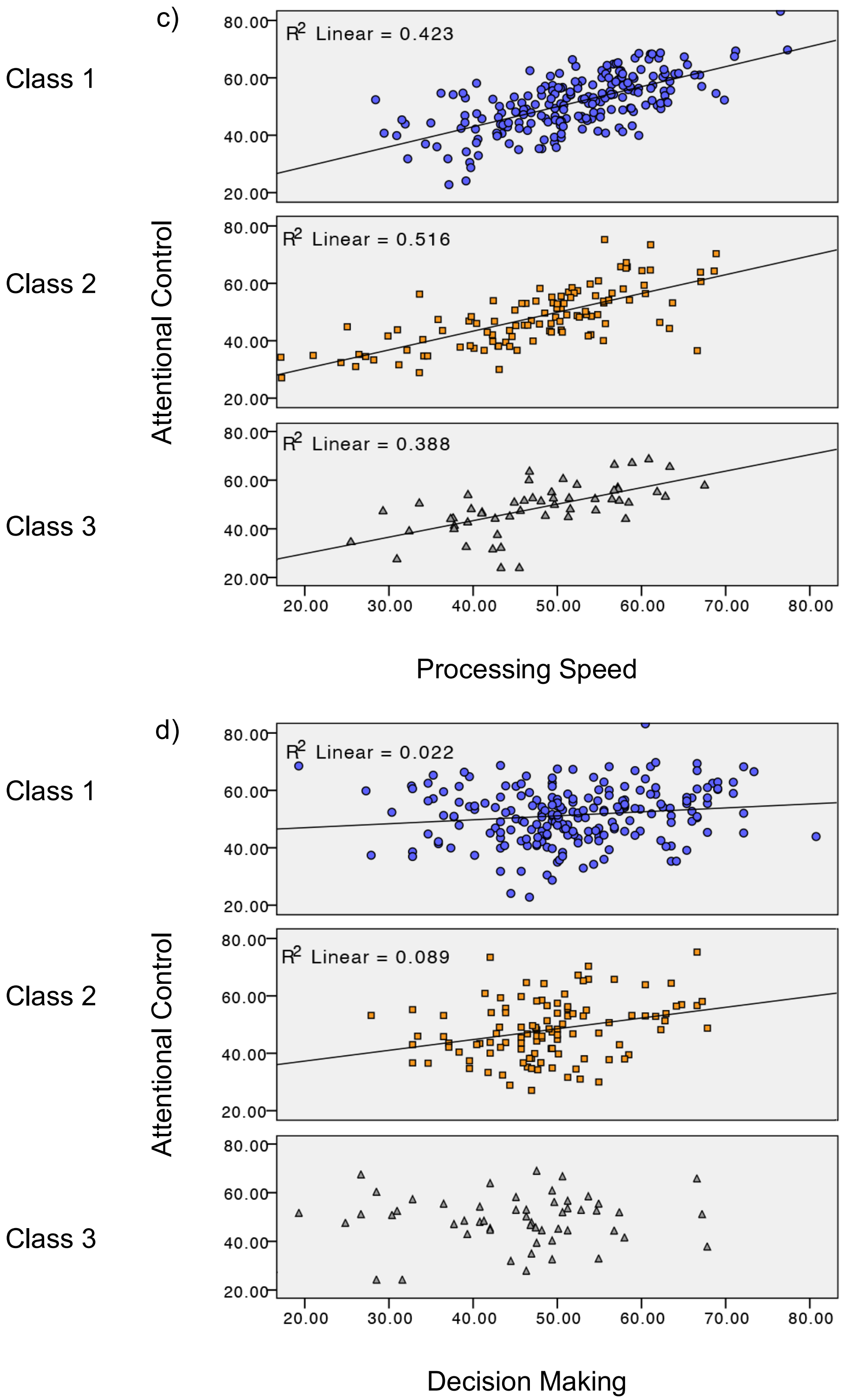
Table C1: Summary of the Class Homogeneities and Class Separations (with Respect to Standardized Mean Differences and Correlational Patterns) for the Five Neurocognitive Indicator Variables

Class	Variable	Class Homogeneity	Class separation (standardized mean difference)	Class separation (correlational patterns)
Class 1	AC	Yes	With C2: No With C3: No	With C2: Yes With C3: Yes
Class 2	AC	Yes	With C1: No With C3: No	With C1: Yes With C3: Yes
Class 3	AC	No	With C1: No With C2: No	With C1: Yes With C2: Yes
Class 1	E&R	No	With C2: No With C3: Yes	With C2: No With C3: Yes
Class 2	E&R	Yes	With C1: No With C3: No	With C1: No With C3: Yes
Class 3	E&R	Yes	With C1: Yes With C2: No	With C1: Yes With C2: Yes
Class 1	Gf	Yes	With C2: Yes With C3: Yes	With C2: Yes With C3: No
Class 2	Gf	Yes	With C1: Yes With C3: Yes	With C1: Yes With C3: Yes
Class 3	Gf	No	With C1: Yes With C2: Yes	With C1: No With C2: Yes
Class 1	PS	Yes	With C2: No With C3: No	With C2: Yes With C3: Yes
Class 2	PS	No	With C1: No With C3: No	With C1: Yes With C3: No
Class 3	PS	Yes	With C1: No With C2: No	With C1: Yes With C2: No
Class 1	DM	No	With C2: No With C3: No	With C2: Yes With C3: Yes
Class 2	DM	Yes	With C1: No With C3: No	With C1: Yes With C3: Yes
Class 3	DM	No	With C1: No With C2: No	With C1: Yes With C2: Yes

Note. Class homogeneity refers to the expectation that study participants belonging to the same class should be more similar to each other in regards to their scores on the indicator variables than they are to participants in other classes (Masyn, 2013). Class separation refers to the expectation that values on indicator variables should yield between-class differences in terms of standardized mean differences and/or differential correlational patterns (Masyn, 2013).
C1 = Class 1; C2 = Class 2; C3 = Class 3; AC = Attentional Control; E&R = Encoding and Retrieval; Gf = Fluid Reasoning (Problem Solving/Reversal Learning); PS = Processing Speed; DM = Decision Making.

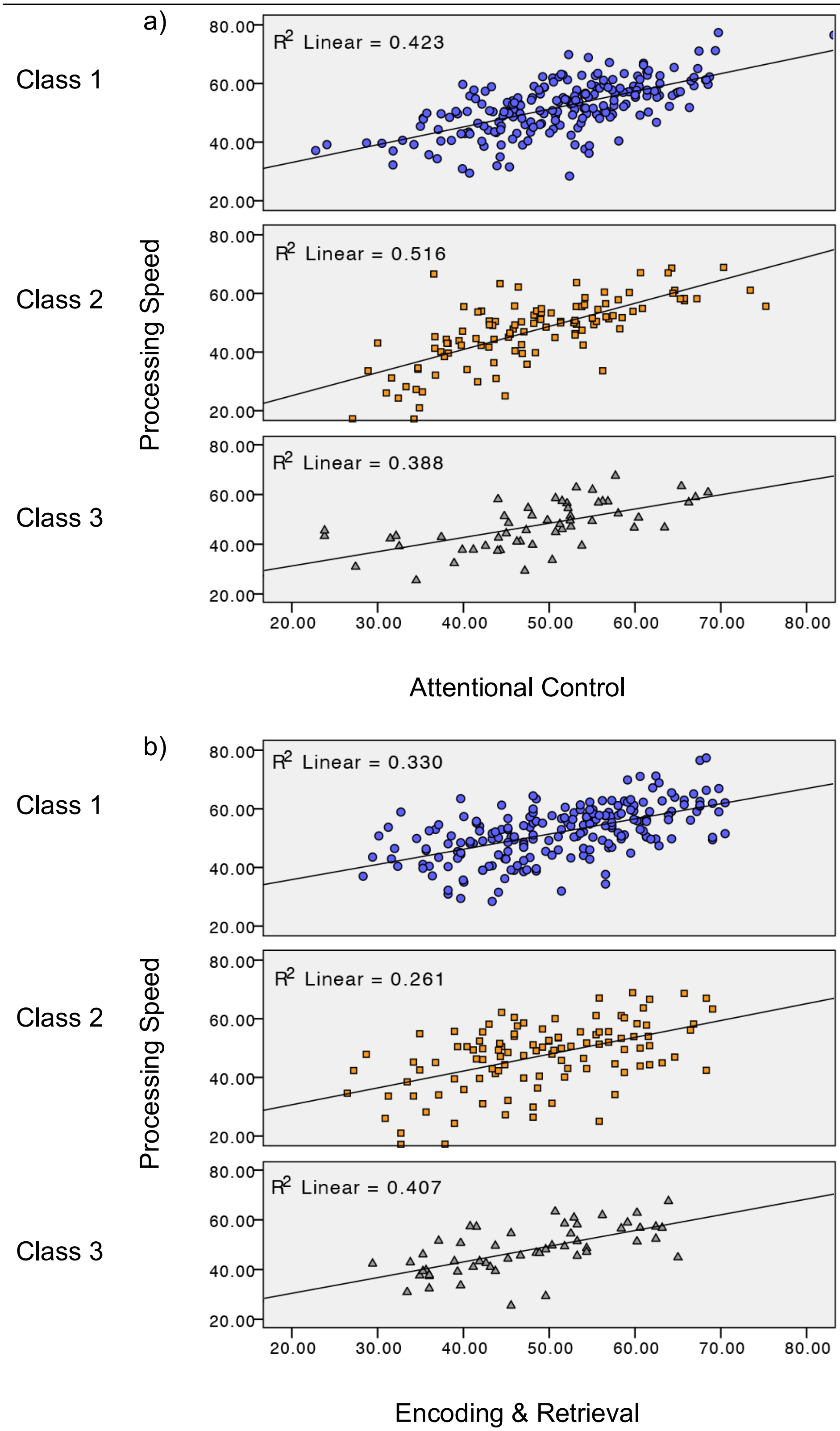
Figure C1: Scatterplots for Attentional Control (AC) and Comparison Indicators per Class

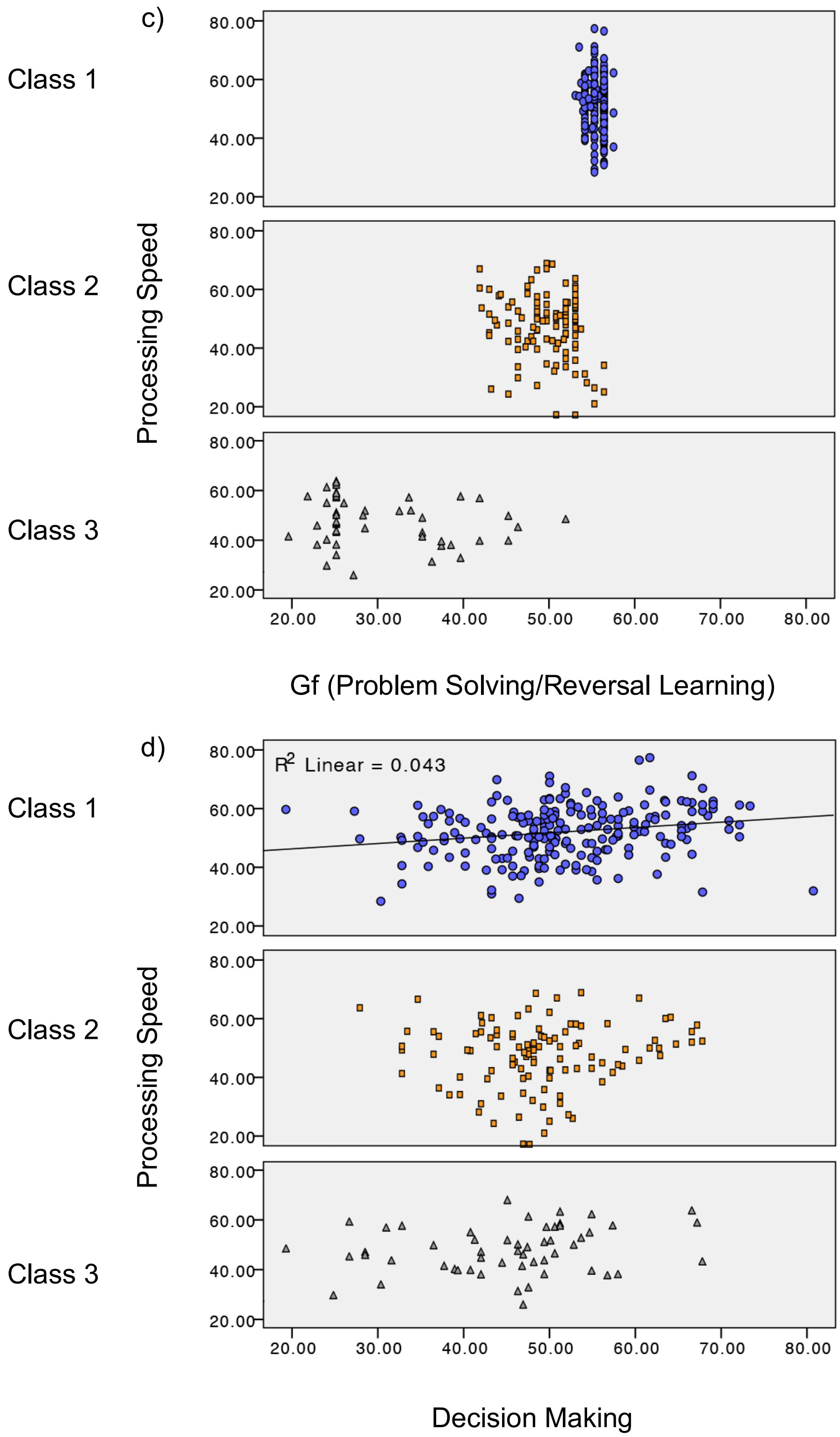




Note. Figure displays scatter plots of observed standardized sample values marked by modal latent class assignment based on the unconditional three-class LPA for a) Attentional Control (AC) vs. Encoding & Retrieval (E&R), b) AC vs. Fluid Reasoning (Problem Solving/Reversal Learning; Gf), c) AC vs. Processing Speed (PS), and d) AC vs. Decision Making (DM). For a) – d), the trend lines depict the observed statistically significant within-class bivariate linear associations.

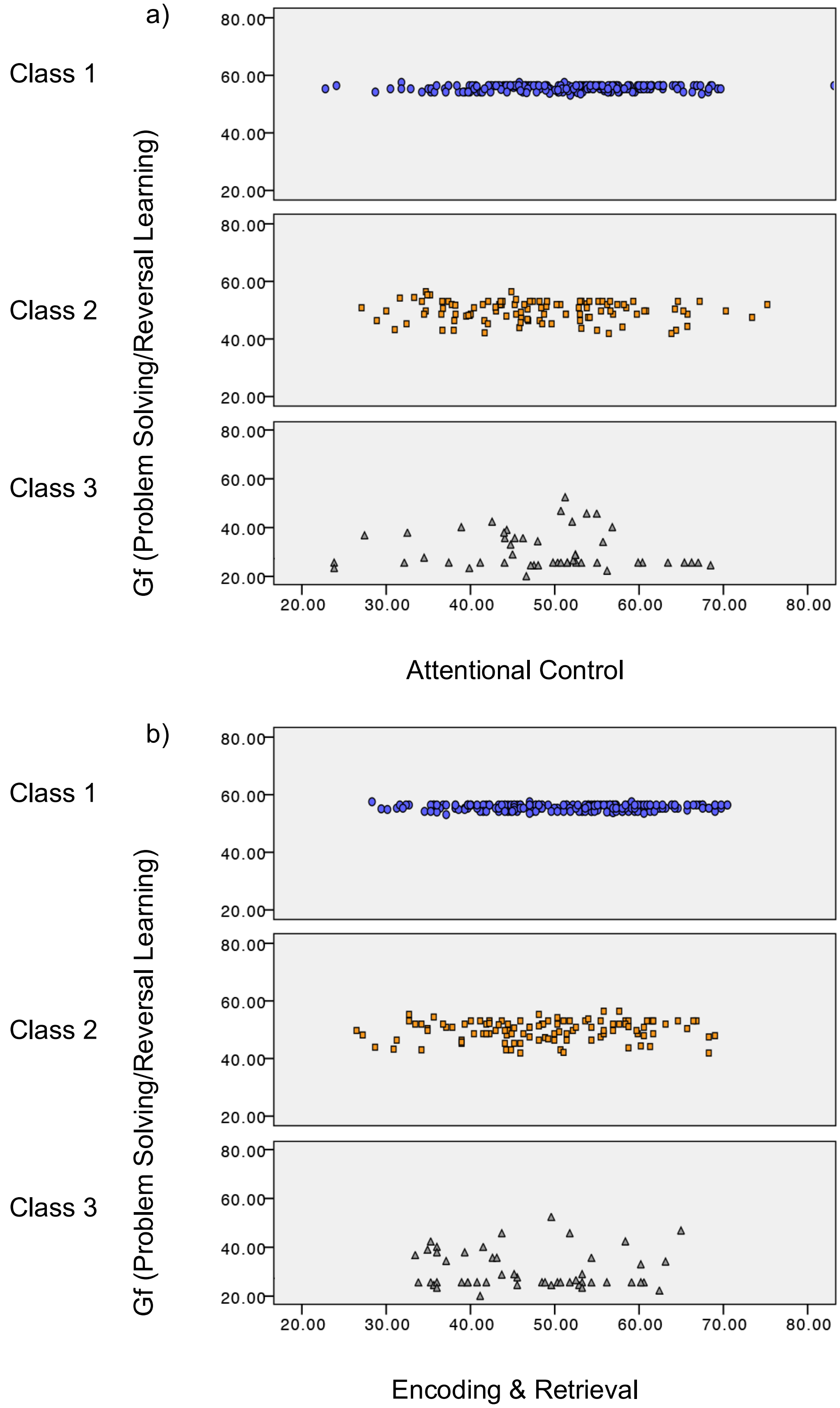
Figure C2: Scatterplots for Processing Speed and Comparison Indicators per Class

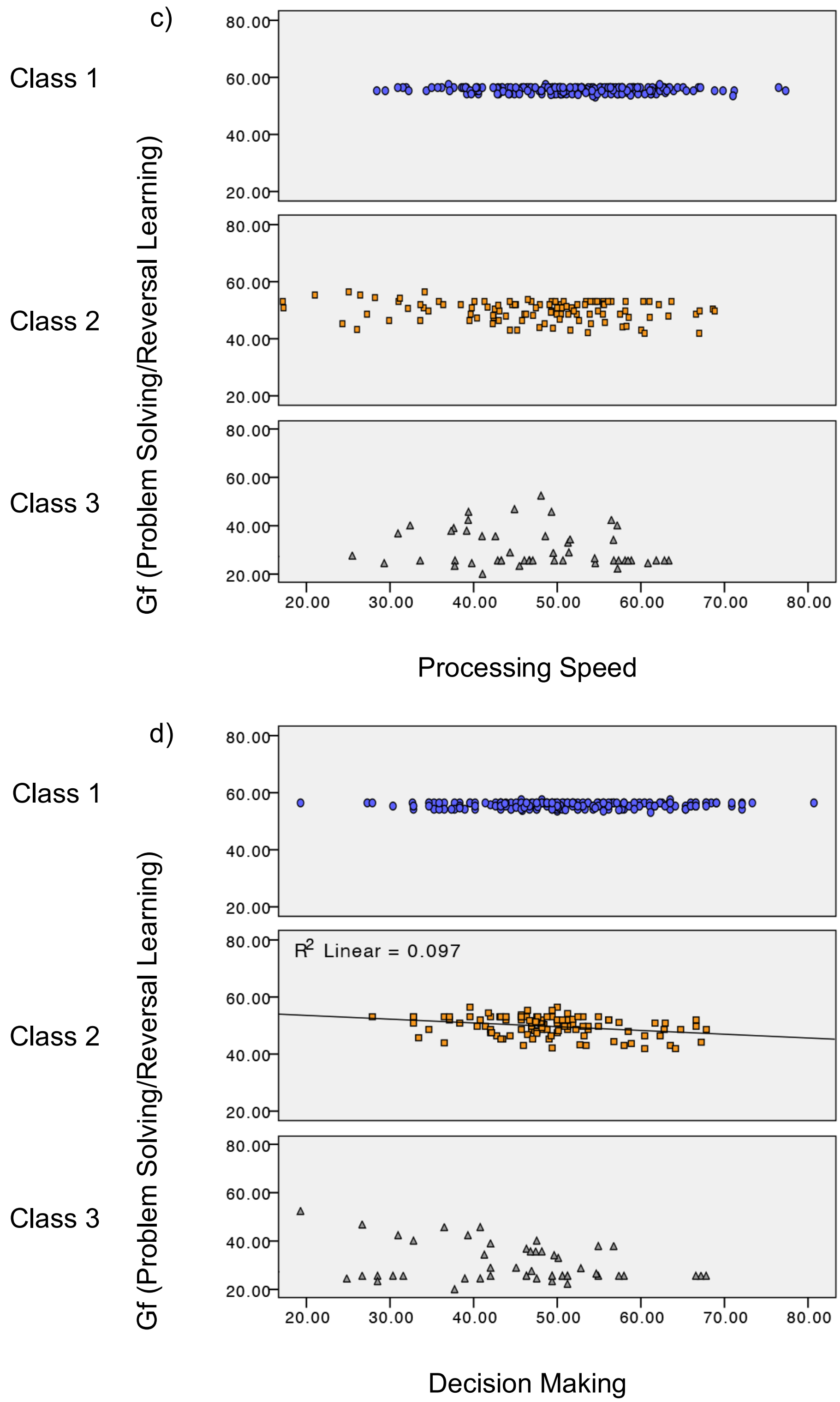




Note. Figure displays scatter plots of observed standardized sample values marked by modal latent class assignment based on the unconditional three-class LPA for a) Processing Speed (PS) vs. Attentional Control (AC), b) PS vs. Encoding & Retrieval (ER), c) PS vs. Fluid Reasoning (Problem Solving/Reversal Learning; Gf), and d) PS vs. Decision Making (DM). For a) – d), the trend lines depict the observed statistically significant within-class bivariate linear associations.

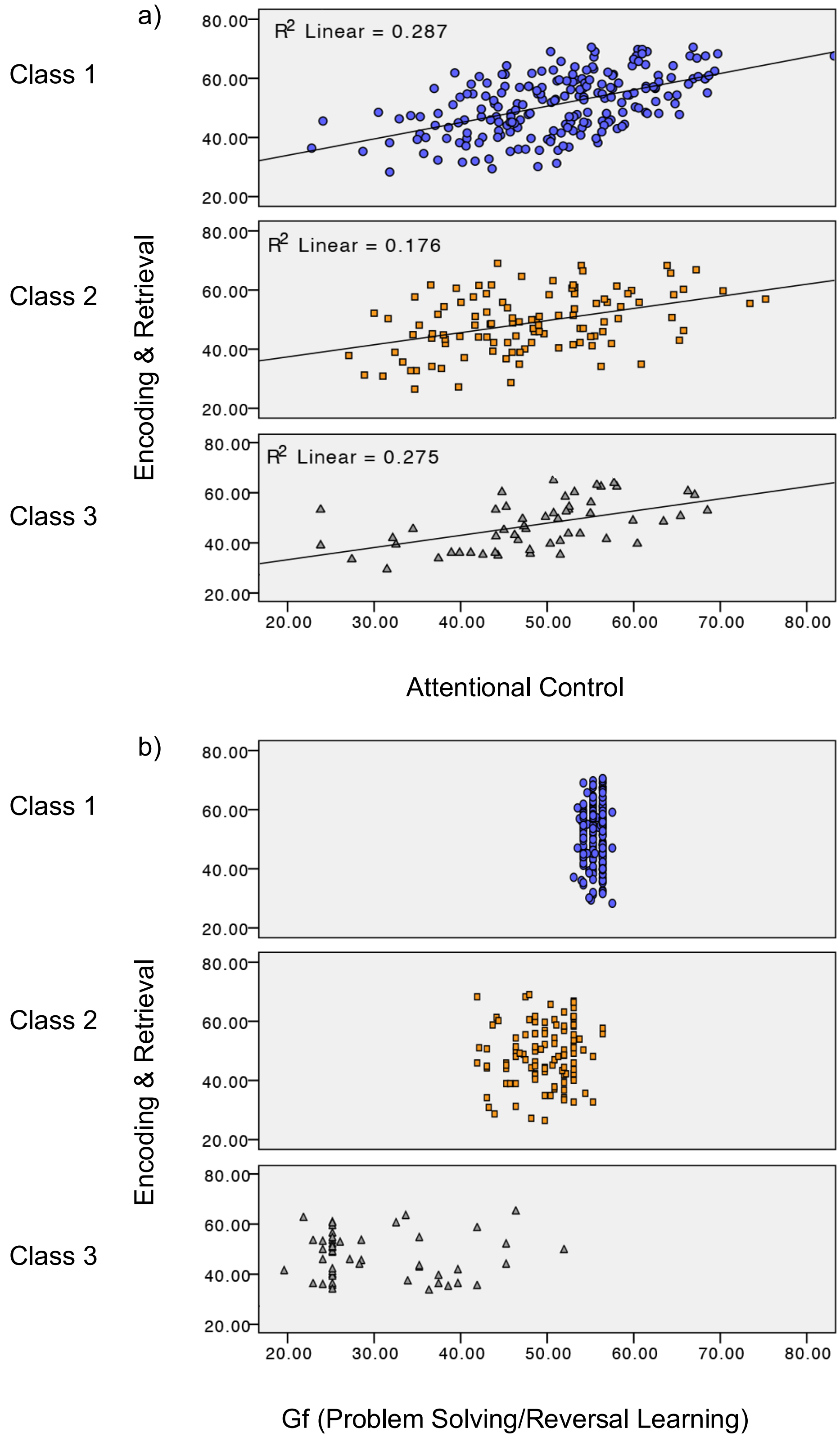
Figure C3: **Scatterplots for Fluid Reasoning (Problem Solving/Reversal Learning) and Comparison Indicators per Class**

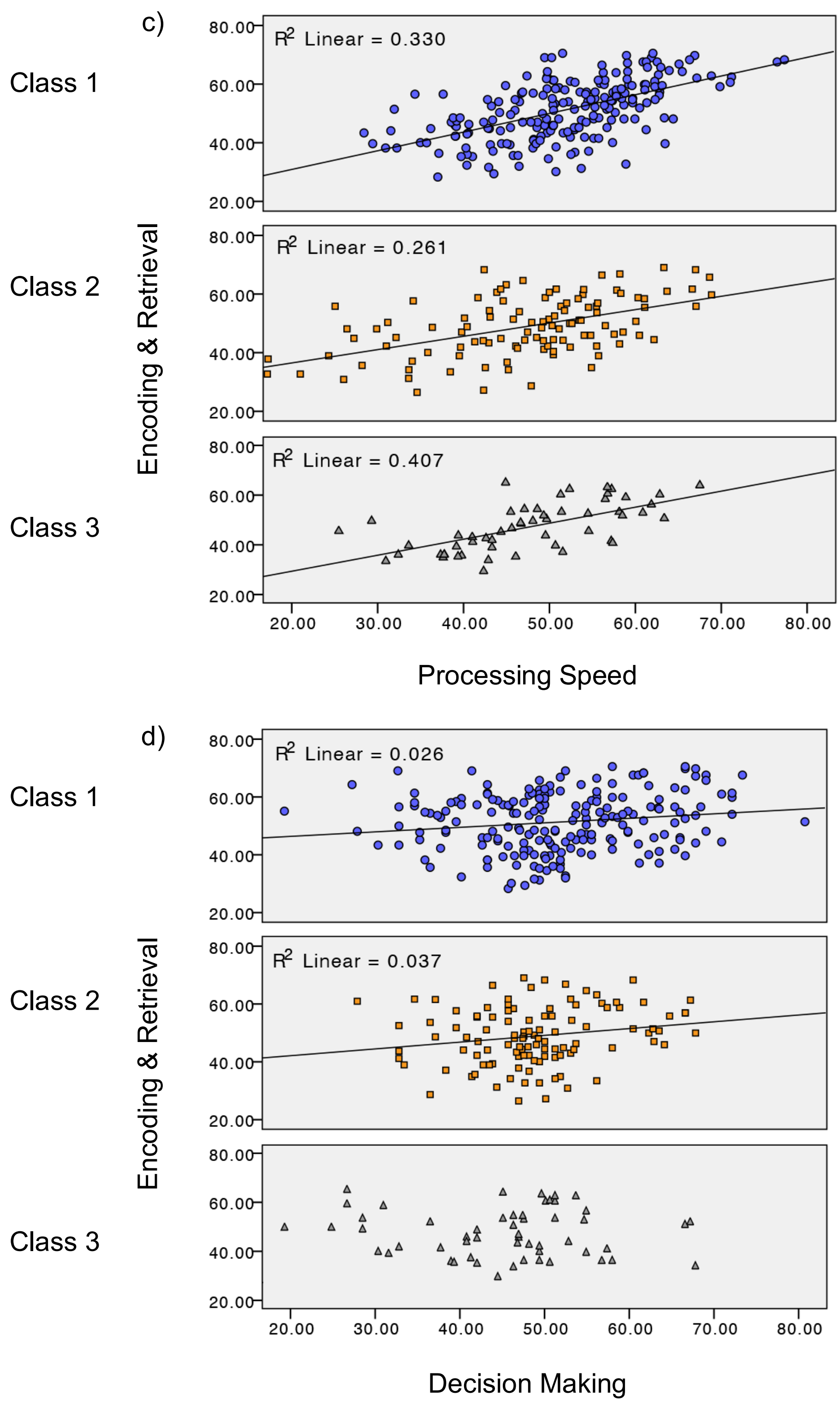




Note. Figure displays scatter plots of observed standardized sample values marked by modal latent class assignment based on the unconditional three-class LPA for a) Fluid Reasoning (Problem Solving/Reversal Learning; Gf) vs. Attentional Control (AC), b) Gf vs. Encoding & Retrieval (ER), c) Gf vs. Processing Speed (PS), and d) Gf vs. Decision Making (DM). For a) – d), the trend lines depict the observed statistically significant within-class bivariate linear associations.

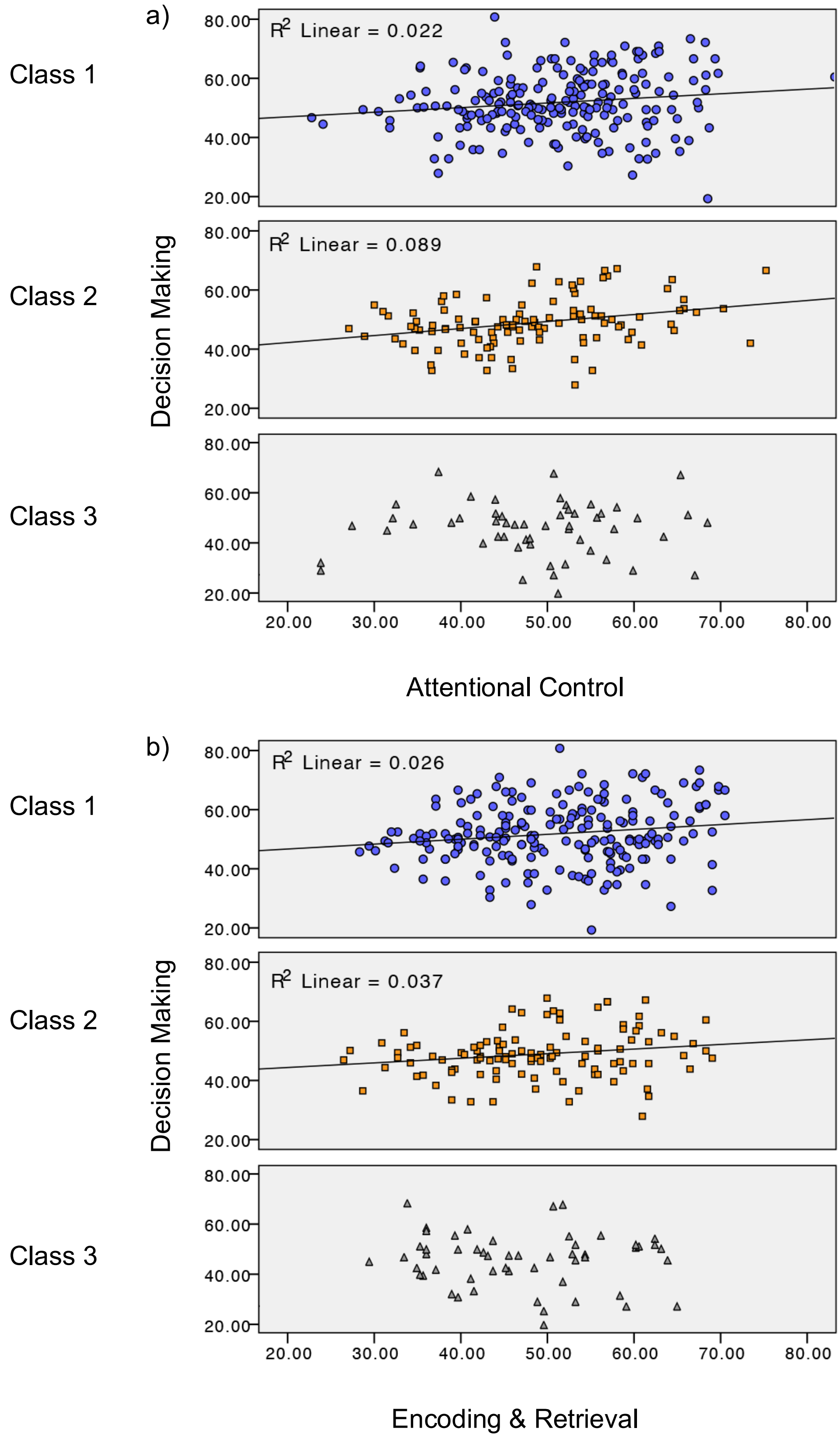
Figure C4: Scatterplots for Encoding & Retrieval (E&R) and Comparison Indicators per Class

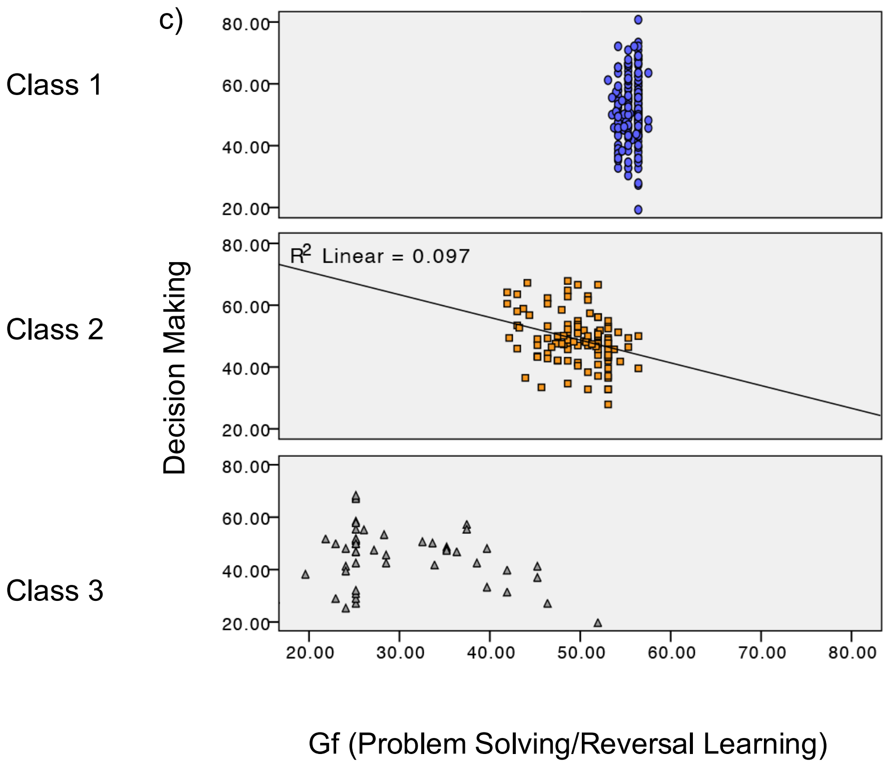


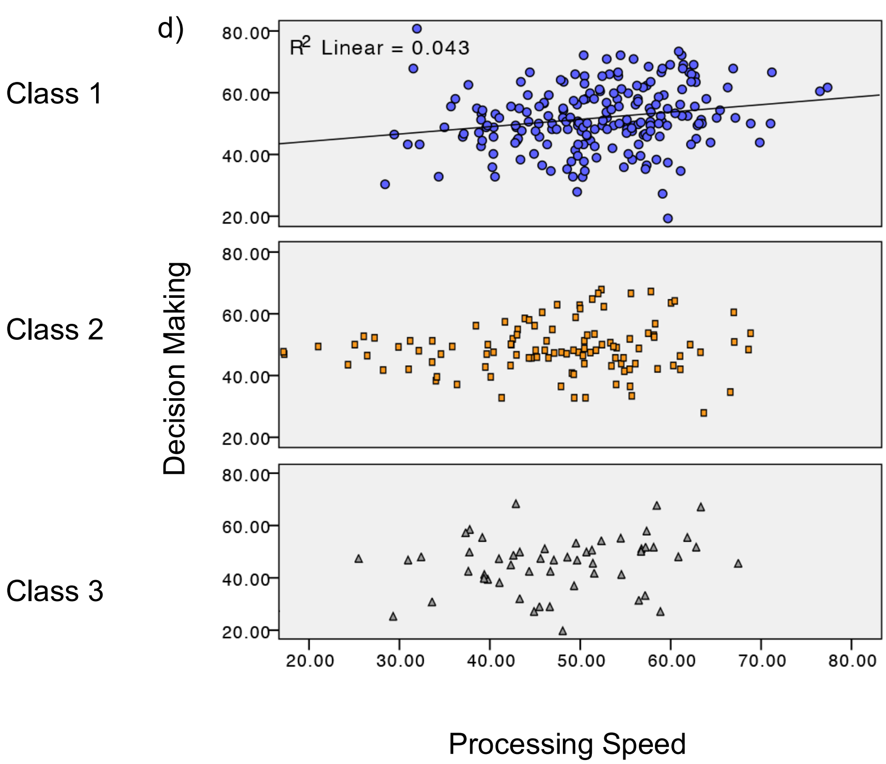


Note. Figure displays scatter plots of observed standardized sample values marked by modal latent class assignment based on the unconditional three-class LPA for a) Encoding & Retrieval (E&R) vs. Attentional Control (AC), b) E&R vs. Fluid Reasoning (Problem Solving/Reversal Learning; Gf), c) E&R vs. Processing Speed (PS), and d) E&R vs. Decision Making (DM). For a) – d), the trend lines depict the observed statistically significant within-class bivariate linear associations.

Figure C5: Scatterplots for Decision Making and Comparison Indicators per Class







Note. Figure displays scatter plots of observed standardized sample values marked by modal latent class assignment based on the unconditional three-class LPA for a) Decision Making (DM) vs. Attentional Control (AC), b) DM vs. Encoding & Retrieval (ER), c) DM vs. Fluid Reasoning (Problem Solving/Reversal Learning; Gf), and d) DM vs. Processing Speed (PS). For a) – d), the trend lines depict the observed statistically significant within-class bivariate linear associations.

Appendix D.

Evaluation of Interaction Between Class and Cognition on Psychosis Symptoms

In order to test whether any group differences existed in the associations between neurocognitive performance and symptoms of psychosis, three separate hierarchical regression analyses were conducted as specified previously. As seen in Tables D1 – D7, while a main effect of neurocognitive performance could be detected for all psychosis symptom predictions, no significant interactions between class and cognitive performance were found, indicating a comparable association between neurocognition and psychosis symptom severity across all three classes.

Table D1: Hierarchical Regression of Age, Neurocognitive Performance, Class Membership, and Neurocognitive Performance x Class Membership on Psychosis/Disorganization Factor Scores.

Block	Variable	*B*	*SE B*	β	*p*-value	R^2	ΔR^2	F_{change}
1	-					0.03		9.39**
	Age	-0.07	0.02	-0.16	0.002			
2	-					0.12	0.09	7.24***
	Age	-0.12	0.03	-0.27	0.000			
	AC	-0.06	0.04	-0.10	0.154			
	PS	-0.11	0.04	-0.18	0.016			
	Gf	-0.06	0.03	-0.10	0.062			
	E&R	-0.04	0.04	-0.07	0.302			
	DM	0.02	0.03	0.03	0.507			
3	-					0.14	0.02	4.19*
	Age	-0.12	0.02	-0.26	0.000			
	AC	-0.05	0.04	-0.09	0.211			
	PS	-0.11	0.04	-0.19	0.012			
	Gf	-0.21	0.08	-0.36	0.006			
	E&R	-0.04	0.04	-0.06	0.306			
	DM	0.01	0.03	0.01	0.816			
	C2	0.07	0.83	0.01	0.933			
	C3	-4.98	2.28	-0.30	0.029			

* Significant at $p < .05$
** Significant at $p < .01$
*** Significant at $p < .001$
Note. B = Unstandardized regression coefficients; *SE B* = Standard error of unstandardized regression coefficients; β = Standardized regression coefficients; R^2 = Coefficients of determination (i.e., the proportion of the variance in Psychosis/Disorganization that is predictable from the variables in the regression model); AC = Attentional Control; E&R = Encoding and Retrieval; Gf = Fluid Reasoning (Problem Solving/Reversal Learning); PS = Processing Speed; DM = Decision Making; C2 = Class 2 membership; C3 = Class 3 membership. The unstandardized and standardized regression coefficients for C2 and C3 represent comparisons of members of Class 2 and Class 3, respectively, to members of Class 1 on severity of psychosis symptoms. For clarity, block 4 has been omitted from the table due to a lack of significant improvements in model prediction by the addition of any neurocognition x class membership interaction terms. Full data available upon request.

Table D2: Hierarchical Regression of Age, Neurocognitive Performance, Class Membership, and Neurocognitive Performance x Class Membership on Negative Symptoms/Hostility Factor Scores.

Block	Variable	*B*	*SE B*	β	*p*-value	R^2	ΔR^2	F_{change}
1	-					0.00		1.01
	Age	-0.01	0.01	-0.05	0.316			
2	-					0.09	0.09	6.77***
	Age	-0.04	0.01	-0.16	0.005			
	AC	-0.02	0.02	-0.09	0.336			
	PS	-0.05	0.02	-0.15	0.052			
	Gf	-0.03	0.02	-0.08	0.120			
	E&R	-0.03	0.02	-0.10	0.114			
	DM	-0.02	0.02	-0.06	0.256			
3	-					0.10	0.01	2.30
	Age	-0.04	0.01	-0.15	0.008			
	AC	-0.02	0.02	-0.06	0.420			
	PS	-0.05	0.02	-0.17	0.027			
	Gf	-0.11	0.04	-0.34	0.011			
	E&R	-0.03	0.02	-0.10	0.132			
	DM	-0.03	0.02	-0.09	0.114			
	C2	-0.51	0.44	-0.08	0.256			
	C3	-2.59	1.22	-0.30	0.034			

* Significant at $p < .05$
** Significant at $p < .01$
*** Significant at $p < .001$
Note. *B* = Unstandardized regression coefficients; *SE B* = Standard error of unstandardized regression coefficients; β = Standardized regression coefficients; R^2 = Coefficients of determination (i.e., the proportion of the variance in Negative Symptoms/Hostility that is predictable from the variables in the regression model); AC = Attentional Control; E&R = Encoding and Retrieval; Gf = Fluid Reasoning (Problem Solving/Reversal Learning); PS = Processing Speed; DM = Decision Making; C2 = Class 2 membership; C3 = Class 3 membership. The unstandardized and standardized regression coefficients for C2 and C3 represent comparisons of members of Class 2 and Class 3, respectively, to members of Class 1 on severity of psychosis symptoms. For clarity, block 4 has been omitted from the table due to a lack of significant improvements in model prediction by the addition of any neurocognition x class membership interaction terms. Full data available upon request.

Table D3: Hierarchical Regression of Age, Neurocognitive Performance, Class Membership, and Neurocognitive Performance x Class Membership on Insight/Awareness Factor Scores.

Block	Variable	*B*	*SE B*	β	*p*-value	R^2	ΔR^2	F_{change}
1	-					0.02		6.14*
	Age	0.01	0.01	0.13	0.014			
2	-					0.08	0.06	4.79***
	Age	0.00	0.01	0.05	0.401			
	AC	-0.00	0.01	-0.03	0.658			
	PS	-0.01	0.01	-0.06	0.441			
	Gf	-0.02	0.01	-0.15	0.004			
	E&R	-0.02	0.01	-0.15	0.020			
	DM	0.01	0.01	0.06	0.243			
3	-					0.09	0.01	1.34
	Age	0.00	0.01	0.05	0.357			
	AC	-0.00	0.01	-0.03	0.727			
	PS	-0.01	0.01	-0.06	0.451			
	Gf	-0.03	0.02	-0.28	0.040			
	E&R	-0.02	0.01	-0.15	0.020			
	DM	0.01	0.01	0.05	0.341			
	C2	0.06	0.16	0.02	0.719			
	C3	-0.45	0.44	-0.14	0.308			

* Significant at p <.05
** Significant at p < .01
*** Significant at p < .001
Note. *B* = Unstandardized regression coefficients; *SE B* = Standard error of unstandardized regression coefficients; β = Standardized regression coefficients; R^2 = Coefficients of determination (i.e., the proportion of the variance in Insight/Awareness that is predictable from the variables in the regression model); AC = Attentional Control; E&R = Encoding and Retrieval; Gf = Fluid Reasoning (Problem Solving/Reversal Learning); PS = Processing Speed; DM = Decision Making; C2 = Class 2 membership; C3 = Class 3 membership.
The unstandardized and standardized regression coefficients for C2 and C3 represent comparisons of members of Class 2 and Class 3, respectively, to members of Class 1 on severity of psychosis symptoms. For clarity, block 4 has been omitted from the table due to a lack of significant improvements in model prediction by the addition of any neurocognition x class membership interaction terms. Full data available upon request.