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THE EVALUATION OF NON-SPECIFIC RISK INDICATORS IN IMPROVING DETECTION OF PSYCHOSIS-SPECTRUM LIABILITY

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by

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Dedication

I would like to dedicate this manuscript to my parents, Debra and John. Without them, none of this would have been possible.

Abstract

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Psychosis-spectrum disorders remain a leading cause of disability for both individuals and society, with early identification and prevention efforts representing a promising avenue of research for addressing these concerns. One potential impediment to improving early risk identification is the historical focus on indicators thought to be exclusive to the psychosis-spectrum. This focus often comes at the expense of non-specific risk factors (e.g., disrupted sleep, adverse childhood experiences) which contribute to the risk of developing psychosis *as well as* other mental illnesses. Research suggests the inclusion of these non-specific factors may improve our ability to identify those at risk. The present research collected data on a wide array of both specific and non-specific risk factors to develop a new, more holistic measure of psychosis-spectrum risk. A novel brief measure was developed, the Inclusive Psychosis Risk Inventory (IPRI), which compared favorably to existing psychosis-spectrum risk measures when looking at multiple fit indices as well as when predicting quality of life. The results of this study suggest the IPRI may provide a more holistic, comprehensive snapshot of psychosis-spectrum risk by including both non-specific and specific risk indicators within a single measure. Future research should seek to replicate these findings in more diverse samples and investigate the IPRI's ability to predict clinical outcomes.

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Chapter 1

Introduction

Psychosis-spectrum[1] disorders remain a leading cause of disability among mental illnesses, despite a relatively low prevalence rate. Additionally, psychosis-spectrum disorders contribute to significant impairment in individuals' lives (Chong et al., 2016; James et al., 2018). Previous research suggests an increased likelihood of premature mortality due to multiple contributing factors (Laursen, 2019; Olfson et al., 2015), including elevated rates of comorbid medical conditions such as cardiovascular disease, diabetes, and obesity (Bahorik et al., 2017; Laursen, 2019).

Beyond the individual level, psychosis-spectrum disorders are costly on a societal level, contributing to considerable financial expense (Chong et al., 2016; Jin & Mosweu, 2017). Within the United States, psychosis-spectrum disorders cost the country anywhere from $25-102 million annually (Chong et al., 2016), with a per-patient cost ranging from $5,946 to $20,073 (Jin & Mosweu, 2017). This financial expense takes many forms, including lost wages/productivity, increased unemployment, as well as increased healthcare utilization/cost (Bouwmans et al., 2015; Jin & Mosweu, 2017). Further, there is often a significant delay between symptom onset and receiving proper treatment. The longer an individual experiences psychosis without receiving proper treatment (i.e., *duration of untreated psychosis*), the worse their symptoms, quality of life, and overall functioning tends to be (Marshall et al., 2005; Penttilä et al., 2014). Thus, longer periods

[1] Within this paper, we use the term psychosis-spectrum broadly to represent literature from along the entirety of the psychosis-spectrum, including schizophrenia specifically. See Guloksuz & Van Os, 2018, for a more thorough discussion of the arguments in favor of using the term "psychosis-spectrum."

of un-identified and untreated psychosis are associated with even greater severity/chronicity of illness and associated lifetime costs (e.g., greater need for inpatient services, ongoing treatment, lost wages, and disruption to relationships, etc.), further highlighting the importance of recognizing early risk signs and engaging in prevention strategies to reduce the likelihood of worsening symptoms or full psychosis.

Therefore, early identification and prevention may be the most effective public health strategy to reducing the individual and societal costs of the psychosis-spectrum (Faraone et al., 2002). Targeted preventions have shown effectiveness in reducing both the likelihood of an individual developing psychosis, as well as reducing sub-clinical symptoms (Hutton & Taylor, 2013), suggesting that the earlier the intervention occurs, the less likely that intensive medication or treatment interventions will be required. This is important because the "first line" of treatment for psychosis is typically antipsychotic medication. Unfortunately, these medications are commonly associated with side effects that negatively impact health, such as development of metabolic disorders (e.g., diabetes) and weight gain that contribute to high premature mortality rates (Laursen, 2019; Olfson et al., 2015; Reynolds & Kirk, 2010). Therefore, early identification and prevention efforts may reduce the need for high levels of these medications and may have numerous secondary-physical health benefits. In addition, antipsychotic medications are not very effective for negative and disorganized symptoms once they have fully emerged (Reynolds & Kirk, 2010). Thus, one of the other benefits of early identification and prevention may be deterring the development of symptoms that are associated with especially poor outcomes and functional impairments that do not seemingly react well to

medication. Further, a review from Aceituno et al., (2019) found that early intervention programs were highly cost-effective, improving quality of life and employment, as well as reducing hospital admissions.

Considering the potential benefits of prevention efforts, it is essential to develop effective methods for identifying psychosis-spectrum risk (Tandon et al., 2012). Unfortunately, current methods for identifying at-risk individuals are limited in their effectiveness (Tandon et al., 2012) and suffer from multiple limitations. One such limitation is a lack of consensus in the psychosis-spectrum risk literature. There are currently many different measures of psychosis-spectrum risk being utilized by research groups belonging to diverse theoretical backgrounds (O'Kane, 2021). For example, there are over 15 measures of a construct called "schizotypy," which is one such conceptualization of psychosis-spectrum risk (Mason, 2015). Considering that Mason's review captured only a portion of the current psychosis-spectrum risk measures (and that more have been published since that review), it is easy to see why some researchers refer to the current array of risk assessments as "overwhelming" (Fonseca-Pedrero et al., 2021, p.19). While there may be some benefits to the array of available measures, there is evidence to suggest that many of the measures assess the same core symptoms and largely capture the same risk variance (O'Kane, 2021). To avoid exacerbating this concern, perhaps it is best to consolidate these measures. Consolidating existing risk measures would allow researchers to include the most informative items from each measure while eliminating redundant items. Cohen et al., (2010) noted that schizotypy symptom definitions within measures frequently do not include the full range of

experiences that may characterize schizotypy (e.g., one schizotypy measure assesses negative symptoms through constricted affect while another measures negative symptoms through social anhedonia). The consolidation process may address this concern by ensuring that the full range of risk symptoms is represented within a broad new measure. Further, incorporating previous risk measures allows for risk researchers to consolidate and build off previous research efforts, as opposed to the relatively common practice of adding assessments to the already "overwhelming" number of risk measures.

A second limitation of existing measures of risk is that they typically adopt methodologies that rely on standard assumptions (e.g., constant variance, normality, linearity). These assumptions may be particularly problematic for schizophrenia risk since it is unlikely the construct of risk is normally distributed, or that relations between items are linear. In fact, some measures of psychosis-spectrum risk were intended to have large positive skew (Chapman et al., 1995; Rawlings et al., 2008). When data are not normally distributed, it is often a signal that there are other problems with the linear model (e.g., nonlinearity or other forms of misspecification; Cohen, Cohen, West, & Aiken, 2013, p. 120). In fact, previous research suggests that measures are often skewed, and the relationships between risk measures may indeed be curvilinear (O'Kane, 2021). Current psychosis-spectrum risk measures are not designed to account for skewness and/or nonlinearity, nor are standard psychometric models equipped to handle these problems. (Alternative models, including Bayesian psychometric models, are better equipped to handle nonlinearity, skewness, etc. and are discussed later in this paper)

A third potential limitation of psychosis-spectrum risk measures is an overly narrow focus on risk indicators believed to be "specific" to psychosis. Risk approaches specific to the psychosis-spectrum typically focus on presumed biological liability for schizophrenia (i.e., genotypic risk), as well as behavioral and symptom-based risk indicators of this underlying vulnerability (i.e., endophenotypic). Measures targeting psychosis-spectrum risk typically ask participants about experiences believed to reflect sub-clinical symptoms of psychosis denoting risk for disorder onset. Typically, this takes the form of asking about sub-clinical experiences such as unusual thoughts, restricted affect, and hallucinatory experiences. For example, one item from the SPQ-BR asks participants to rate their level of agreement with the statement "I often hear a voice speaking my thoughts aloud." (Cohen et al., 2010).

While a focus on specific risk indicators as described above may be useful, measures with this focus frequently omit indicators that may not be specific to the psychosis-spectrum yet still add important predictive value. This omission may be problematic, as current measures of psychosis-spectrum risk do not perfectly capture risk variance (Fonseca-Pedrero et al., 2021; Fusar-Poli et al., 2015; Tandon et al., 2012), suggesting the potential for improvement through incorporating non-specific risk items. Non-specific risk factors are defined in this paper as factors, such as stress, that may influence the development or course of psychosis-spectrum disorders but are not specifically associated with only psychosis-spectrum etiology per se. Other examples of non-specific risk factors include adverse childhood experiences (ACEs) and deficits in social functioning (Hirschfeld et al., 2000; Poole, Dobson, et al., 2017; Poole, Pusch, et

al., 2017; Saris et al., 2017; Spauwen et al., 2006) that, when present in those with underlying liability for a psychosis-spectrum disorder, may increase the rates of transition to disorder. Thus, it may be beneficial to incorporate items reflecting both specific and non-specific risk to capture a more holistic view of psychosis-spectrum risk.

Non-Specific Risk Factors

To reiterate, in this paper non-specific risk factors are those which may influence schizophrenia as well as other aspects of mental health (e.g., anxiety, depression). As an example, consider a pair of monozygotic twins with completely identical genes whose biological mother had a history of schizophrenia. Based on past research with monozygotic twins, one would expect their risk for developing a psychosis-spectrum disorder based on their family history to be around 50% (Gottesman, 1991). Operating under a diathesis-stress framework (Fowles, 1992; Pruessner et al., 2017), additional environmental factors (e.g., life events or stressors) may also contribute to the expression of genetic liability. Returning to our example, let us also assume that the twins were reared in the same general childhood environment, yet one goes on to develop schizophrenia while the other sibling shows no notable psychosis-spectrum symptoms. *What factors may have contributed to the difference in outcome?* Non-specific environmental risk factors (e.g., perceived stress, disrupted sleep, etc.) likely contribute, as well as differences in individual coping strategies developed to respond to these factors (i.e., substance use). Accounting for shared genetic risk factors, it is possible the twin who developed schizophrenia first experienced greater perceived stress, disrupted sleep, and began using marijuana to cope, with those non-specific risk factors

contributing to that twin crossing over the liability threshold for schizophrenia. Meanwhile, the twin who did not develop schizophrenia experienced little perceived stress, consistently obtained quality sleep, and did not engage in consistent substance use. Despite a significant shared specific risk factor, the twins in this scenario experienced different outcomes due to non-specific risk factors. A specific risk measure may have picked up on the specific risk factor present; however, it likely would not capture the differing non-specific risk factors in play and identify the twins as being at equal risk for developing a psychosis-spectrum disorder.

Thus, possibly the greatest benefit from combining specific and non-specific risk variables is the ability to more accurately identify which individuals, under what circumstances, may be at the greatest risk for developing schizophrenia. Previous research has identified improved predictive ability as essential to further development of the psychosis-spectrum literature (Fonseca-Pedrero et al., 2021; Tandon et al., 2012), and it has been argued that consideration of non-specific risk variables may be of unique importance for identifying at-risk individuals (Fowles, 1992). Further, the incorporation of non-specific risk indicators into measures of psychosis-spectrum risk may be consistent with a transdiagnostic approach, such as the Research Domain Criteria (RDoC; Insel et al., 2010). As an example, let us consider the negative symptoms of schizophrenia and psychosis-spectrum risk. Hallmark negative symptoms include alogia, anergia, avolition, blunted affect, and anhedonia (American Psychiatric Association, 2014; Krynicki et al., 2018). Many of those same negative symptoms, including anhedonia and blunted affect, are key targets of multiple psychosis-spectrum risk

measures as well as DSM-5 symptom criteria for major depressive disorder (American Psychiatric Association, 2014; Chapman et al., 1995; Winterstein et al., 2011). Further highlighting potential overlap, a recent systematic review concluded that negative symptoms and depressive features are closely related (Krynicki et al., 2018). As such, there may be little value in attempting to parse out risk that is specific to the psychosis-spectrum from more generalized risk associated with multiple mental illnesses, including psychosis and depression. Additionally, multi-faceted risk measures may better account for individuals at risk for developing a psychosis-spectrum diagnosis comorbid with other mental illnesses, as well as individuals who may be considered at risk for psychosis but only ever experience other forms of mental illness (Tandon et al., 2012).

While there are numerous non-specific risk factors which can and should be explored, this study focuses on stress, family mental health history, social functioning, sleep, personality traits (i.e., neuroticism and extroversion), depression, anxiety, substance use, and quality of life (QOL). The connection between these variables and the psychosis-spectrum is briefly discussed next.

Stress

Stress, in multiple forms, has frequently been associated with increased risk for developing a psychosis-spectrum disorder (Van Winkel et al., 2008) as well as other mental illnesses (Hammen, 2005; Morgado et al., 2013). A specific group of stressors which has received unique attention are adverse childhood experiences (ACEs). Measures of ACEs often inquire about childhood experiences of physical abuse, sexual abuse, emotional abuse, emotional neglect, and physical neglect (Bernstein et al., 2003).

Within the psychosis-spectrum, self-reported experience of ACEs has been associated with the onset of psychotic symptoms, even after controlling for potential confounds (Setién-Suero et al., 2020; Spauwen et al., 2006). Previous research has suggested ACEs to be a risk factor for other mental illnesses as well, including depression and anxiety (Poole, Dobson, et al., 2017; Poole, Pusch, et al., 2017). Further, research indicates the experience of ACEs increases the likelihood of later development of mental illness (Zarse et al., 2019).

Another common measurement of stress, distinct from yet frequently overlapping with ACEs, is perceived stress. Perceived stress refers to an individual's appraisal of stress in their lives (Cohen et al., 1983). Perceived stress has been associated with both schizotypy and a psychosis-spectrum disorder (Horan et al., 2007; Streit et al., 2016). Additionally, higher levels of perceived stress are often reported in bipolar disorder, social anxiety, and post-traumatic stress disorder (PTSD Connor et al., 2007; Streit et al., 2016). Stress, in its various forms, is often considered a major factor in the development of psychosis-spectrum disorders, with the diathesis-stress model representing one prominent etiological model (Fowles, 1992; Pruessner et al., 2017). The diathesis-stress model is also commonly used to explain the etiology of other mental illnesses as well, including post-traumatic stress disorder (PTSD) and depression (Colodro-Conde et al., 2018; McKeever & Huff, 2003). As previously mentioned, the diathesis-stress model posits that disorder may emerge through a combination of biological and/or environmental factors (i.e., stress). Some may develop a psychosis-spectrum disorder due solely to biological factors, while in other cases the development of a psychosis-spectrum

disorder may be due to a combination of biological and environmental factors. The diathesis-stress model posits that a liability threshold is crossed, and that differing combinations of biological and environmental factors may be responsible for an individual crossing the threshold (see the twins scenario discussed above for an example of this). ACEs and perceived stress are a few of many environmental factors which may influence this process. As a whole, the stress literature strongly suggests the importance of stress as a non-specific risk factor which may improve the predictive ability of a new psychosis-spectrum risk measure.

Social Functioning

Social functioning deficits represent another risk factor both for psychosis-spectrum disorders as well as other forms of mental illness. Measures of social functioning typically assess quantity and quality of social interactions, presence of social support, and ability to form relationships (Birchwood et al., 1990). Within the psychosis-spectrum literature, social functioning has previously been recognized as a major risk factor, with past risk calculators for the development of a psychosis-spectrum diagnosis including social functioning as a predictor (Cannon et al., 2016b). Other measures of risk such as the SPQ-BR include social anxiety, a closely related variable, in their assessment of psychosis-spectrum risk (Cohen et al., 2010). Social functioning has also been identified as a core deficit frequently seen in schizophrenia (Birchwood et al., 1990). Outside of the psychosis-spectrum literature, social functioning has been found to be associated with depression and anxiety (Saris et al., 2017), as well as other mental illnesses including obsessive-compulsive disorder (OCD; Bystritsky et al., 2001). On the

whole, previous research indicates that deficits in social functioning may be predictive of psychosis-spectrum disorders as well as other mental illnesses and is often impaired in individuals experiencing mental illness. Given how closely related social functioning is with mental illness—whether before or after illness onset—, adding items measuring social functioning to risk measures seems likely to improve risk prediction.

Sleep

Along with disordered sleep representing a mental illness of its own, sleep is often disrupted in various other mental illnesses, including along the psychosis-spectrum. Sleep disruption may be measured in many ways, including by self-reported quality and quantity of sleep, self-reported unusual sleep experiences, or more objective measures such as polysomnography (Buysse et al., 1989; Krystal & Edinger, 2008; Watson, 2001). The relationship between schizophrenia and disrupted sleep was first observed by Emil Kraepelin (Foster et al., 2013; Kraepelin, 1919; Manoach & Stickgold, 2009). Since then, research has continued to provide support for a connection between sleep and the psychosis-spectrum, with a recent review concluding that early evidence suggests a relationship between the two across multiple forms of sleep measurement (e.g., self-report, sleep spindles; Davies et al., 2017). Other mental illnesses suggested to be related to disrupted sleep include PTSD and OCD (Miller et al., 2020; Paterson et al., 2013). Overall, the existing sleep literature appears to suggest that including items measuring sleep within a risk measure may improve the measure's predictive ability.

Personality Traits

Various personality traits have been associated with multiple forms of mental illness, including psychosis-spectrum disorders. Two personality traits of particular relevance are neuroticism and extroversion. Increased neuroticism has previously been found to be associated with schizotypy and has been identified as a risk factor for developing schizophrenia (Asai et al., 2011; Van Os & Jones, 2001). Similarly, previous research suggests a relationship between lower self-reported extroversion and greater schizotypy (Asai et al., 2011). The same is true for extroversion and psychotic experiences (Shi et al., 2018). Outside of the psychosis-spectrum, previous research suggests increased neuroticism may be a risk factor for developing depression, anxiety, and OCD (Fullana et al., 2004; Roelofs et al., 2008). Low extroversion has been associated with OCD and PTSD (Fullana et al., 2004; Jaksšić et al., 2012). As a whole, the personality literature indicates that including items measuring extroversion and neuroticism may improve risk prediction.

Affect and Substance Use

Numerous symptoms of poor mental health are comorbid with psychosis-spectrum disorders and contribute to increased liability disorder development, including depression, anxiety, and substance use. As noted earlier, the negative symptoms of schizophrenia and schizotypy closely overlap with depressive symptoms (Krynicki et al., 2018). Additionally, measures of schizotypy such as the SPQ-BR include a social anxiety component (Cohen et al., 2010). Consistent with the above, a systematic review of the literature found positive symptoms of psychosis to be associated with depression and

anxiety (Hartley et al., 2013). Another symptom of mental illness associated with the psychosis-spectrum is substance use. Multiple forms of substance use, including marijuana and alcohol, have been implicated in the development of a psychosis-spectrum diagnosis (Brunette et al., 2018; Setién-Suero et al., 2020). Overall, previous research suggests strong connections between the psychosis-spectrum and other symptoms of poor mental health. As such, incorporating items asking about symptoms of mental health outside of the psychosis-spectrum may improve the predictive ability of a psychosis-spectrum risk measure.

Other Risk Factors

Quality of Life

Quality of life (QOL), whether assessed by subjective (e.g., a participant rating their satisfaction with an area of their life such as love) or objective (e.g., current household income) means has been associated with mental illness, including psychosis-spectrum disorders (Hansson, 2006; Narvaez et al., 2008). While QOL may often be thought of as an outcome variable associated with clinical symptoms (e.g., schizophrenia), QOL impairments have been observed in studies examining schizotypy as well (Cohen & Davis, 2009). Whether examining schizophrenia or schizotypy, a typical finding is that negative symptoms possess a stronger relationship to QOL impairments (Cohen & Davis, 2009; Narvaez et al., 2008). The negative symptom-QOL relationship finding is consistent with other research showing a relationship between QOL impairments, anxiety, and depression (Hansson, 2006; Panayiotou & Karekla, 2013). In summary, reported QOL impairments may be connected to greater risk for,

and/or symptoms of, anxiety, depression, and psychosis-spectrum disorders. As such, for this study QOL will be treated as an outcome variable.

Family History

Genetic associations have been found in numerous mental illnesses, including schizophrenia. A genome-wide analysis found evidence for shared genetic risk factors between schizophrenia, major depressive disorder, bipolar disorder, attention deficit-hyperactivity disorder, and autism spectrum disorder (Smoller et al., 2013). Beyond genomic analysis, one way a person's genetics can be assessed is through a family history (Rich et al., 2004). A study examining family history for mental illness revealed an association between a family history of mental illnesses (e.g., psychosis, bipolar disorder) and increased risk for having those same mental illnesses (Vandeleur et al., 2014). Overall, research findings from both the genetics and family history literatures suggest the importance of heritability in the psychosis-spectrum and mental illness more broadly. Of note, family history may easily be argued to be a specific or non-specific risk factor. For example, a family history of schizophrenia elevates the chances of developing schizophrenia (specific), while a family history for depression increases the likelihood of developing multiple mental illnesses including schizophrenia (non-specific). As such, in this paper a family history of a psychosis-spectrum disorder will be considered a specific risk factor, while a family history for other mental illnesses will be considered non-specific.

Present Study and Aims

For the present study, data was collected on specific and non-specific indicators of psychosis risk to construct a new measure which incorporates both domains. Because many specific risk measures do not capture unique risk variance (O'Kane, 2021), we consolidated many of the existing specific risk measures. Additionally, we incorporated non-specific risk items. Through these efforts, the goal is to improve the field's ability to identify those at risk for a psychosis-spectrum disorder by developing a new measure that attempts to provide a more complete picture of psychosis risk. The new measure accounts for non-linear relationships, and non-specific risk predictors in addition to specific risk predictors. We hypothesized the new risk measure will better estimate psychosis-spectrum risk category (measured by the SIPS) and QOL than current risk measures and yield a more holistic picture of psychosis risk.

Chapter 2

Method

Data Collection Procedures

For this study, data were collected from students at a mid-sized university located in the northeastern United States. Participants were recruited from the university's psychology participant pool, and sample demographic characteristics can be found within Table 1. Given the large number of measures and items which were administered to participants, measures were presented in a randomized order. This randomization was intended to reduce the chance of test fatigue biasing the study results. Missing blocks are assumed to be missing completely at random (MCAR, Rubin, 1978). We used full information maximum likelihood estimate (FIML; Arbuckle, 1996) to estimate parameters in the presence of missing information. To further combat the potential for problematic responding patterns, infrequency items were embedded within the study (Chapman & Chapman, 1986). If participants endorsed two or more infrequency items, their data was dropped from the analysis. Participants had to be 18 years of age or older to participate in the study. All methods and procedures were approved by the university's institutional review board.

Table 1

Demographics

	Total Sample (n = 518)
Age	M = 19.59 (17-54, SD = 2.88)
Gender	
Male	165 (31.9%)
Female	348 (67.2%)
Open-Ended Gender Response	5 (1.0%)
Race or Ethnicity	
Asian/Pacific Islander	50 (9.7%)
Black/African American	68 (13.1%)
Hispanic	67 (12.9%)
Multi-racial	40 (7.7%)
White, Non-Hispanic	290 (56.0%)
Open-Ended Ethnicity Response	4 (3.3%)

Study participants who scored above the predetermined cutoff point on a screener measure, the PQ-B, were contacted to arrange a follow-up interview (described in greater detail within the measures section) using a financial incentive to encourage participation. Participants also were contacted to arrange the follow-up interview if they are determined to fall within the "psychometrically defined schizotypy" category based on their responses to the SPQ-BR (described further below).

Measures

Specific Risk Measures

The following measures of schizotypy were administered to participants: Schizotypal Personality Questionnaire Brief-Revised (SPQ-BR; Cohen et al., 2010), Multidimensional Schizotypy Scale-Brief (MSSB; Gross et al., 2018), and Oxford

Inventory of Feelings and Experiences-short scales (O-LIFE; Mason et al., 2005). These three scales were chosen as they represent different research camps within the risk literature and are frequently used within the literature. The SPQ-BR is a 32-item measure, with αs ranging from 0.87-0.94 across factors (Callaway et al., 2014; Cohen et al., 2010). The SPQ-BR consists of four subscales, disorganization (α= 0.92), cognitive-perceptual (α = 0.94), social anxiety (α = 0.90), and no close friends/constricted affect (α = 0.87; Callaway et al., 2014; Cohen et al., 2010). Reliability information for the measures administered to our sample can be found in Appendix table A. Of note, the constricted affect and social anxiety subscales of the SPQ-BR are frequently examined together as the "interpersonal" subscale; however, for this study will be treated separately. Individuals who score 1.65 standard deviations above the sample mean on the SPQ-BR are considered to meet criteria for psychometrically defined schizotypy, a sub-group believed to denote increased psychosis-spectrum risk. Those that met criteria for psychometrically defined schizotypy were contacted to arrange for participation in a follow-up interview.

The MSSB measures schizotypy using 38 self-report items. Based on two samples the MSSB's α scores range from 0.78-90 across three subscales (Gross et al., 2018). The three MSSB subscales measure negative (α = 0.80, 0.81), disorganized (α = 0.90, 0.89), and positive symptoms of schizotypy (α = 0.78, 0.80). The O-LIFE measures schizotypy using 43 self-report items with an α score range of 0.62-0.80 across four subscales (Mason et al., 2005). The four O-LIFE subscales assess impulsive nonconformity (α =

0.63), introvertive anhedonia (α = 0.62), cognitive disorganization (α = 0.77), and unusual experiences (α = 0.80;).

Frequently utilized as a measurement of schizotypy, psychosis proneness-another conceptualization of psychosis-spectrum risk-was measured by the Wisconsin Schizotypy Scales (WSS; Winterstein et al., 2011). The WSS consists of four scales using a total of 60 items originally found on the Chapman Scales (Chapman et al., 1995), with the scales measuring physical anhedonia (α = 0.62), social anhedonia (α = 0.75), perceptual aberration (α = 0.83), and magical ideation (α = 0.74; Winterstein et al., 2011).

To assess psychotic-like experiences and Ultra-High-Risk (UHR) for psychosis status (additional conceptualizations of schizophrenia risk, with UHR believed to denote significantly elevated risk), all participants were asked to respond to the Prodromal Questionnaire-Brief (PQ-B; Loewy et al., 2011). The PQ-B uses 21 items with an α score of 0.85 (Loewy et al., 2011). Importantly, the PQ-B can be effectively used as a screener measure to determine what individuals may warrant follow-up to determine UHR status (Ered et al., 2018). When utilizing a cutoff score of six, the PQ-B identifies individuals at UHR with 68% specificity and 88% sensitivity (Loewy et al., 2011). The cutoff point of six was used for this study to determine whether to attempt to contact participants for a follow-up interview. The follow-up interview was comprised solely of the Structured Interview for Prodromal Syndromes (SIPS; Miller et al., 2003). The SIPS is a semi-structured interview approximately an hour in length which asks participants about psychosis-spectrum related experiences and symptoms. The SIPS allows for

determination of UHR status and was administered by research assistants trained and certified in its use.

Along with utilizing the more general psychosis-spectrum measures described above, this study used measures of specific psychosis-spectrum symptoms including paranoid thoughts, hallucinations, and delusions. This is in line with the suggestions of Mason, (2015) to supplement general psychosis-spectrum measures with more targeted symptom measures. Paranoid thoughts were measured with the revised Green et al., Paranoid Thoughts Scale (R-GPTS; Freeman et al., 2021). The R-GPTS consists of 18 self-report items measuring ideas of reference and paranoid thoughts ($\alpha > 0.90$; Freeman et al., 2021). Hallucinations were assessed using the Revised Hallucination Scale (RHS; Morrison et al., 2002). The RHS contains 24 self-report items measuring vividness of imagination and daydreaming ($\alpha = 0.88$), as well as tendency to experience auditory ($\alpha = 0.62$) or visual hallucinations ($\alpha = 0.80$; Morrison et al., 2002). Delusions were measured with the 21-item version of the Peters et al., Delusions Inventory (PDI; Peters et al., 2004). The PDI consists of self-report items measuring endorsement of delusions, as well as items assessing the distress, pre-occupation, and level of conviction associated with each delusion ($\alpha = 0.82$; Peters et al., 2004).

Non-Specific Risk Measures

To measure stress, the Perceived Stress Scale (PSS; Cohen et al., 1983), Childhood Trauma Questionnaire Short Form (CTQ-SF; Bernstein et al., 2003), and Depression Anxiety Stress Scales (DASS-21; Henry & Crawford, 2005; Lovibond & Lovibond, 1995) were used. The PSS consists of 14 self-report items asking participants

about stressful experiences in the past month, with an α score range of 0.84-0.86 across three samples (Cohen et al., 1983). Developed to be a briefer form of the original CTQ, the CTQ-SF is comprised of 28 items measuring adverse childhood experiences (ACEs). The CTQ-SF measures physical (α = 0.61-0.78) and emotional neglect (α = 0.85-0.91), as well as physical (α = 0.81-0.86), emotional (α = 0.84-0.89), and sexual abuse (α = 0.92-0.95; Bernstein et al., 2003). The DASS-21 is a brief version of the original DASS, consisting of 21 self-report items measuring depression (α = 0.88), anxiety (α = 0.82), and stress (α = 0.90; Henry & Crawford, 2005).

Family mental health history was assessed using questions developed by the researchers. Information gathered as part of these questions included whether a family member had received treatment for or had been diagnosed with a mental illness, as well as specifying the mental illness (or illnesses) if so.

Social functioning was measured utilizing the Social Functioning Scale (SFS; Birchwood et al., 1990) and First Episode Social Functioning Scale (FESFS; Lecomte et al., 2014). The SFS originally consists of 81 self-report items measuring social functioning. For this study, 9 items were used which assess interpersonal communication (α = 0.71) and social engagement (α = 0.72; Birchwood et al., 1990). The FESFS is a measure of social functioning designed specifically for use within psychosis consisting of 42 self-report items assessing friendships (α = 0.80), independent living skills (α = 0.81), interpersonal interactions (α = 0.80), intimacy (α = 0.75), family (α = 0.63), work relationships (α = 0.67), work abilities (α = 0.65), school relationships (α = 0.73) and educational abilities (α = 0.74; (Lecomte et al., 2014).

Sleep was measured using the Pittsburgh Sleep Quality Index (PSQI; Buysse et al., 1989). The PSQI consists of 19 self-report items measuring various aspects of sleep, including sleep quality, latency, duration, efficiency, disturbance, use of sleeping medication, and daytime dysfunction ($\alpha = 0.83$; Buysse et al., 1989).

To measure extroversion and neuroticism, the Big Five Inventory (BFI; Benet-Martínez & John, 1998) was used. The BFI consists of 44 items measuring each domain of the big five personality traits. For this study, the extraversion ($\alpha = 0.88$) and neuroticism ($\alpha = 0.84$) scales, each consisting of 8 items, were used .

Substance use was assessed using the Alcohol, Smoking and Substance Involvement Screening Test (ASSIST; Ali et al., 2002). The ASSIST is comprised of 61 self-report items assessing cannabis ($\alpha = 0.85$), tobacco ($\alpha = 0.73$), and alcohol use ($\alpha = 0.92$; Ali et al., 2002). While the ASSIST measures other forms of substance use, for this study only the items measuring cannabis, tobacco, and alcohol use were utilized.

To measure quality of life, the Brief Quality of Life Interview (QOLI; Lehman et al., 1995) was administered. The QOLI consists of 43 self-report items assessing objective ($\alpha = 0.44$-0.82 across subdomains) and subjective ($\alpha = 0.79$-0.84 across subdomains) QOL (Lehman et al., 1995).

Social Desirability

Given the sensitive nature of many of the topics our measures assess, it may be possible that participants respond in ways to put themselves in a more positive light, though previous research (O'Kane, 2021) suggests social desirability effects are not likely to influence participant responding on the measures included in this study. Social

desirability was measured using the Marlow-Crowne Social Desirability Scale Brief Form X1 (MCSDSB; Fischer & Fick, 1993).

Demographics

Information regarding participants' age, gender, race/ethnicity, and socioeconomic status was assessed using questions developed by the researchers.

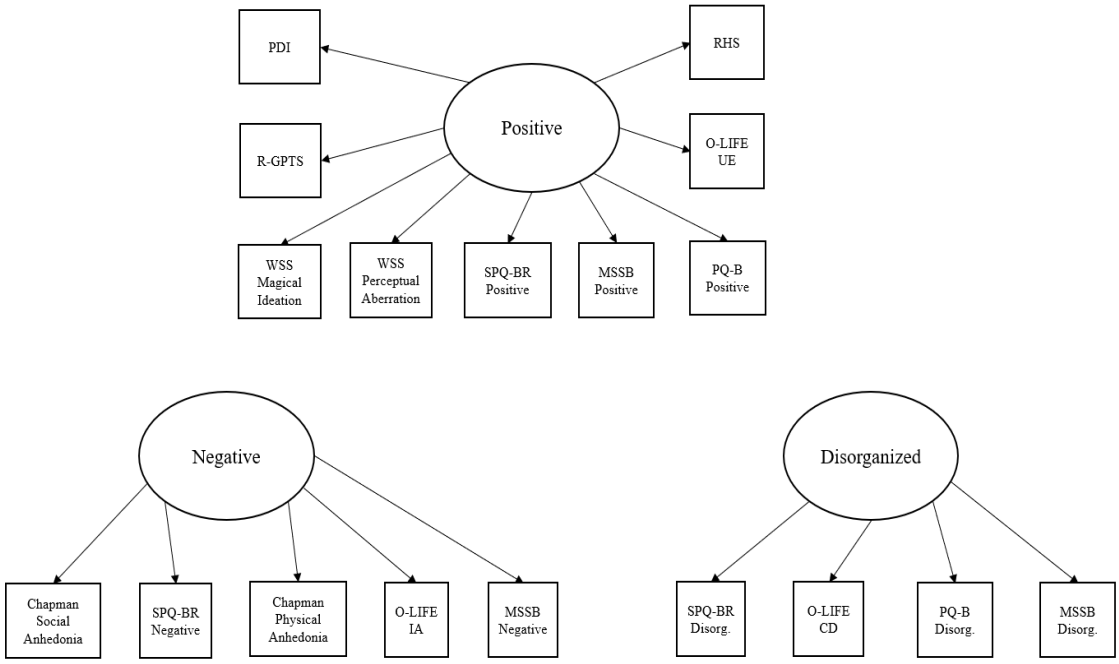
Chapter 3

Data Analytic Plan

For this study, the full model of interest proposes that items measuring positive, negative, and disorganized psychosis-spectrum symptoms will load onto factors representing those symptom clusters. Additionally, the full model suggests that non-specific risk factors (e.g., stress, social functioning) will load onto factors representing each construct. Each latent variable (positive, negative, and disorganized) is assumed to measure some component of psychosis-spectrum risk and thus are assumed to be intercorrelated with one another. Additionally, the model suggests that non-specific risk factors load onto their own latent variables which will be allowed to correlate with the overall psychosis-spectrum risk latent variables. The initial proposed full model of interest (except for the various non-specific risk factors due to visual complexity) can be seen in Figure 1. (See Appendix B for the complete model specification).

Figure 1

Initial Full Model



Note. Boxes represent observed variables (where each box will consist of item parcels), circles represent latent variables. This initial model theorizes that items will load onto factors representing symptom clusters often seen in the psychosis-spectrum. Non-specific risk factors, not depicted above, will be included in the initial model as well, with items loading onto their respective construct (e.g., items from the PSS will load onto a perceived stress factor). We also assume that all latent variables (both specific and nonspecific) are intercorrelated.

Ideally, to evaluate the full model every single item would be fit to a large structural equation model and item factor loadings for each would be calculated. Unfortunately, it is unlikely such a model would be able to be fit as there is a high probability the model-implied variance/covariance matrix would be non-positive definite and/or would fail to converge. Even if a solution were found, it would be extremely computationally intensive to estimate the approximately 600 items and 1,300 parameters required. Instead, we used a combination of item parceling and a bagging algorithm called sembag (Fife, 2023). Item parceling involves summing individual items that measure the same unidimensional construct, then using that sum score as a single indicator[2]. While there is some concern in the literature regarding the use of parcels (Little et al., 2002, 2013), they appear to have important statistical utility so long as the parceling process is carefully considered and parcel-allocation variability (PAV) is properly accounted for (Little et al., 2013; Sterba, 2019). For this study, items were grouped into the same parcel if previous research suggested they belonged to the same subscale and were determined to be measuring the same unidimensional construct.

Once the item parcels were identified, we used the sembag algorithm to identify the top indicators of each latent variable. Based on ensemble methods (e.g., random forest), sembag attempts to estimate the "variable importance" of parcels by fitting hundreds (or thousands) of smaller models, where latent variables/items are randomly sampled. The fits of each of these smaller models are "bagged" (aggregated). This

[2] Using item parcels has another advantage: using item parcels minimized the error of individual items (because averaging reduces variability, by the central limit theorem), making the parcels far more reliable than the individual items. The net effect of this was that the model produced more stable factor loadings.

algorithm requires the user to specify the full model (see Appendix B). Subsequently, at each iteration, sembag samples a subset of paths from the entire model. For our model, each iteration randomly selected five latent variables.[3] We also limited the number of observed variables selected at each iteration to three indicators for each latent variable, where the parcels were also randomly selected. We limited it to three as it is generally the minimum recommended number of observed variables required to identify latent variables (Bollen, 1989). From these smaller (nested) models, sembag fits SEM using standard statistical machinery using the R software lavaan (Rosseel et al., 2020). This process was repeated 10,000 times, and at each stage the algorithm fit these small structural equation models. Note that each of these 10,000 SEMs are *nested* (and much smaller) versions of the large theoretical model.

The algorithm also samples individuals at random, with replacement, such that the sample size at each iteration is 2/3 the size of the entire dataset. At each iteration, the small, nested model is fit using that 2/3 sample. The remaining third (called the "out of bag") sample is used for cross validation and the χ^2 for the out of bag sample is stored. This χ^2 is computed using the observed variance/covariance matrix of the OOB sample and comparing it to the implied variance/covariance matrix. At the conclusion of the algorithm, variable importance is then obtained by computing the difference in χ^2 between observed out of bag (OOB) χ^2 and OOB calculated from a dataset where item scores have been permuted, with higher variable importance suggesting that the variable

[3] In Random Forest models, it is common to randomly select $\sqrt{M}$ variables, where M represents the number of variables. We adapted a similar convention, randomly selecting $\sqrt{27} \approx 5$ latent variables at each iteration.

adds more predictive value to the model. (Once again, this is computed directly from the variance/covariance matrix of the permuted data).

Once we identified variable importance for each parcel, we needed to winnow down the list of plausible parcels for further exploration. The sembag algorithm borrows an approach for variable selection from Geneuer, Poggi, and Tuleau-Malot (2010). After ranking the parcels using variable importance, the algorithm builds a sequence of models. Before doing so, VI scores for each parcel were aggregated across latent variables. Then, the algorithm fits a model including the top-ranking latent variable, then a second model with the latent variables having the first *and* second highest average ranking, and so on. At each stage, some criterion is computed, such as RMSEA, AIC, SRMR, or adjusted R^2, and the model with the best value for the criterion is selected. In our case, our primary aim is predicting QOL. As such, we combined the subjective and objective parcels into a single latent variable called QOL, then computed the adjusted R^2 of this variable at each sequence of modeling. Once we identified the model with the largest adjusted R^2 we then used the variables in this model to build and refine the model. After sembag identified the model, we selected the three parcels/items with the highest variable importance (regardless of their overall importance) for each latent variable included.

Following variable selection, we fit the structural equation model as suggested by sembag. Subsequently, we evaluated the resulting model using primarily visual analysis (as well as inspection of residuals and factor loadings). These visuals guided modifications to the original model (e.g., allowing a parcel to load onto multiple factors, combining latent variables, or introducing residual correlations).

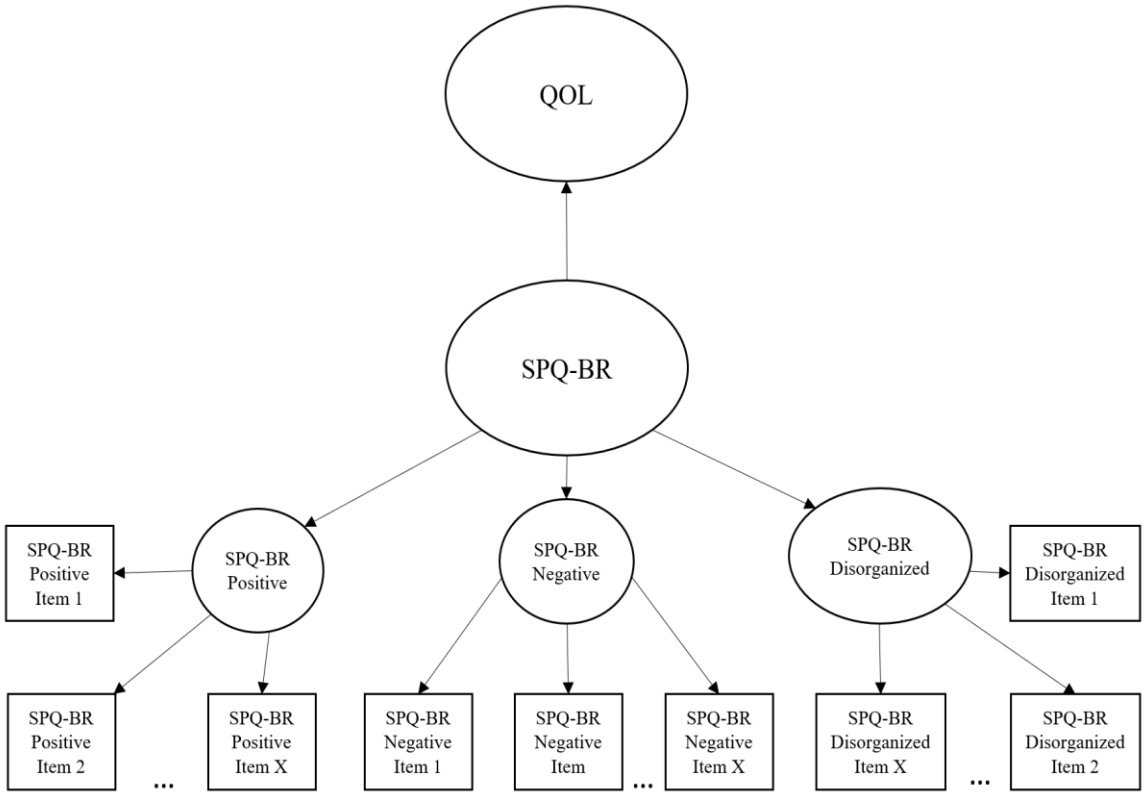
To determine whether a non-specific risk model is better equipped to identify psychosis-spectrum risk, we conducted a model comparison involving two models: a specific risk model, as well as a model including both specific and non-specific risk. Both models were created using the items identified through the parceling and sembag procedures. The better fitting model was determined using adjusted R^2 (of QOL), fit indices (e.g., AIC, BIC, RMSEA, χ^2), as well as visual analysis. While the model including non-specific risk was likely to better predict QOL simply because it has more parameters, we examined whether the added fit was worth the associated additional model complexity. To do so, we used a likelihood ratio test, since the models are nested, as well as model comparison metrics (e.g., AIC, BIC, Bayes Factor), and adjusted R^2.[4]

Additionally, we compared the new risk model to existing risk models. To do so, each scale (e.g., SPQ-BR, O-LIFE) was fit with its own traditional psychometric model. For example, a model for the SPQ-BR had the scale's items load onto their associated sub-scales (positive, negative, and disorganized) which loaded onto the overall SPQ-BR (i.e., SPQ-BR would be modeled as a hierarchical factor analysis). Each of these measure-specific models was then modified to predict QOL (see Figure 2), and then compared to our new risk model. The better fitting model was determined using adjusted R^2 (of QOL), fit indices (e.g., AIC, BIC, RMSEA, χ^2), as well as visual analysis.

[4] Traditionally, R^2 is defined as $1 - \left[\frac{(1-R^2)(k-1)}{n-k-1}\right]$, where N is the sample size and *k* is the number of predictors in the model. Because we are estimating this value in a SEM, we should technically base *k* on the number of exogenous variables used to predict QOL. However, this estimate may not be conservative enough since each of those exogenous variables require estimating. As such, we based *k* on the number of parameters estimated (factor loadings and regression paths). This provides a lower bound (i.e., very conservative) estimate of the adjusted R^2

Figure 2

Measure-Specific Model



Note. Boxes represent observed variables, circles represent latent variables. The measure-specific models theorize that a measure's items (in this case the SPQ-BR) will load onto sub-scale factors which then load onto the overall measure factor. The higher order factor will then load onto (or predict) QOL, whose items are omitted for brevity.

Chapter 4

Results

Demographic characteristics for the sample are located within Table 1 of the data collection procedures section. Mean, standard deviation, reliability information and gender differences on measure scores can be found in Appendix Table A. Of note, females in our sample frequently scored higher on psychosis-spectrum risk measures (i.e., SPQ-BR, O-LIFE, PQ-B, R-GPTS), which is consistent with other findings in the literature (Bora & Baysan Arabaci, 2009; Fonseca-Pedrero et al., 2021). Correlations among measures can be found in Appendices C and D. To account for potential social desirability effects on participant responses, we examined bivariate correlations between the MCSDSB and other measures of interest. The strongest correlation was with the extraversion subscale of the BFI (r = 0.21), with most correlation values falling under + or - .01. Overall, the weak correlations between social desirability and other measures of interest appeared to suggest it is unlikely that social desirability had a substantial impact on participant responding. Therefore, we did not control for social desirability effects in the rest of the analyses.

Table 2 shows the "variable importance" ($\chi^2_{shuffled} - \chi^2_{OOB}$) for each parcel. This table only includes the top three most important indicators for each latent variable selected by the variable selection component of the sembag algorithm. (The only exception to this was family mental health history, for which we kept four indicators as the model had negative observed variances when only including three). This table suggests the PDI follow-up items (those that ask about frequency, level of belief, and

distress) were particularly important in predicting QOL, with a notable drop off in variable importance from PDI distress to maternal mental health history. The most important specific risk items were positive symptoms (e.g., PDI, SPQ-BR suspiciousness/ideas of reference, PQ-B positive, etc.)

Table 2

SEMBAG Variable Importance

Parcel/Item	Latent Variable Associated With	Variable Importance
PDI Frequency	PDI	2650.55
PDI Level of Belief	PDI	2091.46
PDI Distress	PDI	1662.17
Maternal Mental Health History	Mental Health History	868.10
Maternal Mental Health Diagnosis	Mental Health History	862.37
Paternal Mental Health Diagnosis	Mental Health History	788.30
Paternal Mental Health Treatment	Mental Health History	748.98
FESFS Friends	Social Functioning	489.02
QOL Daily Activities	Subjective QOL	440.37
FESFS Independent	Social Functioning	424.71
QOL Health	Subjective QOL	424.45
FESFS Interacting	Social Functioning	414.30
DASS Item 17	Depression	346.11
DASS Item 16	Depression	331.26
SPQ-BR Suspiciousness	SPQ-BR Positive	319.22
DASS Item 10	Depression	314.87
SPQ-BR Ideas of Reference	SPQ-BR Positive	306.87
PQ-B Positive	Positive Schizotypy	273.67
O-LIFE CD	Disorganized Schizotypy	273.42
QOL Family	Subjective QOL	265.85
SPQ-BR Constricted Affect	SPQ-BR Negative	261.86
MSSB Disorganized	Disorganized Schizotypy	254.36
O-LIFE UE	Positive Schizotypy	249.89
SPQ-BR No Close Friends	SPQ-BR Negative	235.10
FESFS Family	Family	213.39
SPQ-BR Social Anxiety	SPQ-BR Negative	209.14
MSSB Positive	Positive Schizotypy	206.49
SPQ-BR Unusual Perception	SPQ-BR Positive	202.20
CTQ Emotional Abuse	Family	198.75
CTQ Emotional Neglect	Family	172.43
PQ-B Disorganized	Disorganized Schizotypy	163.26

Using these variable importance metrics, we computed the average rank for each latent variable (based on the ranks of the parcels). As mentioned previously, sembag uses variable importance information to fit sequential latent variable models starting with the latent variable with the highest average variable importance (PDI in our case), as well as the QOL variable to allow us to compute adjusted R^2. Sembag then adds to this model at each iteration the next highest ranked latent variable. While there were 28 latent variables total, SEM could only estimate the top nine variables before yielding model-implied variance/covariance matrices that were non-positive definite. Also, the highest adjusted R^2 came from the model with the first nine latent variables. For these reasons, we limited the remainder of our analysis to the first nine latent variables.

The average ranks of the latent variables are displayed in Table 3. Similar to what was suggested by the variable importance estimates of Table 2, the PDI emerged as the most important latent variable. Overall, the sembag model suggested keeping a mix of specific risk measure sub-scales from the SPQ-BR, O-LIFE, MSSB, PQ-B, and PDI. With regards to non-specific risk variables, sembag suggested keeping multiple items/parcels pertaining to social functioning, depression, family (including ACEs such as childhood emotional abuse/neglect), and family history. Somewhat surprisingly, no parcels measuring sleep, stress, extraversion/neuroticism, or general anxiety survived the sembag algorithm. Further, no items/parcels from the WSS, RHS, or R-GPTS were included. Using item parceling and sembag, we were able to narrow down the initial 600 items and 1300 parameters to 24 items/parcels and 96 parameters.

Table 3

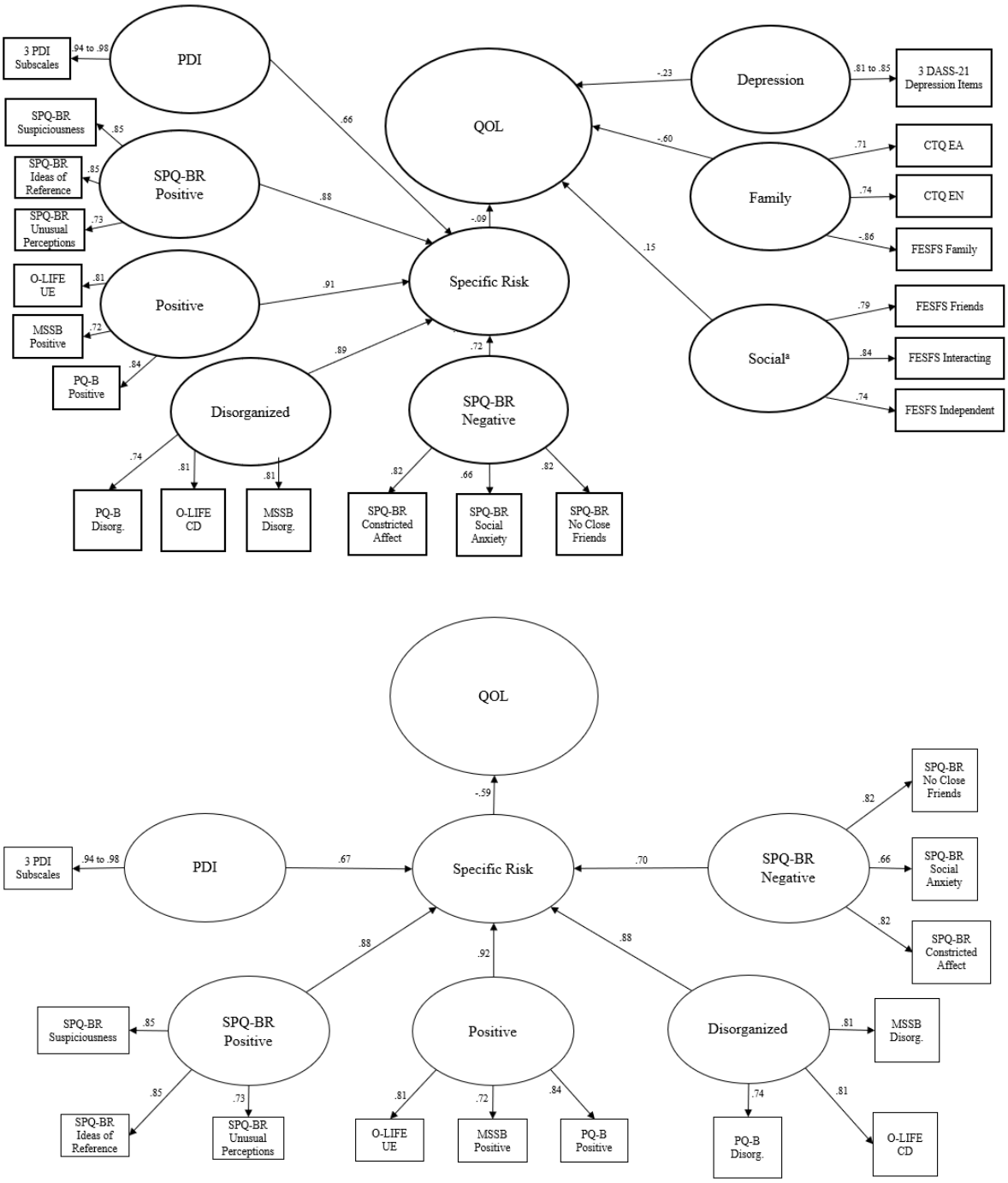
Sembag Variable Rank and Estimates

Latent Variable	Average Rank	χ^2	DF	R^2	Adjusted R^2
PDI	2.00	177.87	26	0.09	0.08
Mental Health History	5.5	209.81	51	0.11	0.10
Depression	26.86	294.18	84	0.35	0.34
SPQ-BR Negative	33.2	341.15	109	0.38	0.37
Social Functioning	34.7	488.43	155	0.56	0.56
Disorganized Schizotypy	36.67	582.65	209	0.56	0.55
Subjective QOL	36.7	*QOL was the outcome variable, so it was not modeled specifically in this step*			
Positive Schizotypy	41.2	823.20	271	0.56	0.55
SPQ-BR Positive	46.25	1000.29	341	0.59	0.59
Family/ACEs	46.83	1407.79	389	0.76	0.75

Note. DF = Degrees of Freedom

Figure 3

Full Model Based on Sembag (top), Reduced Model (bottom)



Note. Boxes represent observed variables, circles represent latent variables. Both models

theorize that items will load onto factors representing risk factors often seen in the psychosis-spectrum. All exogenous variables are assumed to be correlated.

After identifying the best model using sembag, we then built the model suggested for further exploration. Initially, the model had issues with negative observed variances, which was solved by adding the fourth indicator back to family mental health history and loading the specific risk variables onto a "risk" latent variable which in turn loaded onto QOL. Upon further inspection, family mental health history appeared to add little to the model's ability to predict QOL. As such, we removed family mental health history from the model, which improved the model's fit while also simplifying the model. The final model after these revisions is shown at the top of Figure 3.

Figure 4 visualizes trail plots from the model shown at the top of Figure 3. These plots show the five *worst*-fitting relationships (i.e., the five relationships the model struggled most to reproduce). The diagonals within a trial plot visualize the histograms of residuals (i.e., "disturbances" in SEM terminology) for each variable. The upper triangle of the scatterplot matrix shows the observed parcel-by-parcel relationships, while the lower triangle displays a "disturbance-dependence plot," which shows the scatterplot after subtracting out the fit of the model. The red lines in each trail plot depict the SEM-implied fit between two variables, while the blue lines show loess lines between those same two variables. The closer the SEM-implied red line is to the loess line, the better the proposed SEM model fits. Trail plots default to visualizing the variables with the worst misfit. Except for some curvilinearity seemingly due to outliers, the proposed SEM

model appears to fit the data well, as indicated by the close alignment between red/blue lines across the worst-fitting relationships. Of note, the curvilinearity we encountered was less than expected and did not appear to be problematic, therefore we chose not to attempt to model the curvilinearity using Bayesian psychometric modeling.

Figure 4

Trail Plot of the Sembag Model

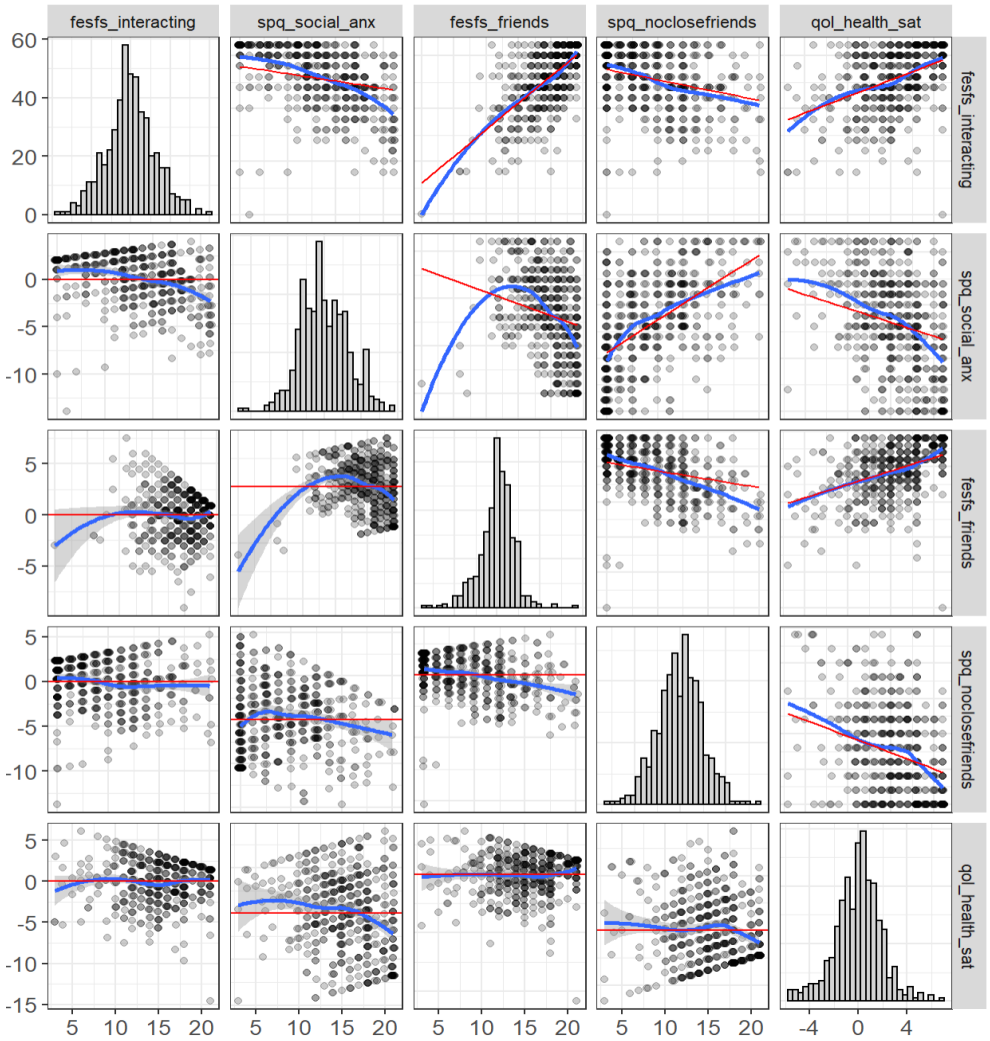


Table 4 contains model estimates such as factor loadings and regression weights for the final model. These estimates show that most of the remaining variables in the model have strong standardized factor loadings, ranging from 0.66 (for SPQ-BR social anxiety and PDI's loading onto risk) to 0.98 (for PDI frequency). The PDI's factor loadings are notably high, possibly because the items related to distress, frequency, and level of belief are all follow-up items requiring a participant to first endorse a symptom. Thus, there may be a shared underlying characteristic among participants who do endorse a symptom at all that the model may be capturing. The PDI's high factor loadings may also be partly attributable to the high number of items included (a potential of 63). The SPQ-BR social anxiety subscale and the PDI's loading onto risk were the only non-QOL parcels to have a standardized factor loading below +/- 0.7. Looking at the path coefficients, the "family/ACEs" latent variable best predicted QOL, which may be, in part, due to childhood emotional abuse/neglect being particularly detrimental to QOL. It could also be due to QOL including a family subscale. Psychosis-spectrum specific risk, on the other hand, had the lowest regression weight, suggesting that depression, family/ACEs, and social functioning are better predictors of QOL.

Table 4

Sembag Model Estimates

Latent Variables	Observed Variables	Unstandardized Estimates	Standardized Estimates	Standard Error	z-value
PDI	PDI Frequency	1	0.98		
	PDI Level of Belief	0.97	0.96	0.02	59.04**
	PDI Distress	0.95	0.94	0.02	51.08**
SPQ-BR Positive	SPQ-BR Suspiciousness	1	0.85		
	SPQ-BR Ideas of Reference	1.16	0.85	0.05	22.35**
	SPQ-BR Unusual Perceptions	0.97	0.73	0.06	17.74**
Positive Schizotypy	PQ-B Positive	1	0.84		
	O-LIFE UE	0.31	0.81	0.02	19.49**
	MSSB Positive	0.22	0.72	0.01	16.79**
SPQ-BR Negative	SPQ-BR Constricted Affect	1	0.82		
	SPQ-BR No Close Friends	1.19	0.82	0.06	18.49**
	SPQ-BR Social Anxiety	1.35	0.66	0.10	14.02**
Disorganized Schizotypy	O-LIFE CD	1	0.81		
	MSSB Disorganized	0.94	0.81	0.05	18.85**
	PQ-B Disorganized	0.63	0.74	0.04	16.80**
Risk	SPQ-BR Negative	1	0.72		
	Disorganized Schizotypy	1.51	0.89	0.12	12.62**
	Positive Schizotypy	4.14	0.90	0.33	12.46**
	SPQ-BR Positive	1.37	0.88	0.10	13.40**
	PDI	4.33	0.66	0.38	11.46**
Family/ACEs	CTQ EA	1	0.71		
	CTQ EN	1.19	0.74	0.08	14.57**
	FESFS Family	-0.63	-0.86	0.04	-15.25**
Depression	DASS Item 10	1	0.85		
	DASS Item 16	0.94	0.85	0.04	21.60**
	DASS Item 17	1.00	0.81	0.05	19.58**
Social Functioning	FESFS Friends	1	0.79		
	FESFS Independent	0.60	0.74	0.04	16.00**
	FESFS Interacting	0.82	0.84	0.05	17.18**
QOL	QOL Daily Activities	1	0.68		
	QOL Health	0.99	0.81	0.06	15.47**
	QOL Family	0.72	0.74	0.06	12.39**

Latent Variables	Observed Variables	Unstandardized Estimates	Standardized Estimates	Standard Error	z-value
Regression Weights (Predicting QOL)	Risk	-0.17	-0.08	0.11	-1.47
	Depression	-0.99	-0.23	0.24	-4.11**
	Family/ACEs	-0.56	-0.60	0.07	-8.47**
	Social Functioning	0.16	0.15	0.07	2.49*

** = p<.05, ** = p<.01*

Specific Risk Versus Specific and Non-Specific Risk

Next, we fit a "reduced" model that consists solely of the remaining specific parcels (negative, positive, and disorganized schizotypy). Recall that we did this to evaluate whether non-specific risk adds predictive ability (and whether that added predictive ability is worth the added complexity) to our models of risk. To do so, we compared this reduced model to the aforementioned "full" model.

Figure 5 shows the trail plot for the reduced model (the model shown at the bottom of Figure 3, while Table 5 contains model estimates (factor loadings and path coefficients) for the reduced model. Looking at Figure 5, the model appears to fit the data well (as indicated by the close proximity of the red/blue lines), with the exception of some underestimation among the SPQ-BR subscales.

Like the full model, the reduced model had strong standardized factor loadings, ranging from 0.67 to 0.98 (See Table 5). Also similar, the PDI stood out for its high standardized factor loadings, with the PDI follow-up items' factor loadings ranging from 0.94 to 0.98. While the indicators for PDI had strong loadings, the PDI latent variable had the lowest standardized factor loading of the variables loading onto the hierarchical "Risk" variable, with a factor loading of 0.69. Many of the other items loading onto risk

ask about delusions, as well as other positive symptoms such as hallucinations. It is possible the PDI's unique focus on delusions may capture some unique information that measures attempting to capture a wider picture do not. Looking at the path coefficients, risk predicted QOL well, with a standardized factor loading of -0.59.

Figure 5

Trail Plot of the Reduced Model

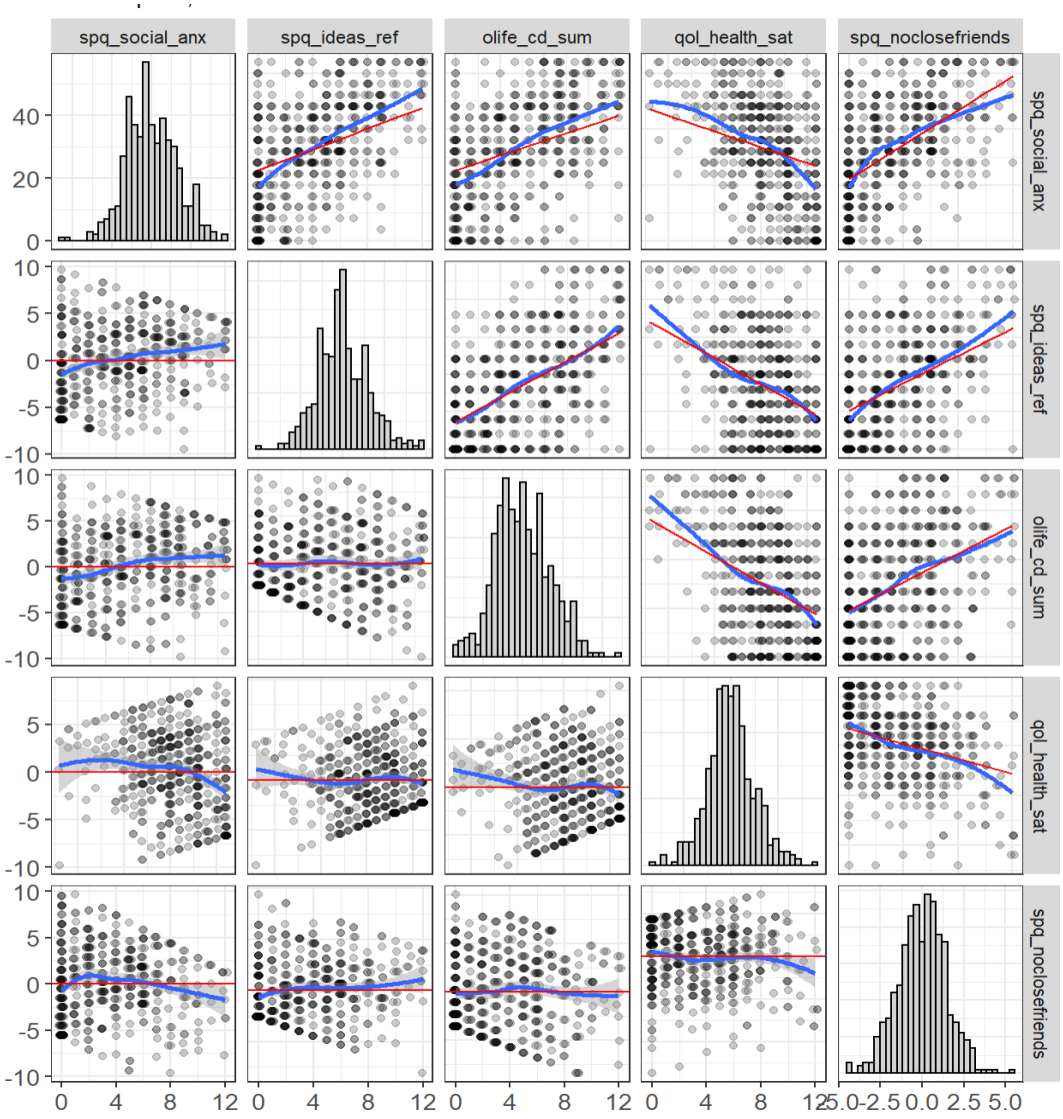


Table 5

Reduced Model Estimates

Latent Variables	Observed Variables	Unstandardized Estimates	Standardized Estimates	Standard Error	z-value
PDI	PDI Frequency	1	0.98		
	PDI Level of Belief	0.97	0.96	0.02	59.06*
	PDI Distress	0.95	0.94	0.02	51.06*
SPQ-BR Positive	SPQ-BR Suspiciousness	1	0.85		
	SPQ-BR Ideas of Reference	1.16	0.85	0.05	22.30*
	SPQ-BR Unusual Perception	0.97	0.73	0.06	17.73*
Positive Schizotypy	PQ-B Positive	1	0.84		
	O-LIFE UE	0.31	0.81	0.02	19.60*
	MSSB Positive	0.22	0.72	0.01	16.86*
SPQ-BR Negative	SPQ-BR Constricted Affect	1	0.82		
	SPQ-BR No Close Friends	1.19	0.82	0.07	18.34*
	SPQ-BR Social Anxiety	1.35	0.66	0.10	13.94*
Disorganized Schizotypy	O-LIFE CD	1	0.81		
	MSSB Disorganized	0.95	0.81	0.05	18.73*
	PQ-B Disorganized	0.63	0.74	0.04	16.75*
Risk	SPQ-BR Negative	1.00	0.70		
	Disorganized Schizotypy	1.54	0.88	0.13	12.16*
	Positive Schizotypy	4.30	0.92	0.36	12.11*
	SPQ-BR Positive	1.42	0.88	0.11	13.04*
	PDI	4.56	0.67	0.40	11.35*
Regression Weights	Risk	-1.22	-0.59	0.14	-8.89*

* = $p<.01$

Table 6 contains model comparison estimates[5] for the reduced and full models such as AIC, BIC, and RMSEA. The RMSEA, adjusted R^2, and R^2 favors the full model while the AIC, BIC, CFI, SRMR, and χ^2 favor the reduced model. Note that the full model predicts the outcome (QOL) substantially better than the reduced model (R^2 of 0.77 for the full model vs 0.35 for the reduced) but does so at a cost in terms of degrees of freedom (requiring an additional 180 DF). More specifically, the full (nonspecific) model contains an additional 36 parameters. Adjusted R^2, which attempts to account for model complexity, also heavily favored the full model (Adjusted $R^2$of 0.71 for the full model versus 0.26 for the reduced model)[6].

Overall, both models appear to fit the data similarly well, except for metrics which heavily penalize models with additional degrees of freedom (AIC/BIC, favoring the reduced) and χ^2 (also favoring the reduced). Thus, the reduced model may fit the data more coherently and simply, but at the cost of substantial predictive ability. Given the overall similarity and substantially better R^2 (both adjusted and unadjusted), we proceeded to develop the new risk measure from the full model's framework, with the additional rationale that the non-specific items included on the new risk measure may be cut later in the process[6].

[5] Fit indices are typically used to evaluate the "global fit" of a model (Jackson et al., 2009), which can be problematic (Fife et al., 2021). Fit indices are very sensitive to factors unrelated to fit (e.g., size of factor loadings, number of parameters, sample size; see (Browne et al., 2002; Shi et al., 2019). It is better to use the fit indices to *compare* models as we have done here (see Widaman & Thompson, 2003).

[6] There are multiple reasons why comparing models with AIC/BIC/RMSEA, etc. may not be ideal. In SEM, fit is evaluated using agreement between the fitted versus implied variance/covariance matrix. This is likely not the best measure of fit, as fit is weighted composite of the fit of the measurement model and fit of the

Table 6

Model Comparison Metrics for Full and Reduced Models

Fit Indicator	Full Model	Reduced Model
Degrees of Freedom	309	129
χ^2	1402.48	641.06
RMSEA	0.088	0.089
(90% Confidence Interval)	(0.08-0.09)	(0.08-0.10)
SRMR	0.07	0.06
AIC	61,117.62	44,147.89
BIC	61,519.89	44,399.31
CFI	0.89	0.92
R^2 (for QOL latent variable)	0.76	0.35
Adjusted R^2	0.71	0.26

structural model. For our purposes, we are more interested in structural error (which is directly related to predictive utility) than in measurement error, particularly since we are using (presumably) already validated/reliable indicators in our modeling. Thus, it is possible that adding the non-specific risk measures increases measurement error disproportional to structural error. If that is the case, AIC/BIC are penalizing the model more than we would intend. R^2 is likely the best approximation to what we are truly interested in but does not penalize for complexity. However, the adjusted R squared does penalize for complexity, which is why we have included it in Table 6. Our adjustment is likely an overly conservative one, as it penalizes a model for all parameters in the model, as opposed to only penalizing for parameters used to directly predict QOL (e.g., depression, risk, social functioning).

Item Evaluation and New Risk Measure

The previous analyses suggested which latent variables (and parcels) are most important in predicting QOL. While this model seems to do well at predicting QOL, it also requires a *lot* of items; though there are only 27 items/parcels, each parcel contains multiple items. The total number of items required to create these parcels is 182, which is a lot of items for a single measure. For this reason, we sought to reduce the number of items to a more reasonable amount. To do this, we evaluated the remaining specific and non-specific risk items from the final model using factor analysis to determine which items to include in a new psychosis-spectrum risk measure.

We first disaggregated the remaining (post-sembag) parcels to the individual items and fit nine factor analyses (one for each latent variable, not including QOL). From these models, we identified the three items with the largest standardized factor loadings. For the PDI, we chose three endorsement items, meaning if a participant endorsed each endorsement item, they would be asked nine additional questions, three for each endorsement item. Again, we chose three items because that is the minimum recommended number of observed variables needed to identify latent variables (Bollen, 1989). We chose no more than three because we wanted to minimize participant fatigue as well as maximize potential clinical utility.

Once we identified the top three items for each latent variable, we then fit new factor analysis models with only the top three indicators. This resulted in a measure with

24 items (or 34 if including all PDI and PQ-B follow-up items; see Appendix E for a list of the items included in the new measure and Appendix A for information such as reliability and average scores), the Inclusive Psychosis Risk Inventory (IPRI). To address issues with model convergence, we summed the PDI follow-up items into their respective subscales. See Table 7 for estimates obtained from the item-level model and Table 8 for model estimates. PQ-B Item 14 had the lowest standardized factor loading (0.55). This may be attributable to PQ-B Item 14 loading onto the same factor as two items which originated from the same measure (O-LIFE Items 7 and 9). Other than PQ-B Item 14, the standardized factor loadings were consistently strong, ranging from 0.61 (FESFS item eleven) to 0.94 (PDI frequency sum). Similar to when looking at the full model with parcels, the PDI had strong standardized factor loadings, though the PDI latent variable continued to have the lowest standardized factor loading of the variables loading onto the hierarchical "risk" variable, with a factor loading of 0.54. SPQ-BR positive loaded onto risk the best, with a standardized factor loading of 0.77.

When calculating IPRI total scores, we estimated factor scores (from the unstandardized factor loadings and regression weights of each item and latent variable, respectively) to weight those items and variables by their importance to the model. For example, an item with a higher unstandardized factor loading, such as FESFS Item 14, would be weighted more heavily than FESFS Item 11 when calculating an individual's

score on the IPRI. In other words, scores on FESFS Item 14 would contribute more to the final sum score[7].

While most scales use unweighted estimates (e.g., by just summing all items to acquire a total score), we used weighted estimates (computed via factor score estimates). We did so for two reasons. First, some of the items included in the IPRI use true/false or yes/no scales, while others use likert-scales. If we were to score the measure using simple sum scores (or even standardized factor loadings), the likert items would more heavily (and unfairly) influence total scores. The estimated factor scores account for the scaling of the original variables.

The second reason we used weighted estimates was because the IPRI was more consistent with a "congeneric model" (see Lord & Novick, 1968; McNeish & Wilf, 2020). When one uses a sum score, they are implicitly assuming a "tau-equivalent" model, which states that each variable is equally reliable. This is clearly not the case. (Indeed, tau-equivalent models are quite rare; Schweizer, 2012). Since our items differed in the strength of their factor loadings, a congeneric model is more appropriate, which necessitates a weighted score. To demonstrate the importance of weighting when calculating the IPRI sum score, we compared the estimated factor scores (i.e., the weighted IPRI scores) and unweighted IPRI total score's ability to predict QOL. The

[7] It is important to remember that for factor analysis models, the *items* are the dependent variable while the factors are the predictor variables. For this reason, you can't compute factor scores by simply multiplying the factor loadings by the item values, then summing them up. For example, the factor score for the latent variable "Negative Schizotypy" would not be computed as 1×SPQ 11 + 1.055×SPQ 16 + 0.952×SPQ 19. Rather, it would be correct to say that SPQ_19 = 0.952×Negative Schizotypy, SPQ 16 = 0.952×Negative Schizotypy, etc. Factor scores are typically computed from the matrix of factor loadings/factor intercorrelations, as well as the model-implied variance/covariance matrix.

weighted IPRI total score (R^2 = 0.49) predicted weighted QOL much more effectively than the unweighted IPRI score predicted the unweighted QOL (R^2 = 0.07) total score.

Table 7

Item-Level Factor Loadings

Latent Variables	Observed Variables	Unstandardized Estimates	Standardized Estimates	Standard Error	z-value	*p*-value
Negative Schizotypy	SPQ-BR Item 11	1.00	0.85			
	SPQ-BR Item 16	1.05	0.88	0.05	23.26	<0.001
	SPQ-BR Item 19	0.95	0.81	0.05	20.60	<0.001
Positive Schizotypy	O-LIFE Item 7	1.00	0.76			
	O-LIFE Item 9	0.89	0.68	0.08	10.68	<0.001
	PQ-B Item 14	1.56	0.55	0.30	5.26	<0.001
SPQ-BR Positive	SPQ-BR Item 26	1.00	0.87			
	SPQ-BR Item 27	1.01	0.85	0.05	20.73	<0.001
	SPQ-BR Item 29	0.77	0.67	0.05	15.74	<0.001
PDI	PDI Distress Sum	1.00	0.92			
	PDI Frequency Sum	0.99	0.94	0.03	37.98	<0.001
	PDI Level of Belief Sum	0.99	0.93	0.03	36.44	<0.001
Disorganized Schizotypy	MSSB Item 6	1.00	0.74			
	MSSB Item 18	0.94	0.75	0.07	14.20	<0.001
	MSSB Item 33	0.94	0.72	0.07	13.59	<0.001
Risk	Negative Schizotypy	1.00	0.66			
	Positive Schizotypy	0.33	0.69	0.04	8.81	<0.001
	SPQ-BR Positive	1.16	0.77	0.11	11.05	<0.001
	PDI	2.11	0.54	0.24	8.90	<0.001
	Disorganized Schizotypy	0.34	0.75	0.04	9.67	<0.001
Family/ACEs	CTQ Item 23	1.00	0.87			
	CTQ Item 24	1.22	0.95	0.04	30.97	<0.001
	CTQ Item 25	1.22	0.91	0.04	28.60	<0.001
Depression	DASS Item 10	1.00	0.85			
	DASS Item 16	0.93	0.85	0.04	21.56	<0.001
	DASS Item 17	1.00	0.81	0.05	19.60	<0.001
Social Functioning	FESFS Item 11	1.00	0.61			
	FESFS Item 13	1.33	0.84	0.10	13.58	<0.001
	FESFS Item 14	1.53	0.88	0.11	13.29	<0.001
Regression Weights	Risk	-1.29	-0.25	0.37	-3.53	<0.001
	Depression	-1.51	-0.29	0.30	-5.03	<0.001
	Social Functioning	0.63	0.09	0.45	1.40	0.161
	Family/ACEs	1.32	0.35	0.19	6.78	<0.001

New Risk Measure Versus Old Risk Measures

After we identified the final set of items that comprise the IPRI, we compared the model representing the IPRI to pre-existing risk measure models: the SPQ-BR, MSSB, WSS, O-LIFE, and PQ-B (see Table 8 for model estimates). Each model was favored by different estimates. χ^2 most favored the IPRI and least favored the WSS. AIC/BIC most favored the PQ-B, which is relatively unsurprising given that the PQ-B also has the lowest degrees of freedom. AIC/BIC least favored the SPQ-BR, even though it has fewer degrees of freedom than other models. The CFI favored the IPRI and least favored the WSS. R^2 and adjusted R^2 overwhelmingly favored the IPRI, which is unsurprising given that we built the measure while considering QOL. The O-LIFE was favored the second most by R^2, while the PQ-B was least favored. The SPQ-BR was favored the second most by adjusted R^2, while the WSS was least favored (note: a negative adjusted R^2 indicates worse fit). RMSEA slightly favored the IPRI, the MSSB, O-LIFE, and WSS, though suggested each model fit the data well. SRMR slightly favored the MSSB, O-LIFE, and WSS. The PQ-B was the least favored by SRMR. Overall, the IPRI was favored by CFI, χ^2, R^2 and adjusted R^2. The IPRI was not the least favored by any estimate. The second most favored model overall appeared to be the MSSB, being tied for most favored by RMSEA and SRMR, as well as second most favored by AIC/BIC and CFI. The least favored model overall appeared to be the SPQ-BR, being least favored by RMSEA and AIC/BIC while not being most favored by any estimate.

Table 8

Model Comparison Metrics for New and Pre-Existing Psychosis-Spectrum Risk Models

Fit Indicator	IPRI	SPQ-BR	MSSB	O-LIFE	WSS	PQ-B
Degrees of Freedom	309	659	896	1117	2069	321
χ^2	662.28	3219.65	2102.16	2337.75	4518.12	822.59
RMSEA	0.05	0.09	0.05	0.05	0.05	0.06
(90% CI)	(0.04-0.05)	(0.09-0.09)	(0.05-0.06)	(0.04-0.05)	(0.05-0.05)	(0.05-0.06)
SRMR	0.06	0.07	0.06	0.06	0.06	0.14
AIC	34,167.00	60,325.45	26,125.16	36,666.63	28,168.22	22,058.95
BIC	34,570.25	60,829.51	26,704.83	37,326.11	29,041.92	22,411.79
CFI	0.96	0.76	0.82	0.81	0.68	0.78
R^2 (for QOL)	0.52	0.27	0.25	0.32	0.17	0.16
Adjusted R^2 (for QOL)	0.41	0.04	-0.04	0.004	-0.44	-0.02

SIPS Follow-Up Interviews

We reached out to 170 participants who completed the first phase of the study and met the follow-up criteria. Of those 170, ten participants expressed interest initially, however they were not responsive to follow-up. Eight participants completed the SIPS follow-up interview, a notably smaller number than the originally intended forty. Of those eight, none met criteria to be considered at ultra-high-risk for a psychosis-spectrum

diagnosis. As such, we did not attempt to compare the ability to predict SIPS risk status of the IPRI to pre-existing risk measures.

Chapter 5

Discussion

The present study sought to investigate the merits of consolidating existing specific and non-specific measures of psychosis-spectrum risk into a new, more holistic risk measure, the Inclusive Psychosis Risk Inventory (IPRI). This new measure would address concerns with the plethora of existing (often overlapping) risk measures which may be dividing limited researcher resources. By including non-specific risk indicators, the IPRI may be able to better detect psychosis-spectrum risk that more targeted measures may miss.

The results of the study suggest a new measure of risk including a combination of pre-existing specific and non-specific risk may convey many benefits. By including multiple non-specific risk variables, a suggestion made previously in the literature (Fowles, 1992) though seemingly ignored, the IPRI may better predict an individual's risk by attempting to capture a more complete picture that more closely aligns with lived experiences. In support of this, more fit indices favored the IPRI than existing risk measures, and the IPRI was better at predicting QOL. Further, psychosis-spectrum specific risk was only the third-best predictor of QOL in our study, being outperformed by both depression and adverse childhood experiences. Additionally, the inclusion of non-specific risk indicators is seemingly consistent with transdiagnostic approaches such as RDoC (Insel et al., 2010), which may suggest that negative symptoms and symptoms of depression are not easily distinguishable.

The inclusion of non-specific risk indicators also seems likely to better reflect reality, where non-specific risk factors may contribute meaningfully to an assessment of an individual's risk and ultimate clinical outcome.

For example, the monozygotic twins' scenario from the introduction serves as an illustration of how non-specific factors may differentially influence individuals with equal biological risk. Perhaps one twin reported experiencing depressive symptoms, perceived childhood emotional neglect, and greater difficulty with social functioning, while the other twin reported none of those experiences. A strong argument based on both research (Cannon et al., 2016; Setién-Suero et al., 2020) and clinical observation could be made that the twin reporting those challenges would be at greater risk for eventually developing psychosis-spectrum symptoms. Despite this, current psychosis-spectrum risk measures do not ask about any of those experiences. The multi-faceted nature of the IPRI may better account for individuals at risk for developing a psychosis-spectrum diagnosis comorbid with other mental illnesses. Similarly, the IPRI may better account for individuals who may be considered at risk for a psychosis-spectrum diagnosis but only ever experience other forms of mental illness (Tandon et al., 2012). This is consistent with previous research which has identified improved predictive ability as essential to further development of the psychosis-spectrum literature (Fonseca-Pedrero et al., 2021; Tandon et al., 2012).

While developing and evaluating the IPRI, we examined issues such as non-normality and non-linearity which may be common to psychosis-spectrum risk measures but are seldom discussed. When these issues are discussed, it is common for researchers

to mention that heavily skewed data are actually intended (Chapman et al., 1995; Rawlings et al., 2008). This can be problematic as it may suggest other issues with the measure/model (such as nonlinearity or misspecification; Cohen, Cohen, West, & Aiken, 2013, p. 120). However, neither of these statistical assumptions appeared to be violated by the IPRI. Of course, future research should continue to evaluate these assumptions to ensure they are not violated, and if they are to adequately address them, potentially through use of methodologies such as Bayesian psychometric modeling.

Considering the above, the present study appears to provide strong initial support for consolidation within the IPRI. Depending on the findings of future research, a form of the IPRI may eventually replace the "overwhelming" (Fonseca-Pedrero et al., 2021, p.19) current number of measures of psychosis-spectrum risk. This may allow researchers to consolidate their efforts and encourage more targeted psychosis-spectrum research. More targeted research efforts may also facilitate refinement of the IPRI into a clinically useful measure, such as how the PHQ-9 is used in a wide range of healthcare settings to screen for/monitor symptoms of depression (Arroll et al., 2010; Costantini et al., 2021). This may be particularly true for college students, as the IPRI was developed with a sample comprising entirely of college students, though future research may investigate the use of the IPRI in other populations. Perhaps most importantly, the IPRI may help improve early identification efforts, reduce the duration of untreated psychosis, and ultimately improve clinical outcomes.

Interestingly, females in our sample often scored higher on psychosis-spectrum risk measures, specifically the SPQ-BR, O-LIFE, PQ-B, and R-GPTS. While the

literature on gender and psychosis-spectrum risk is mixed, there is some suggestion that females score higher on positive psychosis-spectrum symptoms (Bora & Baysan Arabaci, 2009; Fonseca-Pedrero et al., 2021). These findings may be consistent with the results of our study, as two of the measures with female score elevations (the PQ-B and R-GPTS) focus almost exclusively on positive symptoms, while the other two (the SPQ-BR and O-LIFE), contain more items measuring positive symptoms than other domains. One item from the PQ-B was included, while six items from the SPQ-BR were included, which may explain why, on average, females also reported higher scores on the IPRI. While beyond the scope of the present study, future research may consider addressing this difference in scores by differently weighting male and female scores.

Within the present study, we assigned different weights to IPRI items (computed via estimated factor scores) based on their importance to the model and prediction of the outcome of interest, determined by unstandardized factor loadings and regression weights, respectively. We would expect the weights to differ across populations and, as further data are collected, it may allow researchers to tailor the weights to the individual or population studied. Compare this to current psychosis-spectrum risk measures, which nearly always apply equal weights to all items. This assumes every item is equally important for every person when totaling their total scores, an assumption that is unlikely to be true. To better facilitate IPRI scoring and weighting, we plan to release a freely available tool online that will allow researchers and clinicians alike to input participant scores and receive both weighted and non-weighted total scores, as well as sub-scale scores (e.g., for specific and non-specific risk).

Strengths, Limitations, and Future Directions

There are a few important limitations to this study to note. First, the present study originally sought to compare the IPRI's ability to predict an individual's psychosis-spectrum risk status to the predictive ability of other risk measures. Unfortunately, only eight participants completed the follow-up interview, and none of those participants were considered at ultra-high-risk (UHR) for a psychosis-spectrum diagnosis. Thus, our ability to connect the IPRI to clinical outcomes (e.g., UHR, development of schizophrenia, etc.) was minimal. Future studies may seek to place a greater priority on establishing a connection to clinical outcomes and longitudinally comparing various risk measures' ability to predict clinical outcomes. The generalizability of the study is limited by the sample consisting solely of college students, the majority of whom were white and female. Future studies may wish to replicate these findings with a more diverse sample to extend generalizability.

The present study had many strengths as well. To the best of our knowledge, the present study included the most psychosis-spectrum risk measures concurrently of any single study to date. Future studies may build off this by including multiple psychosis-spectrum risk measures within the same study to allow for more direct comparisons. While there are many existing psychosis-spectrum risk measures, few studies include more than one (Mason, 2015; O'Kane, 2021). Further, to the best of our knowledge, no prior psychosis-spectrum risk measure has attempted to include non-specific risk items (e.g., depressive symptoms, family mental health history, social functioning). While the study's generalizability is limited by consisting of college students, this also represents a

strength, as the traditional college student's age falls within a period where individuals often first demonstrate psychosis-spectrum symptoms (NIMH, 2018), presenting a unique opportunity to study the emergence of psychosis-spectrum symptoms. Given the sample used to develop the IPRI, it may be uniquely suited to be used as a general screener measure for the college student population.

Along with the above, future research may continue to investigate which specific and non-specific risk items are the most important to include in the IPRI. It is unlikely that the present study included every relevant specific and non-specific risk factor imaginable, and different items may be more or less important for differing populations as well as different outcomes. Further, as additional data are collected, the weighting for different IPRI items can be refined and better tailored to the characteristics (e.g., age, gender, race/ethnicity, education level) of the individual being assessed. This may represent a promising way to account for frequently observed differences in various populations' psychosis-spectrum risk (Bora & Baysan Arabaci, 2009; Fonseca-Pedrero et al., 2021; Mcgrath et al., 2015).

Conclusion

In conclusion, the present study sought to integrate a variety of specific and non-specific measures of psychosis-spectrum measures into a single measure, the IPRI, to better our ability to detect psychosis-spectrum risk. This new measure of psychosis-spectrum risk compared favorably to many pre-existing risk measures on a variety of fit indicators as well as better predicted QOL, even after adjusting for differences in measure complexity. Additionally, the IPRI did not raise any noteworthy concerns with statistical

assumptions such as linearity and normality that are often found with other psychosis-spectrum risk measures. Further, the IPRI facilitates dynamic weighting of scores which can be further tuned with future research. Overall, the IPRI represents a promising new measure of psychosis-spectrum risk which attempts to take a more holistic perspective, including both specific and non-specific risk indicators. Future research may continue to investigate what combination of specific and non-specific risk indicators leads to the strongest predictive ability.

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Appendix A

Measure Means, Standard Deviations, and Cronbach's α for Total Sample (n =493)

	Total α	Total Sample M (SD)	Male (n = 160)	Female (n = 328)	*t (p)*
IPRI	0.73	-0.02 (0.68)	-.17 (0.57)	0.07 (0.71)	-4.03**
SPQ-BR	0.94	43.34 (23.84)	39.04 (22.15)	44.98 (24.17)	-2.70**
MSSB	0.88	6.26 (5.97)	5.64 (5.62)	6.49 (6.08)	-1.52
O-LIFE	0.89	12.30 (7.90)	10.66 (7.45)	12.95 (7.94)	-3.12**
PQB	N/A	8.91 (10.56)	6.36 (8.06)	10.01 (11.36)	-4.09**
WSS	0.82	9.19 (6.00)	8.73 (6.06)	9.38 (5.93)	-1.13
PDI Endorse	0.67	25.04 (4.13)	24.78 (3.01)	25.11 (4.57)	-0.94
R-GPTS	0.94	33.19 (15.03)	30.89 (13.07)	34.24 (15.68)	-2.48*
RHS	0.93	28.93 (11.10)	27.79 (8.82)	29.36 (12.03)	-1.64
SDS	0.37	6.35 (1.84)	6.33 (1.92)	6.36 (1.82)	-0.16
Objective QOL	0.66	28.79 (5.52)	28.98 (4.53)	28.64 (5.97)	0.69
Subjective QOL	0.95	114.57 (26.45)	117.16 (22.84)	113.70 (27.86)	1.46
FESFS	0.92	91.98 (15.72)	92.92 (13.75)	91.67 (16.64)	0.88
SFS IC	0.03	13.76 (7.85)	14.91 (9.32)	13.23 (7.02)	2.02*
SFS SE	0.48	12.39 (2.75)	12.20 (2.52)	12.49 (2.84)	-1.12
BFI E	0.51	28.22 (5.04)	27.98 (4.81)	28.43 (5.11)	-0.95
BFI N	0.43	25.53 (4.82)	24.83 (4.25)	25.83 (5.05)	-2.29*
Tobacco Use	0.84	7.30 (3.54)	7.47 (3.39)	7.21 (3.61)	0.77
Alcohol Use	0.75	8.73 (3.25)	8.99 (3.40)	8.56 (3.17)	1.32
Cannabis Use	0.79	8.09 (3.65)	8.33 (3.95)	7.93 (3.48)	1.09
CTQ	0.91	38.77 (15.37)	38.39 (13.81)	38.91 (16.16)	-0.37
DASS	0.94	48.25 (12.61)	46.14 (12.28)	49.00 (12.55)	-2.40*
PSS	0.81	14.13 (6.03)	12.62 (5.16)	14.76 (6.24)	-4.00**

Note: IPRI = Inclusive Psychosis Risk Inventory; SPQ-BR = Schizotypal Personality Questionnaire-Brief Revised; MSSB = Multidimensional Schizotypy Scale Brief; O-LIFE = Oxford-Liverpool Inventory of Feelings and Experiences; PQB = Prodromal Questionnaire Brief Distress Score; WSS = Wisconsin Schizotypy Scales; PDI Endorse =

Peters et al., Delusions Inventory; R-GPTS = revised Green et al., Paranoid Thoughts Scale; RHS = Revised Hallucination Scale; SDS = Marlowe Crowne Social Desirability Scale; Objective QOL = Lehman Quality of Life Interview Objective Subscale; Subjective QOL = Lehman Quality of Life Interview Subjective Subscale; FESFS = First Episode Social Functioning Scale; SFS IC = Social Functioning Scale Interpersonal Communication Subscale; SFS SE = Social Functioning Social Engagement Subscale; BFI E = Big Five Inventory Extraversion Subscale; BFI N = Big Five Inventory Neuroticism Subscale; Tobacco/Alcohol/Cannabis Use = Alcohol, Smoking and Substance Involvement Screening Test (ASSIST) Tobacco/Alcohol/Cannabis Subscales; CTQ = Childhood Trauma Questionnaire; DASS = Depression, Anxiety Stress Scales; PSS = Perceived Stress Scale

** = $p<.05$, ** = $p<.01$*

Appendix B

Lavaan Syntax for SEM Model Input into SEMBAG

```
full.model ='

pdi=~ pdi_dis + pdi_think + pdi_true + pdi_end
spq.pos=~ spq_mag_think + spq_suspic + spq_unus_percep + spq_ideas_ref
wss.pos=~ wss_mi_sum + wss_per_sum
  pos.schiz =~ mssb_pos_sum + pqb_posdis_sum + olife_ue_sum + r_gpts + rhs
wss.neg=~ wss_phys_sum + wss_sa_sum
spq.neg=~ spq_constricted_affect + spq_noclosefriends + spq_social_anx
  neg.schiz =~ mssb_neg_sum + olife_ia_sum
spq.dis=~spq_eccentric_behavior + spq_odd_speech
dis.schiz =~ mssb_dis_sum + olife_cd_sum +  pqb_disdis_sum
impulsive.nonconformity =~ olife_in_sum
pss_negative =~pss_1 + pss_2 + pss_3 + pss_9 + pss_10
pss_positive=~ pss_4 + pss_5 + pss_6 +pss_7 + pss_8
dass_str =~dass_211 + dass_216 + dass_218 + dass_2111 + dass_2112 + dass_2114 + dass_2118
abuse=~ ctq_pa + ctq_ea + ctq_sa
neglect=~ ctq_pn + ctq_en
sf =~ fesfs_friends + fesfs_independent + fesfs_interacting + fesfs_intimacy + fesfs_family +
    fesfs_work_relationship + fesfs_work_abilities + sfs_ic_sum + sfs_se_sum
social.anxiety=~spq_social_anx + bfi11 + bfi7 + spq_noclosefriends
social=~ qol_social_sat + qol_social_obj
subjective =~  qol_living_situation_sat + qol_daily_activities_sat + qol_family_sat +
    qol_social_sat + qol_finance_sat + qol_job_sat + qol_living_safety_sat + qol_health_sat
objective =~ qol_daily_activities_obj + qol_family_obj + qol_social_obj + qol_finances_obj
dep =~ dass_213 + dass_215 + dass_2110 + dass_2113 + dass_2116 +
  dass_2117 + dass_2121
anx=~ dass_212 + dass_214 + dass_217 + dass_219 + dass_2115 +
  dass_2119 + dass_2120
substance =~ tobacco + alcohol + cannabis
extra =~ bfi1 + bfi2 + bfi3 + bfi4 + bfi5 + bfi6 + bfi7 + bfi8
neuro =~ bfi9 + bfi10 + bfi11 + bfi12 + bfi13 + bfi14 + bfi15 + bfi16
sle =~ sleep_latency + sleep_efficiency + sleep_disturb + day_dysfunc + psqi5 + psqi18 + psqi19
family =~ fesfs_family + ctq_en + ctq_ea + qol_family_sat + qol_family_obj'
```

Appendix C

Correlations Between Specific Risk Subscales

Measure	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1. SPQ-BR Positive	1												
2. SPQ-BR Negative	.60	1											
3. SPQ-BR Disorganized	.69	.62	1										
4. MSSB Positive	.63	.28	.46	1									
5. MSSB Negative	.26	.41	.23	.18	1								
6. MSSB Disorganized	.51	.48	.60	.55	.30	1							
7. WSS Physical Anhedonia	.05	.19	.08	.06	.33	.17	1						
8. WSS Social Anhedonia	.26	.52	.23	.14	.57	.30	.32	1					
9. WSS Magical Ideation	.61	.28	.45	.69	.09	.45	.01	.12	1				
10. WSS Perceptual	.39	.26	.39	.47	.20	.44	.12	.21	.50	1			
11. O-LIFE UE	.64	.37	.56	.65	.19	.54	.08	.19	.62	.52	1		
12. O-LIFE CD	.51	.55	.60	.38	.19	.65	.08	.33	.44	.39	.60	1	
13. O-LIFE IA	.29	.53	.28	.13	.53	.35	.41	.63	.12	.18	.21	.36	1
14. O-LIFE IN	.46	.28	.48	.48	.18	.48	.13	.18	.41	.43	.51	.49	.23

Note: SPQ-BR = Schizotypal Personality Questionnaire-Brief Revised; MSSB = Multidimensional Schizotypy Scale Brief; WSS = Wisconsin Schizotypy Scales; O-LIFE = Oxford-Liverpool Inventory of Feelings and Experiences; UE = Unusual Experiences; CD = Cognitive Disorganization; IA = Introvertive Anhedonia; IN = Impulsive Nonconformity

Appendix D

Correlations Among Risk Measures

Measure	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.
1. SPQ-BR	1																				
2. MSSB	.67	1																			
3. WSS	.58	.68	1																		
4. O-LIFE	.72	.72	.66	1																	
5. PQ-B	.66	.61	.52	.69	1																
6. RHS	.54	.58	.49	.58	.55	1															
7. R-GPTS	.51	.51	.47	.55	.52	.49	1														
8. PDI	.41	.43	.41	.48	.44	.42	.41	1													
9. CTQ	.39	.43	.41	.44	.34	.33	.29	.32	1												
10. SFS SE	-.36	-.36	-.31	-.33	-.30	-.19	-.18	.02	-.19	1											
11. SFS IC	-.29	-.20	-.26	-.20	-.20	-.10	-.09	-.06	-.10	.29	1										
12. Tobacco	.18	.21	.13	.30	.16	.21	.24	.26	.21	-.01	.17	1									
13. Alcohol	.15	.20	.09	.22	.09	.13	.17	.15	.15	-.04	.17	.53	1								
14. Cannabis	.23	.23	.14	.29	.18	.18	.15	.20	.19	-.07	.12	.50	.51	1							
15. Objective	.31	.29	.25	.32	.18	.32	.22	.35	.24	-.16	-.19	.10	-.00	.06	1						
16. Subjective	-.46	-.37	-.31	-.42	-.33	-.19	-.25	-.05	-.39	.46	.28	-.05	-.14	-.19	-.09	1					
17. FESFS	-.42	-.37	-.36	-.41	-.30	-.12	-.19	.01	-.30	.49	.32	.04	-.04	-.12	-.10	.64	1				
18. Extrav.	-.18	-.10	-.12	-.09	-.07	.04	-.00	.12	-.08	.33	.23	.07	-.04	-.07	-.12	.33	.45	1			
19. Neurot.	.33	.22	.17	.33	.27	.31	.26	.25	.19	.00	-.00	.17	.07	.09	.24	-.11	.05	.36	1		
20. PSS	.50	.45	.37	.57	.51	.48	.43	.23	.37	-.25	-.16	.21	.15	.22	.27	-.38	-.26	-.03	.32	1	
21. DASS	.77	.51	.41	.58	.57	.41	.42	.36	.28	-.25	-.10	.22	.23	.31	.22	-.32	-.27	-.15	.31	.40	1
22. IPRI	.74	.61	.54	.68	.71	.53	.52	.63	.48	-.26	-.18	.29	.15	.27	.31	-.36	-.25	-.10	.33	.51	.35

Note: SPQ-BR = Schizotypal Personality Questionnaire-Brief Revised; MSSB = Multidimensional Schizotypy Scale Brief; WSS = Wisconsin Schizotypy Scales; O-LIFE = Oxford-Liverpool Inventory of Feelings and Experiences; PQB = Prodromal Questionnaire

Brief Distress Score; RHS = Revised Hallucination Scale; R-GPTS = revised Green et al., Paranoid Thoughts Scale; PDI = Peters et al., Delusions Inventory; CTQ = Childhood Trauma Questionnaire; SFS SE = Social Functioning Social Engagement Subscale; SFS IC = Social Functioning Scale Interpersonal Communication Subscale; Tobacco/Alcohol/Cannabis = Alcohol, Smoking and Substance Involvement Screening Test (ASSIST) Tobacco/Alcohol/Cannabis Subscales; Objective = Lehman Quality of Life Interview Objective Subscale; Subjective = Lehman Quality of Life Interview Subjective Subscale; FESFS = First Episode Social Functioning Scale; Extrav. = Big Five Inventory Extraversion Subscale; Neurot. = Big Five Inventory Neuroticism Subscale; PSS = Perceived Stress Scale; DASS = Depression, Anxiety Stress Scales; IPRI = Inclusive Psychosis Risk Inventory

Appendix E

IPRI Items and Response Scales

Original Item Scale and Label	Item Content	Response Scale
SPQ-BR Item 11	I get anxious when meeting people for the first time	Strongly disagree (0), Disagree (1), Neutral (2), Agree (3), Strongly Agree (4)
SPQ-BR Item 16	Do you often feel nervous when you are in a group of unfamiliar people?	Strongly disagree (0), Disagree (1), Neutral (2), Agree (3), Strongly Agree (4)
SPQ-BR Item 19	I feel very uncomfortable in social situations involving unfamiliar people	Strongly disagree (0), Disagree (1), Neutral (2), Agree (3), Strongly Agree (4)
SPQ-BR Item 26	Do you sometimes feel that other people are watching you?	Strongly disagree (0), Disagree (1), Neutral (2), Agree (3), Strongly Agree (4)
SPQ-BR Item 27	Do you sometimes feel that people are talking about you?	Strongly disagree (0), Disagree (1), Neutral (2), Agree (3), Strongly Agree (4)
SPQ-BR Item 29	Do you often have to keep an eye out to stop people from taking advantage of you?	Strongly disagree (0), Disagree (1), Neutral (2), Agree (3), Strongly Agree (4)
O-LIFE Item 7	Do ideas and insights sometimes come to you so fast that you cannot express them at all?	Yes (1), No (0)
O-LIFE Item 9	Does a passing thought ever seem so real it frightens you?	Yes (1), No (0)
PQ-B Item 14	Have you been confused at times whether something you experienced was real or imaginary?	Yes (1), No (0), if yes ask follow-up
PQ-B Item 14 Follow-up	When this happens I feel frightened, concerned, or it causes problems for me	Strongly disagree (0), Disagree (1), Neutral (2), Agree (3), Strongly Agree (4)
PDI Item 15	Do you ever feel that people look at you oddly because of your appearance?	Yes (1), No (0), if yes ask follow-ups
PDI Item 18	Do your thoughts ever feel alien to you in some way?	Yes (1), No (0), if yes ask follow-ups
PDI Item 21	Do you ever feel as if some people are not what they seem to be?	Yes (1), No (0), if yes ask follow-ups
PDI Level of Distress	How distressing is this for you?	Not at all distressing (1), 2, 3, 4, Very distressing (5)
PDI Thought Frequency	How often you think about this?	Hardly ever think about it (1), 2, 3, 4, Think about it all the time (5)

PDI Level of Belief	How true do you believe this is?	Don't believe it's true (1), 2, 3, 4, Believe it is absolutely true (5)
MSSB Item 6	Most of the time I find it very difficult to get my thoughts in order	True (1), False (0)
MSSB Item 18	My thoughts and behaviors feel random and unfocused	True (1), False (0)
MSSB Item 33	I often have difficulty organizing what I am supposed to be doing	True (1), False (0)
CTQ Item 23	During childhood (0-18), I felt loved	Never true (5), Rarely true (4), Sometimes true (3), Often true (2), Always true (1)
CTQ Item 24	During childhood (0-18), my family felt close	Never true (5), Rarely true (4), Sometimes true (3), Often true (2), Always true (1)
CTQ Item 25	During childhood (0-18), my family was a source of strength	Never true (5), Rarely true (4), Sometimes true (3), Often true (2), Always true (1)
DASS Item 10	Over the past week, I felt that I had nothing to look forward to	Did not apply to me at all (0), Applied to me to some degree, or some of the time (1), Applied to me a considerable degree, or a good part of time (2), Applied to me very much, or most of the time (3)
DASS Item 16	Over the past week, I was unable to become enthusiastic about anything	Did not apply to me at all (0), Applied to me to some degree, or some of the time (1), Applied to me a considerable degree, or a good part of time (2), Applied to me very much, or most of the time (3)
DASS Item 17	Over the past week, I felt that I wasn't worth much as a person	Did not apply to me at all (0), Applied to me to some degree, or some of the time (1), Applied to me a considerable degree, or a good part of time (2), Applied to me very much, or most of the time (3)
FESFS Item 11	I find it easy to talk with people my age I know just a little bit	Totally disagree (3), Somewhat disagree (2), Somewhat agree (1), Totally agree (0)
FESFS Item 13	I find it easy to interact with waiters, cashiers, and salespeople (e.g., small talk, asking for information, making a purchase)	Totally disagree (3), Somewhat disagree (2), Somewhat agree (1), Totally agree (0)
FESFS Item 14	I find it easy to interact with authority figures (e.g., teacher, boss, doctor, others' parents)	Totally disagree (3), Somewhat disagree (2), Somewhat agree (1), Totally agree (0)