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The many faces of schizophrenia risk: Can measures of risk be aggregated?

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THE MANY FACES OF SCHIZOPHRENIA RISK: CAN MEASURES OF RISK BE AGGREGATED?

by

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Abstract

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There are currently many different conceptualizations of schizophrenia risk, which we argue is detrimental to any efforts to build a cumulative science in this area. This paper sought to evaluate various conceptualizations of schizophrenia risk and the extent to which they overlap. This paper attempts to identify overlap by utilizing meta-analytic methods in conjunction with data collected from a sample of undergraduate college students (n = 80). To do so, we first collected estimates of various schizophrenia risk measures and risk correlates from the literature. These estimates were subsequently combined with collected data. This paper attempted to analyze review data and collected data using meta-analytic structural equation modeling (MASEM) in a novel way. Analysis of our collected data provided support for a hybrid model where risk subscales loaded onto symptom clusters and two risk measures (SPQ-BR and O-LIFE) captured unique variance. Overall, our results appear to support a movement towards consolidating the fragmented risk literature and identified specific risk measures which may be candidates for consolidation. Future research in this area may expand data collection efforts and examine risk measures at an item level with the ultimate goal of developing a novel risk measure which incorporates pre-existing measures.

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Chapter 1

Introduction

Schizophrenia is one of the leading causes of disability worldwide (Vos et al., 2017) and is associated with premature mortality (Olfson, Gerhard, Huang, Crystal, & Stroup, 2015) as well as increased unemployment rates (Bouwmans, De Sonneville, Mulder, & Hakkaart-van Roijen, 2015) and medical comorbidities (Bahorik, Satre, Kline-Simon, Weisner, & Campbell, 2017; Weber, Cowan, Millikan, & Niebuhr, 2009). Furthermore, a review from Knapp, Mangalore, & Simon (2004) suggested schizophrenia costs the United States around $32.5 billion in 1990, which would equate to roughly $64.6 billion today. One of the best ways to reduce the societal burden of schizophrenia, and its associated impairments, may be through identifying individuals at-risk for psychosis to provide targeted prevention (Faraone, Brown, Glatt, & Tsuang, 2002; Hutton & Taylor, 2013). Previous research demonstrated that prevention efforts can help reduce the risk of developing psychosis, as well as mitigate symptomology (Hutton & Taylor, 2013).

In order to develop effective prevention programs, individuals at risk for transitioning to a schizophrenia-spectrum disorder must first be accurately and reliably identified. Unfortunately, current risk assessment tools are limited in their predictive utility and frequently fail to identify which individuals transition to a schizophrenia-spectrum disorder (Tandon, Shah, Keshavan, & Tandon, 2012). A likely contributor to inaccuracy in identifying who will transition to a schizophrenia-spectrum disorder is the lack of consensus over what constitutes “risk”. There are many groups of risk researchers with similar research goals operating under different paradigms. For example, there are adherents to Meehl’s original schizotypy conceptualization (early 1960’s) that contrast

with more recent schizotypy conceptualizations (e.g., Multidimensional Schizotypy; Gross, Kwapil, Raulin, Silvia, & Barrantes-Vidal, 2018; Vollema & Van Den Bosch, 1995). Certain models avoid the term schizotypy all-together and emphasize 'attenuated symptoms' such as psychosis proneness, psychotic-like experiences, clinical-high-risk (CHR), and ultra-high-risk (UHR). While there may be some theoretical differences between these different conceptualizations, different camps often use terminology interchangeably (Kwapil & Barrantes-Vidal, 2015; Tandon et al., 2012). If possible, a consolidation of these various risk conceptualizations would likely improve the efficacy of risk identification, improve our ability to accurately identify which at-risk individuals will transition, and strengthen our theoretical/etiological models for schizophrenia and related disorders.

In the following paragraphs we will explore the benefits of a more cumulative and synthesized view of risk for psychosis, as well as discuss a few of the major conceptualizations for risk in the literature. Following that, we will describe common correlates of risk indicators, then propose a methodology for consolidating these various camps of research, ultimately aiding to construct a more cumulative science.

Cumulative Science: The Road to Risk Identification?

Investigators from these divergent psychosis-risk 'camps' frequently conduct similar forms of research, with similar aims. For example, researchers working under the frameworks of schizotypy and clinical high-risk both conduct research on how risk for psychosis relates to social functioning (Addington, Penn, Woods, Addington, & Perkins, 2008; Henry, Bailey, & Rendell, 2008). Similarly, researchers examining schizotypy and psychotic-like experiences both consider the possible association of cannabis use with

symptom presentation and severity (Stewart, Cohen, & Copeland, 2010; Van Gastel, Kahn, & Boks, 2013). However, the evaluation of important phenomena under diverse conceptualizations is inefficient and works against building a cohesive foundation of knowledge. If there were a unified conceptualization, using the same measures and same theoretical underpinnings, it would be easier for researchers to expand and refine each other's work. This would accelerate the development of an extensive risk literature and contribute to greater advances in risk identification, so long as this unification does not exclude important phenomena or oversimplify the risk construct. Indeed, as noted by Henriques (2003) psychology cannot reach maturity as a science without shared theoretical underpinnings.

Unfortunately, combining these divergent conceptualizations is not an easy task. For example, it is unclear how these overlapping conceptualizations may best be combined with regards to predictive value and theoretical underpinnings. Ideally, there would be some way to study the existing research literature and incorporate past findings despite the different constructs of psychosis risk that were employed. However, to create the necessary links between the fragmented data within the literature there would need to be available studies that directly compare the assessment measures/indices of interest. Of course, researchers could begin anew (e.g., the proposed Research Domain Criteria (RDoC) system; Insel et al., 2010), collecting large amounts of data from participants across multiple biological and psychosocial levels. Unfortunately, this option is inefficient and will likely take decades to bear fruit. Fortunately, we propose novel quantitative methodology which will provide a powerful 'hybrid' solution where archival research can be combined with contemporary data collection to synthesize insights

gleaned from the existing divergent camps regarding risk. Before we speak of these approaches, we review a few of these various risk conceptualizations.

Risk Conceptualization Frameworks

Schizotypy

In his seminal work, Meehl (1962) used the terms schizotaxia and schizotypy to describe risk. Schizotaxia referred to an individual's genetic predisposition towards developing schizophrenia. On the other hand, schizotypy refers to behaviors (or other phenomena) that reflect a presumed genetic/biological predisposition toward developing schizophrenia interacting with environmental risk factors. Schizotypy remains a useful term to describe a set of risk indicators (i.e., specific behaviors, cognitive-perceptual experiences, etc.) which can be targeted for intervention. Even when using the common term of schizotypy, researchers often conceptualize risk differently. Raine (1994) based his conceptualization of schizotypy on the criteria for *schizotypal personality disorder* seen in the DSM-III, to create the Schizotypal Personality Questionnaire (SPQ). This conceptualization includes nine major sub-scales: Ideas of Reference, Excessive Social Anxiety, Odd Beliefs or Magical Thinking, Unusual Perceptual Experiences, Odd or Eccentric Behavior, No Close Friends, Odd Speech, Constricted Affect, and Suspiciousness (Raine, 1991). The revised version (SPQ-BR) developed by Cohen, Matthews, Najolia, and Brown (2010) also traces its roots back to the DSM criteria. While there are many differences between these conceptualizations, most agree schizotypy includes clusters of positive, negative, and disorganized symptoms (Cohen et al., 2010; Gross, Kwapil, Raulin, Silvia, & Barrantes-Vidal, 2018; Kwapil et al., 2008a)

and that schizotypy is associated with risk for developing schizophrenia (Horan, Reise, Subotnik, Ventura, & Nuechterlein, 2008; Meehl, 1990).

Most commonly, theorists view schizotypy on a spectrum of symptoms, ranging from those who theoretically exhibit no/few symptoms (a subclinical population) to those with a schizophrenia-spectrum diagnosis (see Kwapil & Barrantes-Vidal, 2015 for a breakdown of the spectrum). However, Meehl and his contemporaries (e.g., Lenzenweger, 2006) believe that there is a qualitative, or taxonic, model of risk where schizophrenia represents a phenotype which emerges only at the highest level of risk (Lenzenweger, 2006b; Meehl, 1962). However, even the theorists that view risk on a continuum have devised ways of identifying those at the far end of the continuum for special consideration (e.g., psychometrically defined schizotypy; Cohen & Najolia, 2011). Still, of all the risk conceptualization discussed in this paper, the dimensional view of schizotypy attempts to capture the widest range of risk indicators, allowing for usage in non-clinical populations (see Figure 1).

Psychosis Proneness

Another common conceptualization for risk uses terminology such as "psychosis proneness" and "psychotic-like experiences." These terms typically refer to an individual's predisposition to developing psychosis (or a schizophrenia-spectrum diagnosis) and is composed of subscales measuring magical ideation (positive), social anhedonia (negative), physical anhedonia (negative), and perceptual aberration (positive) (Chapman, Chapman, Kwapil, Eckblad, & Zinser, 1994). Of note, psychosis proneness and psychotic-like experiences were historically studied in participants with an identified family member diagnosed with schizophrenia, although more contemporary research has

shifted to discerning 'traits' that can be identified even in the absence of a definitive family history (Chapman et al., 1994). On the risk spectrum, psychotic-like experiences and psychosis proneness would likely overlap heavily with schizotypy (see Figure 1). For example, one item on the SPQ-BR asks "Do you believe in telepathy (mind-reading?)" while another asks "Have you ever felt that you are communicating with another person telepathically (by mind-reading)?" (Cohen et al., 2010). The Magical Ideation scale of the Wisconsin Schizotypy Scales (Winterstein et al., 2011) covers similar content, with true or false items such as "I have sometimes felt that strangers were reading my mind." Similar content can be found within the O-LIFE (Mason et al., 1995) and MSSB (Gross, Kwapil, Raulin, et al., 2018) as well, with the O-LIFE asking "Do you think that you could learn to read other's minds if you wanted to?" and the MSSB contains a true or false item stating "I have sometimes felt that strangers were reading my mind." This example extends to the PQ-B (Loewy et al., 2011), which asks "Have you had experiences with telepathy, psychic forces, or fortune telling?" Given the high degree of overlap between these conceptualizations and their measures, there may be ample room to synthesize these conceptualizations.

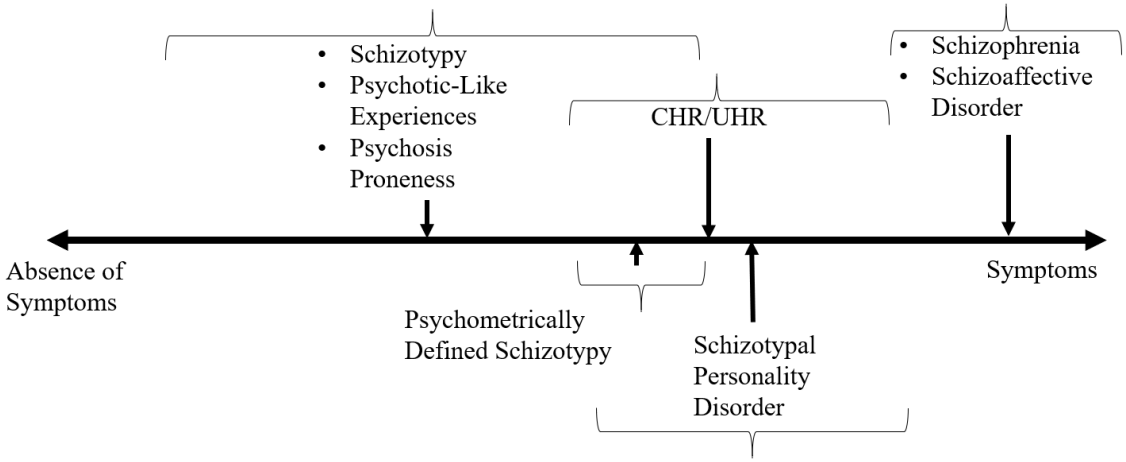
Clinical/Ultra-High-Risk

An additional conceptualization of risk uses the terminology "clinical-high-risk" (CHR) and "ultra-high-risk" (UHR) for psychosis/schizophrenia. CHR and UHR are usually determined by exceeding a particular score on various risk measures. For example, CHR individuals must present either attenuated positive symptoms, a brief limited intermittent psychotic episode, or genetic risk with a decline in psychosocial functioning (Fusar-Poli et al., 2013). An interesting development within this area of

research is the development of risk calculators to predict transition to psychosis (Cannon et al., 2016; Fusar-Poli et al., 2019). Those calculators can, given certain information, such as age; family history of psychosis; and trauma history, predict the probability of experiencing psychosis. However, current risk calculators are limited in that they require the individual to have already been identified through a mental health care system, greatly limiting their ability for early identification and prevention. On the schizophrenia-spectrum, CHR and UHR would likely fall closer to schizophrenia than psychotic-like experiences, psychosis proneness, and schizotypy (see Figure 1).

Figure 1

The Schizophrenia-Spectrum



Clearly, there are many different conceptualizations and measures of risk for schizophrenia. In fact, Mason (2015) identified over 20 measures of schizotypy (Mason, 2015). Since Mason's (2015) review, more schizotypy scales have been developed, only

adding to that number (Kwapil et al., 2018). That number also does not include all risk measurements for schizophrenia, only those tied to schizotypy. This can be a problem, as this can lead to the fragmentation of an already relatively niche literature. Further, having researchers conduct studies looking at risk with different definitions can greatly impede any effort to build a cumulative science within this area and improve progress in more effectively identifying those at risk for schizophrenia.

Risk Correlates

Ideally, various studies utilizing risk instruments would measure risk using *multiple* scales in the same study (e.g., SPQ-BR and Chapman Scales). This would make it much easier to consolidate those various risk measures as we would be able to use meta-analytic methods (e.g., meta-analytic structural equation modeling, or MASEM) to aggregate across those studies. Unfortunately, researchers rarely utilize multiple measures of risk as they frequently work exclusively within their framework. This makes it difficult to utilize meta-analytic methods.

However, researchers often measure common *correlates* of risk. For example, researchers frequently examine quality of life (Cohen & Davis, 2009; Fusar-Poli et al., 2015), social functioning (Henry et al., 2008; Raghavan, Ramamurthy, & Rangaswamy, 2017), and stress (Dinzeo, Cohen, Nienow, & Docherty, 2004; Pruessner, Iyer, Faridi, Joober, & Malla, 2011). These associations may help consolidate these various camps as they provide a validity anchor from one study to the next. For example, if one study investigates schizotypy and quality of life, while another studies UHR and quality of life, the common variable (quality of life) may provide insights into how these two measures (schizotypy and UHR) are associated. This additional information may be particularly

valuable when considering how infrequently multiple conceptualizations of risk are studied within the same study. In cases where those direct links between camps are absent, we may be able to utilize risk correlates as an indirect link between camps.

A few (of many) correlates of risk include quality of life (QOL; Cohen & Davis, 2009; Fusar-Poli et al., 2015), social functioning (Henry et al., 2008; Raghavan et al., 2017), and stress (Dinzeo et al., 2004; Pruessner et al., 2011). QOL refers to an individual's satisfaction with their life, as well as more objective indicators such as their socioeconomic status (Cohen & Davis, 2009). QOL has often been linked to risk, with lower QOL frequently being associated with higher levels of risk (Addington et al., 2008; Cohen & Davis, 2009; Horan, Blanchard, Clark, & Green, 2008). Social functioning represents another important construct relevant to risk as both an environmental predictor and outcome. Social functioning is frequently characterized by difficulties interacting with others, lack of social support, and an inability to form close relationships (Birchwood, Smith, Cochrane, Wetton, & Copestake, 1990). It is well documented that impairments to social functioning have been associated with schizophrenia-spectrum symptoms (Addington et al., 2008; Kwapil, Barrantes-Vidal, & Silvia, 2008b).

Stress is an additional variable of interest to risk, as both a predictor and outcome. One of the most widely utilized etiological theories regarding the development of schizophrenia is the diathesis-stress model (Fowles, 1992). The diathesis-stress model posits stress is closely linked to the development of schizophrenia. For example, higher levels of stress and stress reactivity are frequently associated with greater risk (Dinzeo et al., 2004; Myin-Germeys, Delespaul, & van Os, 2005; Van Os, Linscott, Myin-Germeys, Delespaul, & Krabbendam, 2009). Previous research in this area suggests a bidirectional

relationship between physiological/psychological stress sensitivity and risk, particularly after encountering stressful life events (Grattan & Linscott, 2019).

In the present study, we sought to systematically and quantitatively review the existing risk literature for schizophrenia/psychosis. Specifically, we were interested in gathering estimates of various risk measures' associations with one another, as well as other important constructs such as quality of life (QOL), social functioning, and stress. By gathering these estimates, we believe that we will take 'the first step' towards synthesizing the various schizophrenia-risk conceptualizations. The ultimate synthesis of these data may involve several additional steps, but it will be useful to first provide insights which will guide further refinement.

Quantitative Literature Reviews

Earlier, we discussed the value of archivally consolidating the divergent risk conceptualizations. Unfortunately, this would historically prove to be a Herculean task. While meta-analysis is typically used to aggregate *the same* estimates across studies, it is not ideal for situations where researchers investigate *different* variables. MASEM is better suited for this task. One MASEM approach, called the multivariate two-stage SEM uses a mixed model approach. Under this approach, MASEM handles instances where a correlation from a particular study is missing by estimating the average (fixed effect) correlation. For example, one study might not measure and report the correlation between the SPQ-BR and UHR status. MASEM estimates this missing correlation by borrowing information from each individual study.

However, a major limitation of MASEM is that it cannot handle situations where specific pairwise correlations are missing from *all* studies. For example, if no study ever measured risk using both SPQ-BR and the Chapman scales, MASEM will report an error. One suggested approach to handling this is to set the missing correlations to zero (e.g., Jak, 2015). This approach is problematic because it may bias parameter estimates toward zero. To avoid this problem, the authors of the current paper will utilize a quantitative literature review (QLR) methodology. Rather than setting missing correlations to zero, this method utilizes a multiple imputation approach. When correlations are missing from all studies under investigation, QLRs impute the missing values temporarily using noninformative Bayesian priors, estimate the model's parameters, then update the estimates based on the newly updated model. As such, a multiple imputation approach does not bias parameter estimates in the same way as if one were to set correlations to zero (Furlow & Beretvas, 2010).

QLRs provide an ideal tool to handle entirely absent correlations in our attempt to consolidate risk literature since correlations between risk measures from the various frameworks are frequently missing. However, the number of missing correlations may be quite extreme, and it is unclear if QLR methodology will produce meaningful estimates. To evaluate this, we will compare the estimates generated by the QLR to estimates gathered from newly collected data. Not only will the QLR-generated estimates increase the precision of the data-generated estimates, but the data-generated estimates will provide a validity check of the adequacy of the QLR algorithm. Hand in hand, we hope the two will provide converging evidence across multiple methodologies.

In summary, the purpose of this project is two-fold: first, we attempt to identify whether the various risk frameworks can be consolidated into one cohesive schizophrenia risk conceptualization. Our second purpose is to evaluate QLR's ability to estimate intercorrelations in the presence of a large quantity of missing correlations. Because this research is primarily exploratory in nature, we have few specific hypotheses. Rather, we will use the data to inform our research questions (and vice versa; see Fife & Rodgers, 2019).

Chapter 2

Method

Literature Review

The present study began by collecting bivariate estimates of relationships between various risk measures, prediction of transition to psychosis, and other relevant indicators of functioning such as quality of life (QOL), stress, and social functioning. Descriptive statistics for the estimates gathered from our review can be found in Table 1 (Note that Table 1 only reports statistics for the global scales to save space. When performing the QLR, we intend to utilize the subscales).

Under the consultation of a librarian, we systematically searched PsychINFO, Pubmed, and Google Scholar for articles related to schizophrenia risk (see Appendix for a list and description of studies included in the review). The following terms were used in our search of the literature: “schizotypy”, “ultra-high-risk for psychosis”, “clinical high-risk for psychosis”, “schizophrenia”, “psychosis”, “schizotypal symptoms”, “quality of life”, “QOL”, “well-being”, “social functioning”, “SPQ-BR”, “SPQ”, “O-LIFE”, “MSSB”, “PSS”, “Chapman Scales”, “Wisconsin Schizotypy Scales”, “PQ-B”, “SFS”, and “stress”. Various combinations of those terms were used as well, such as “schizotypy and quality of life” or “schizotypy and prediction of schizophrenia.” For a study to be included in this review, the authors had to report at least one measure of a bivariate relationship (e.g., correlation coefficients, Cohen’s *d*, etc.) for any two of the variables in which we were interested. If multiple articles used the same dataset for their analyses, we chose to include the article which contained more estimates.

Table 1

Estimates Included in QLR

Variable	O-LIFE	Chapman Scales	QOL	SPQ	SPQ-B	MSS/MSSB	SF	Stress
O-LIFE	7; (-0.02, .50)		(-0.45, -0.21)					(0.05, 0.45)
Chapman Scales		4; (0.16, 0.73)		(0.01, 0.82)				
QOL	4			(-0.58, -0.38)			(0.23, 0.29)	(-0.67, 0.57)
SPQ		2	2				(-0.31, -0.05)	
SPQ-B						(0.27, 0.56)		
MSS/MSSB					2	3; (0.08, 0.44)		
SF			1	1				
Stress	1		3					

Note. Correlation ranges reported represent associations between and within subscales. Numbers below diagonal represent the number of studies which reported that relationship. Numbers above the diagonal denote the range of the subscale correlations of the reported estimates for that relationship, or the range of correlations reported if multiple estimates were found. Psychotic-like experiences is not included because common measures do not explicitly have subscales, our QLR requires subscales.

Data Collection Procedures

We collected data from 80 students at a mid-sized university in the northeastern United States. Our sample predominantly identified as female (n=42), followed by male (n=37) and other (non-binary; n=1), with a mean age of 19.43 (SD=1.78). The majority of our sample identified as White (non-Hispanic; n=54), followed by Black (n=10), Hispanic/Latinx (n=6), Asian/Pacific Islander (n=4), and other (multi-racial, Indian; n=6). All procedures and methods were approved by the relevant IRB. To be eligible for participation participants had to be at least 18 years of age. Data were collected online through the university's psychology participant pool.

Participants who scored above a predetermined cutoff point on a screener measure (PQ-B) were contacted to arrange a follow-up interview (described in more detail below). Of the 9 participants contacted, none responded to arrange the follow-up interview. This poor follow-up rate was likely due to multiple factors, including "zoom fatigue" experienced by many students during the COVID-19 pandemic, as well as follow-up study not offering credit for students' essentials psychology course. Due to this low follow-up rate, the follow-up interview component of data collection will be prioritized for a future research project.

Measures

Schizotypy and Psychosis Proneness

We utilized the following measures of schizotypy within our data collection: Schizotypal Personality Questionnaire Brief-Revised (SPQ-BR; Cohen et al., 2010), Oxford Liverpool Inventory of Feelings and Experiences-short scales (O-LIFE; Mason,

Linney, & Claridge, 2005), and Multidimensional Schizotypy Scale-Brief (MSSB; (Gross et al., 2018). The SPQ-BR is a 32-item measure of schizotypy with αs ranging from 0.87-0.94 across factor scores (Callaway, Cohen, Matthews, & Dinzeo, 2014; Cohen et al., 2010). The SPQ-BR consists of three to four subscales, cognitive-perceptual (α = 0.94), no close friends/constricted affect (α = 0.87), social anxiety (α = 0.90), and disorganization (α= 0.92; Callaway et al., 2014; Cohen et al., 2010). The O-LIFE is a 43-item measure of schizotypy with αs ranging from 0.62-0.80 across subscales (Mason et al., 2005). The O-LIFE consists of four subscales, unusual experiences (α = .80), cognitive disorganization (α = 0.77), introvertive anhedonia (α = 0.62), and impulsive nonconformity (α = 0.63; Mason et al., 2005). The MSSB is a 38-item measure of schizotypy with αs across two samples ranging from 0.78-0.90 across subscales (Gross et al., 2018). The MSSB consists of three subscales, positive (α = 0.78, 0.80) negative (α = 0.80, 0.81), and disorganized (α = 0.90, 0.89; Gross et al., 2018). We will measure psychosis proneness using the Wisconsin Schizotypy Scales (WSS; Winterstein et al., 2011) consisting of the magical ideation (α = 0.74), perceptual aberration (α = 0.83), social anhedonia (α = 0.75), and physical anhedonia (α = 0.62) (Winterstein et al., 2011). The brief versions of the Wisconsin Schizotypy Scales contain a total of 60 items evenly distributed among the 4 scales (Winterstein et al., 2011), with items from the WSS originating from the Chapman Scales.

In total, we measured risk using 173 items (this number does not include items assessing risk correlates). Clearly, administering such a large number of items may have induced subject fatigue. To reduce potential bias due to the effects of fatigue, measures were presented in a randomized order to participants. Due to the random order of our

measures, any missing data in the study were considered missing completely at random, meaning the missing data should not bias our estimates. Fortunately, only two individuals partially completed measures.

Psychotic-Like Experiences and Ultra-High-Risk

To gather data on psychotic-like experiences and those at Ultra-High-Risk for psychosis, the Prodromal Questionnaire-Brief was administered to all participants (PQ-B; Loewy, Pearson, Vinogradov, Bearden, & Cannon, 2011). The PQ-B is a 21-item measure which has been used to measure psychotic-like experiences as well as identify individuals who may be at ultra-high-risk for psychosis (Ered, Cooper, & Ellman, 2018; Loewy et al., 2011). The PQ-B has an α of 0.85 (Loewy et al., 2011).

Recall that a UHR diagnosis requires an interview, which can be time intensive. Additionally, very few college students are likely to be considered UHR. For efficiency, the PQ-B was used as a screener measure. Using a cutoff score of six, the PQ-B has shown an ability to identify individuals at ultra-high-risk with 88% sensitivity and 68% specificity (Loewy et al., 2011). Participants who scored above the cutoff point of six on the measure's distress score were contacted to arrange a follow up interview. This follow up interview consisted of the Structured Interview for Prodromal Syndromes (SIPS; Miller et al., 2003) to determine UHR status and was conducted by a research assistant who was trained and certified to administer the interview.

The PQ-B does not contain subscales (or at least they are not reported in the literature). While the items themselves could presumably be separated into subscales (e.g., positive, negative, disorganized), it is impossible to do so with archival data. It is

critical for our QLR analysis to have subscales, because having the subscales allows us to determine whether certain subscales measure the same latent constructs (e.g., the positive subscale of the SPQ and the positive subscale of the Chapman scale). Because no studies report subscale estimates for PQ-B, this measure was not included in our QLR analysis. However, upon collecting data, we were able to identify subscales to include within our models. As a result, the PQ-B was not included in our QLR but was included in our data collection analysis, where it was identified to have items measuring positive symptoms and disorganized symptoms.

Risk Correlates

The following measures of common risk correlates were included in our data collection: Perceived Stress Scale (PSS; Cohen, Kamarck, & Mermelstein, 1983), Social Functioning Scale (SFS; Birchwood et al., 1990), Short Form 36-item Health Survey (SF-36; McHorney, Ware, & Raczek, 1993; Ware & Sherbourne, 1992), and a modified version of the Brief Quality of Life Interview (QOLI; Lehman, Kernan, Postrado, 1995). The PSS is a 14-item measure of stress which has demonstrated adequate reliability, with α scores ranging from 0.84-0.86 across three separate samples (Cohen et al., 1983). The SFS is an 81-item measure of social functioning which has demonstrated acceptable reliability, with α scores ranging from 0.69-0.87 across subscales (Birchwood et al., 1990). The SFS consists of seven subscales, withdrawal (α = 0.72), interpersonal (α = 0.71), prosocial (α = 0.82), recreation (α = 0.69), independence-competence (α = 0.87), independence-performance (α = 0.85), and employment occupation (Birchwood et al., 1990). For this study, 9 items from the SFS covering interpersonal communication and social engagement were used. The SF-36 is a 36-item measure of quality of life which

has demonstrated adequate reliability, with α scores ranging from 0.75-0.92 across subscales (McHorney, Ware, Rachel Lu, & Sherbourne, 1994). The SF-36 consists of eight subscales, physical functioning (α = 0.92), role limitation due to physical health problems (α = 0.87), bodily pain (α = 0.82), general health perceptions (α = 0.78), vitality (α = 0.85), social functioning (α = 0.78), role limitations due to emotional problems (α = 0.75), and mental health (α = 0.80; McHorney et al., 1994). To measure quality of life, we utilized the brief version of Lehman's QOLI (Lehman, Kernan, Postrado, 1995). This version contains 43 total items measuring subjective and objective QOL. The QOLI has demonstrated mostly acceptable reliability with a α score range of 0.79-0.84 for subjective QOL and a α score range of 0.44-0.82, for the subdomains of objective QOL (Lehman, 1996).

Social Desirability

To address concerns of social desirability on participant responding, the Marlow-Crowne Social Desirability Scale Brief Form XI (MCSDSB; Fischer & Fick, 1993; Strahan & Gerbasi, 1972) was utilized. The MCSDSB is a self-report scale consisting of 10 items answered true or false with an α of .79 (Fischer & Fick, 1993).

Demographics

We collected data on participants' demographic characteristics. Demographics in which we were interested included: age, gender, race/ethnicity, and family mental health history as well as whether the participant had sought mental health treatment before.

Chapter 3

Data Analytic Plan

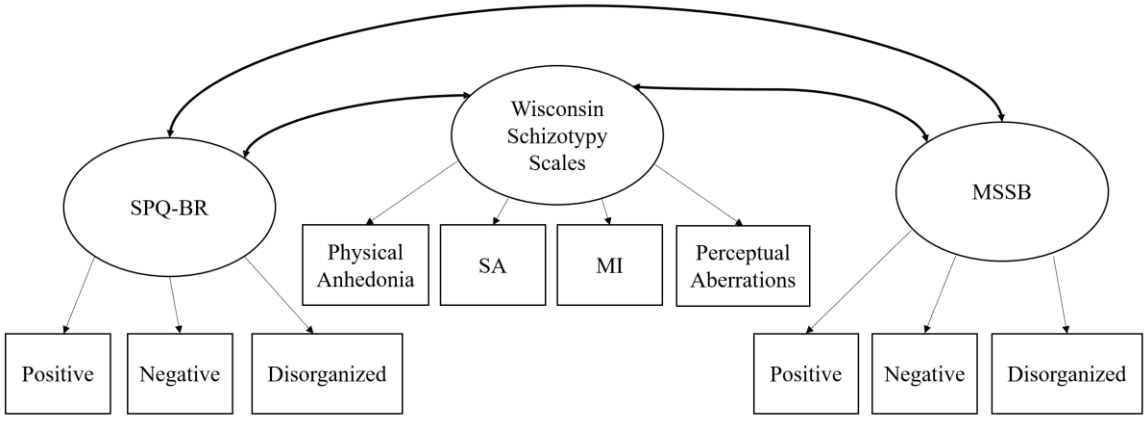
QLR

The QLR algorithm requires correlation matrices from each study collected. Once obtained, these matrices were entered as inputs into the `qlr` package in R (Fife, 2020). This algorithm, which is based on multivariate two-stage structural equation modeling (TSSEM; Jak, 2015) strings out the correlations in column format (i.e., one column per pairwise correlation). In our case, this yielded a matrix of 666 columns (e.g., Q-Life/Chapman, O-Life/QOL, Chapman/QOL, etc.) and 26 rows (one row per study). Once in column format, the algorithm identifies columns where some (but not all) correlations are missing. It then uses the completed columns to impute with multiple imputation t the missing correlations. For those columns where *all* correlations are missing (e.g., the SPQ/O-Life relationship), the algorithm then inputs noninformative Bayesian priors (in this case, random values from a beta distribution with shape parameters of four and four, which yields a distribution with mass centered on zero and lower probabilities for high correlations). At this point in the algorithm, the entire 666 by 26 matrix is complete, with mostly imputed values. Once this is done, the matrix is converted back into a symmetric (correlation) matrix by taking the average of each column, then the algorithm fits the two structural equation models. Finally, the algorithm repeats this process 1,000 times, generating 1,000 fitted SEMs. These fitted SEMs will each have different parameter estimates (e.g., factor loadings, residual variances), each of which constitutes a sample from the posterior distribution.

Additionally, at each of the 1,000 iterations, we will fit two different confirmatory factor analysis models. One of those models, called "Measure-Based Model," assumes every measure of risk is a unique latent variable (though each measure is allowed to correlate with the others). For this model, all subscales are treated as indicator variables. (See Figure 2).

Figure 2

Path Diagram of Measure-Based Model

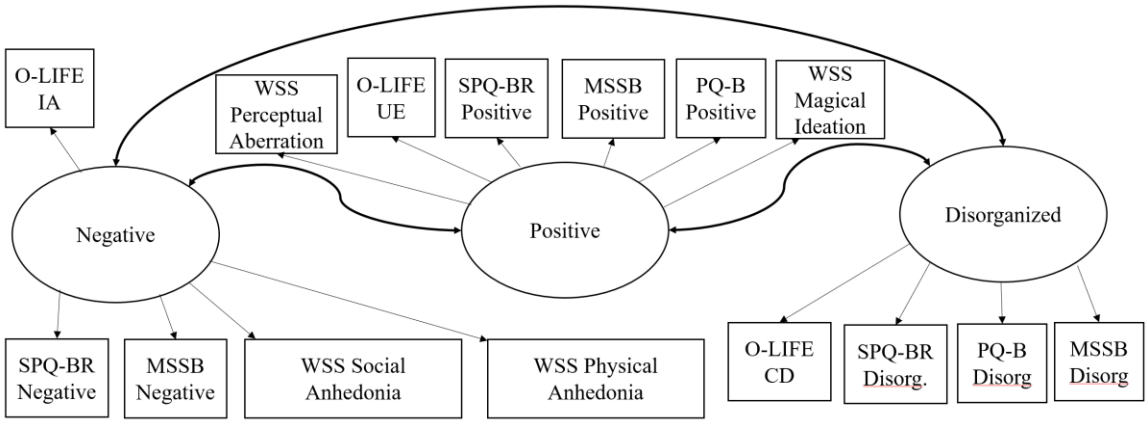


Note. Boxes represent observed variables, circles represent latent variables. This model theorizes that each measure of risk captures distinct latent variables. Not all included measures are pictured. Measures of risk correlates not included as they are not critical to the SEM; they are solely being used to estimate missing correlations. O-LIFE is not included for sake of visual complexity. SA = Social Anhedonia; MI = Magical Ideation

The other model, "Symptom-Based Model," also treats the subscales of each measure as an indicator of risk, but these subscales load onto common latent variables. The latent variables we proposed include Positive, Negative, and Disorganized. See Figure 3 for a path diagram.

Figure 3

Path Diagram of Symptom-Based Model



Note. Boxes represent observed variables, circles represent latent variables. This model theorizes that each measure's subscales will load into common latent variables.

Ideally, the algorithm will yield 1,000 unique fitted models. However, there is the possibility the algorithm will fail to converge on some (or many) of these iterations. If it fails to converge, parameter estimates cannot be trusted. Also, fit indices will not be computed. For those occasions where the algorithm does converge, we will record parameter estimates and fit indices. Provided there are enough occasions of convergence,

we will be able to estimate *distributions* of fit indices, which represent samples from a posterior distribution. In this case, we will utilize the distribution of fit indices to determine which model fits better. For example, if 95% of RMSEA values fit better for one model over another, we would favor that model. The same will be held true for other measures of fit.

Naturally, both models required modifications, as this analysis was partially exploratory in that no prior study has examined similar models (see Fife & Rodgers, 2020). Modifications were driven by theory, modification indices, and residual analysis, culminating in a third model, the "Modified Model." The process of creating this modified model occurred after our other analyses.

In addition to estimating fit indices, we also recorded parameter estimates from the models (factor loadings, variance explained, regression weights for outcomes). To determine whether QLR is able to estimate valuable information from such a sparse matrix, we identified whether the *standardized* estimates span the entire range of potential values (i.e., approximately -1 to +1 for factor loadings/regression weights, and 0 to +1 for variance explained). If they did span the entire range (or closely span the entire range), the QLR was essentially useless. It is possible that some estimates span the entire range (e.g., a factor loading for the Disorganized latent variable), while others do not. As such, we identified which factor loadings were informative.

Data Collection Analysis

Similar to our analysis in the previous step, we utilized the actual data to fit the three models (Measure-Based, Symptom-Based, and Modified) using the `lavaan`

package in R (Rosseel et al., 2020). We assessed fit for each model using global and local fit indices, residual analysis, as well as visual indicators (utilizing the R package `flexplavaan`; Fife et al., 2021a; Fife et al., 2021). To further determine the utility of QLR, we identified whether the actual estimates obtained from data collection fell within the 95% credible intervals from the QLR analysis. Once again, it is possible that some estimates fell within the range of the credible intervals, while others do not. We report the proportion that do.

QLR and Data Analysis

QLR was developed with the intention of providing a means of generating priors for Bayesian-based hypotheses. As such, the initial QLR analysis allowed us to integrate the archival data from the literature with new data we collected. To accomplish this, we used the posterior estimates from the QLR analysis as priors for the actual data analysis. These priors were combined with the data to, hopefully, increase the precision of the model's parameter estimates. To do so, we utilized the `blavaan` (Merkle & Rosseel, 2018) package in R. We compared these Bayesian estimates to those obtained from the QLR alone (first analysis) and the uninformed data analysis (second analysis). Once again, we expected the credible intervals for the QLR + Data Analysis (third analysis) to be much narrower than the QLR alone analysis (first analysis) and at least marginally narrower than the data alone analysis (second analysis).

Chapter 4

Results

QLR Analysis

We attempted to fit structural equation models utilizing the estimates gathered from our QLR. Unfortunately, the algorithm failed to converge on a solution in all but four iterations (out of 1,000) of the model. Additionally, the estimates for the 1,000 iterations spanned the entire range of potential estimates (e.g., -1 to +1) meaning they were largely uninformative. This result suggests that a correlation matrix as sparse as the one generated by the present QLR (Table 1) will not produce meaningful estimates, in spite of the missing data strategy employed. As a byproduct of our failed QLR analysis, we were unable to complete the QLR analysis nor the combined QLR and data collection analysis outlined in our data analytic plan. Further, because risk correlate data was collected primarily with the purpose of facilitating a connection between the QLR and data collection, our analyses did not include the risk correlates.

Table 2

Means, Standard Deviations, and Reliability Estimates (n = 78-80)

Measure	Mean	Standard Deviation	Cronbach's α
SPQ-BR Positive	33.73	12.13	0.92
SPQ-BR Negative	27.00	8.14	0.88
SPQ-BR Disorganized	18.52	6.08	0.87
MSSB Positive	2.09	2.86	0.86
MSSB Negative	2.08	2.28	0.74
MSSB Disorganized	2.67	3.73	0.93
WSS Physical Anhedonia	2.39	1.90	0.54
WSS Social Anhedonia	3.10	2.55	0.72
WSS Magical Ideation	2.72	2.90	0.79
WSS Perceptual Aberration	.99	2.72	0.94
O-LIFE UE	3.05	3.09	0.85
O-LIFE CD	4.95	3.59	0.87
O-LIFE IA	2.15	1.81	0.55
O-LIFE IN	2.95	1.91	0.47
PQ-B Total Score	4.89	5.26	0.89
PQ-B Distress Score	14.55	16.66	0.91

Data Collection Analysis

Demographic characteristics of our sample can be found in the data collection procedures section of this paper, with mean, standard deviation, and reliability information from the collected measures displayed in Table 2. To account for potential social desirability effects on our sample, bivariate correlations between the MCSDSB and our variables of interest were examined. Only one of these correlations (O-LIFE

cognitive disorganization; r = -.23, p = .04) emerged as significant, suggesting it is unlikely for social desirability to have influenced our results. As such, social desirability effects were not controlled for in further analyses. Table 3 shows a correlation matrix of the subscales.

Figures 4, 5, and 7 visualize a subset of each model's fit using "trail plots" (Fife, Brunwasser, & Merkle, 2021). The diagonals of trail plots show the histograms of residuals for each variable. The red lines depict the SEM-implied fit between two variables, while the blue lines depict the quadratic or regression line between those same two variables. The closer the SEM-implied red line is to the quadratic or regression line, the better the proposed SEM model fits. The upper triangle of the scatterplot matrices shows the raw data, while the lower triangle displays a "disturbance-dependence plot," which shows the scatterplot after subtracting out the fit of the model.

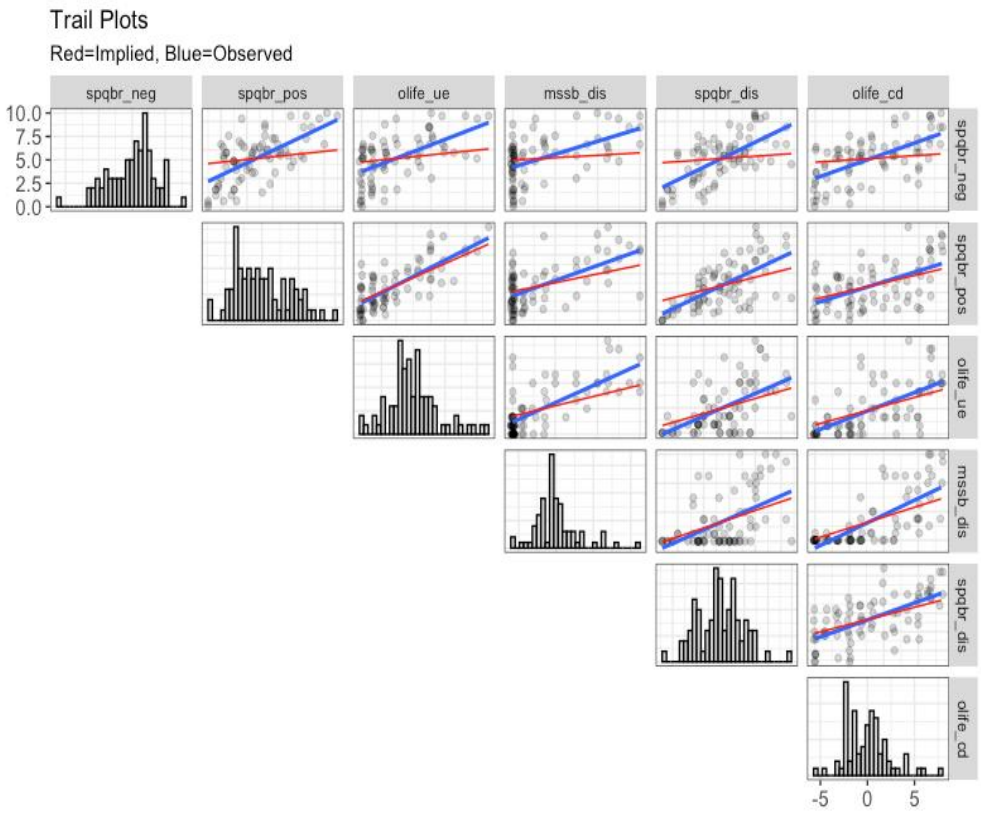
Table 3

Correlations Among Risk Measures

Measure	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.
1. SPQ-BR Positive	1													
2. SPQ-BR Negative	0.65	1												
3. SPQ-BR Disorganized	0.66	0.66	1											
4. MSSB Positive	0.66	0.38	0.40	1										
5. MSSB Negative	0.26	0.29	0.13	0.38	1									
6. MSSB Disorganized	0.62	0.52	0.51	0.58	0.40	1								
7. WSS Physical	-0.02	0.21	0.13	0.15	0.37	0.07	1							
8. WSS Social	0.36	0.50	0.27	0.38	0.72	0.44	0.47	1						
9. WSS Magical Ideation	0.67	0.29	0.42	0.74	0.26	0.49	0.05	0.21	1					
10. WSS Perceptual	0.20	0.06	0.00	0.44	0.42	0.29	0.25	0.47	0.28	1				
11. O-LIFE UE	0.75	0.55	0.54	0.76	0.36	0.72	0.14	0.44	0.65	0.27	1			
12. O-LIFE CD	0.57	0.61	0.64	0.46	0.14	0.73	0.16	0.36	0.39	0.17	0.66	1		
13. O-LIFE IA	0.20	0.36	0.23	0.07	0.50	0.31	0.42	0.57	0.12	0.24	0.22	0.31	1	
14. O-LIFE IN	0.40	0.25	0.29	0.34	0.35	0.53	0.12	0.29	0.29	0.36	0.51	0.42	0.19	1
15. PQ-B Total Distress	0.78	0.57	0.60	0.61	0.25	0.67	0.01	0.29	0.59	0.26	0.81	0.68	0.21	0.50

Figure 4

Symptom-Based Model Trail Plot



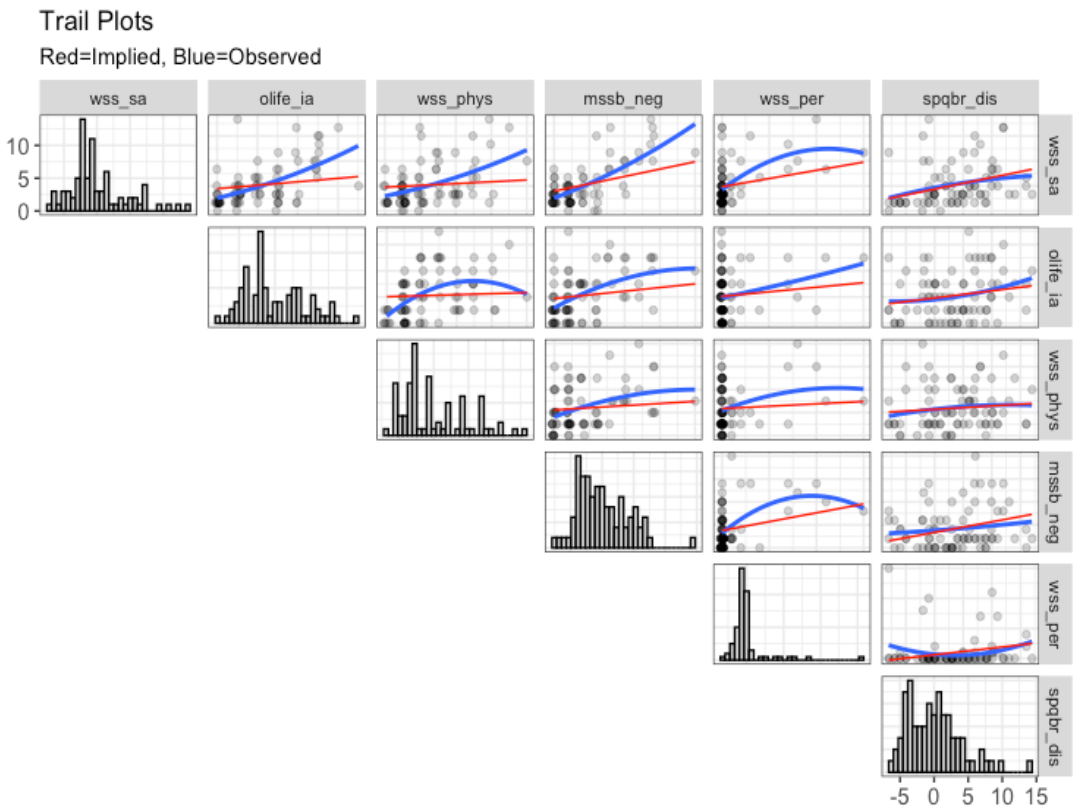
Note. Diagonals show the histograms of residuals for each variable. The red lines depict the SEM-implied fit between two variables, while the blue lines depict the regression line between those same two variables. The closer the SEM-implied red line is to the quadratic line, the better the proposed SEM model fits. The scatterplot matrices show the raw data.

For each trail plot, we chose to visualize the variables that showed the worst misfit. The symptom-based model struggled most to fit the correlations between the SPQ-

BR negative, SPQ-BR disorganized, SPQ-BR positive, O-LIFE unusual experiences, O-LIFE cognitive disorganization, and MSSB disorganized variables. The trail plots of these variables are shown in Figure 4. Notice that in nearly all cases, the model tended to underestimate the correlations between these variables. This suggests that, at least for SPQ-BR (as well as possibly the O-LIFE and MSSB), merely correlating the symptoms does not entirely account for correlations between the subscales.

Figure 5

Measure-Based Model Trail Plot



Note. Diagonals show the histograms of residuals for each variable. The red lines depict the SEM-implied fit between two variables, while the blue lines depict the quadratic line between those same two variables. The closer the SEM-implied red line is to the quadratic line, the better the proposed SEM model fits. The scatterplot matrices show the raw data.

The measure-based model struggled to reproduce correlations between O-LIFE introvertive anhedonia, WSS social anhedonia, MSSB negative, WSS physical anhedonia, WSS perceptual aberration, and SPQ-BR disorganized (see Figure 5). Notice how each of these subscales measure the "Negative" latent variable from the symptom-

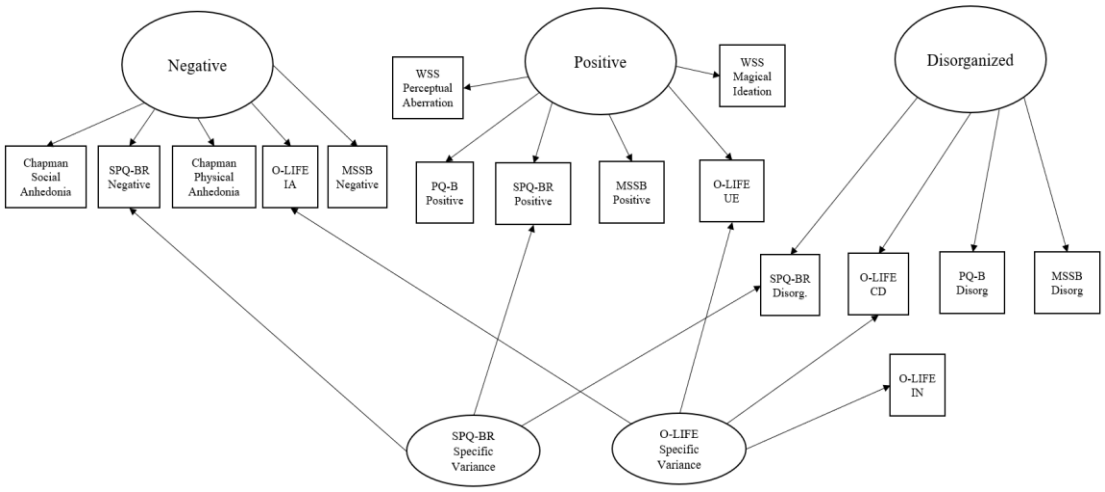
based model. This seems to suggest that a model based exclusively on the measure is inadequate: it misses important information shared *across* measures. Also, these plots seem to suggest that many of the subscales have nonlinear relationships (e.g., between WSS social anhedonia and WSS physical anhedonia) that are not adequately represented by a linear model.

These results seem to suggest that neither a symptom-based nor a measure-based model is adequate: the symptom-based model underestimated correlations *within* measures, while the symptom-based measure underestimated correlations *across* measures. It seems the best-fitting model will combine the strengths of both models.

To identify a modified model, we began by studying the residuals for the measure-based model. As noted previously, the correlations between various subscales were underestimated in the measure-based model (i.e., O-LIFE introvertive anhedonia, WSS social anhedonia, MSSB negative, and WSS physical anhedonia). Since each of these measure negative symptoms, we created an additional latent variable (called "Negative"), then refit the model. Once again, we studied the residuals, identifying which correlations the model failed to reproduce, and again modified the model in such a way that the model better captured the relationships. This process was repeated multiple times until the residuals were small and the visuals suggested agreement between the implied model and observed regression line.

Figure 6

Path Diagram of the Proposed Modified Model



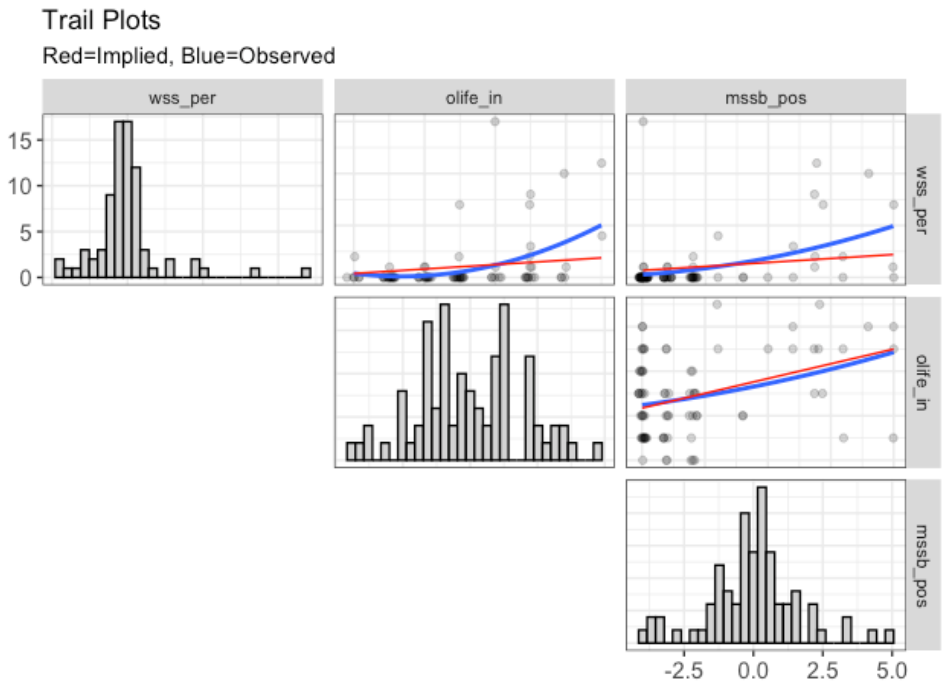
Note. Boxes represent observed variables, circles represent latent variables. The proposed modified model suggests a hybrid model, where subscales load onto symptom clusters as well as their overall measure in the case of the O-LIFE and SPQ-BR. It was assumed that all latent variables in the model were correlated with each other.

The final proposed modified model is shown in Figure 6. This model suggests that these measures all share three latent variables: Negative, Positive, and Disorganized. However, the SPQ-BR and O-LIFE capture additional information that is not captured by these latent variables. Figure 7 shows the trail plots of the three variables with the largest residuals (WSS perceptual aberration, O-LIFE impulsive nonconformity, and MSSB positive). In all cases, the observed slope (blue line) is quite similar to the model-implied slope (red line), though the model-implied slope tends to be more conservative, while the

observed slope seems to be more prone to influence from outliers (e.g., the WSS perceptual aberration and O-LIFE impulsive nonconformity relationship relationship). Also, the quadratic lines indicate the variables may have nonlinear relationships.

Figure 7

Modified Model Trail Plot



Note. Diagonals show the histograms of residuals for each variable. The red lines depict the SEM-implied fit between two variables, while the blue lines depict the quadratic line between those same two variables. The closer the SEM-implied red line is to the quadratic line, the better the proposed SEM model fits. The scatterplot matrices show the raw data.

A collection of fit indices for the measure-based, symptom-based, and modified models can be found in Table 4. Neither the symptom or measure-based model seems to fit well, at least by conventional rules of thumb (Hu & Bentler, 1998; though see Hayduk, 2014; McIntosh, 2007 for arguments against rules of thumb in SEM). Even the modified model appears to fit poorly (again, by conventional rules of thumb). The AIC and BIC appear to favor the symptom-based model over the modified model, however the RMSEA, SRMR, and CFI values favor the modified model. This would suggest that the modified model provides a stronger fit to the data at the expense of added model complexity. However, the best model combines aspects of both the symptom-based and measure-based models. (Granted, the modified model benefited from post-hoc modifications, while the other two models did not. As such, the fits associated with the modified model have an unfair advantage).

Table 4

Data Collection SEM Model Estimates and Fit Indices (n=78)

Fit Indicator	Symptom-Based Model	Measure-Based Model	Modified Model
RMSEA	0.15	0.17	0.12
SRMR	0.13	0.12	0.082
AIC	5832.92	6196.89	6083.40
BIC	5910.70	6295.87	6196.53
CFI	0.78	0.74	0.88

Table 5 shows the parameter estimates for the three models, with Figure 8 visualizing parameter factor loadings. With regards to the symptom-based model, the following subscales had factor loadings over 0.7: SPQ-BR positive, SPQ-BR disorganized, MSSB (all three subscales), O-LIFE unusual experiences, O-LIFE cognitive disorganization, WSS social anhedonia, WSS magical ideation, PQ-B positive, and PQ-B disorganized. Only two subscales had a factor loading of 0.5 or lower, WSS physical anhedonia and WSS perceptual aberration. For the measure-based model, the following subscales had factor loadings above 0.7: SPQ-BR (all three subscales), MSSB positive, MSSB disorganized, O-LIFE unusual experiences, O-LIFE cognitive disorganization, PQ-B positive, and PQ-B disorganized. Subscales with a factor loading of 0.5 or lower were as follows: MSSB negative, O-LIFE introvertive anhedonia, WSS perceptual aberration, and WSS physical anhedonia.

Looking at the modified model, subscales with a factor loading of above 0.7 included: SPQ-BR positive (when loading into the positive symptom variable), SPQ-BR negative (when loading onto the SPQ-BR variable), MSSB (all three subscales), O-LIFE cognitive disorganization (when loading onto the disorganized variable), WSS social anhedonia, WSS magical ideation, PQ-B positive, and PQ-B disorganized. The following subscales had a factor loading of 0.5 or less: SPQ-BR positive (when loading onto the SPQ-BR variable), SPQ-BR negative (when loading onto the SPQ-BR negative variable), SPQ-BR disorganized (when loading onto the disorganized variable), O-LIFE unusual experiences (when loading onto the positive variable), O-LIFE cognitive disorganization (when loading onto the O-LIFE variable), O-LIFE introvertive anhedonia (when loading

onto the O-LIFE variable), and WSS perceptual aberration. Taken together, these results suggest that neither of the original models is adequate: the symptom-based model has higher correlations within subscales than the model suggests, while the measure-based model underestimates correlations between subscales. In addition, both models show evidence of nonlinear effects. As a whole, our data collection analysis appears to favor a hybrid model, where each subscale loads onto a symptom cluster and two measures (SPQ-BR and O-LIFE) seemingly capture unique risk variance. Additionally, our analysis provides insight into which measures best tap into risk symptoms.

Figure 8

Factor Loadings for the Symptom-Based, Measure-Based, and Modified Models

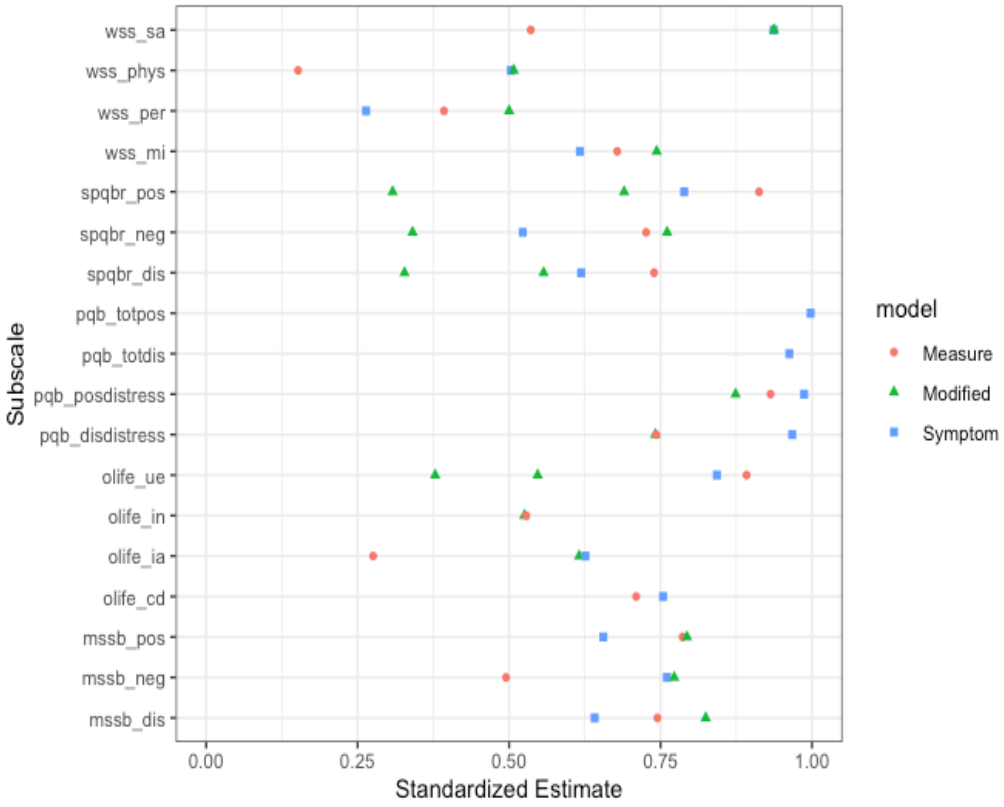


Table 5

Parameter Estimates of the Symptom-Based, Measure-Based, and Modified Models

Variable	Factor Loadings			Variance Explained		
	Symptom-	Measure-	Modified Model	Symptom-	Measure-	Modified
SPQ-BR Positive	0.85	0.91	0.33(SPQ)/0.81(Positive)	0.73	0.83	0.80
SPQ-BR Negative	0.53	0.73	0.77(SPQ)/0.36(Negative)	0.28	0.53	0.83
SPQ-BR Disorganized	0.71	0.74	0.52(SPQ)/0.36(Disorganized)	0.50	0.55	0.63
MSSB Positive	0.79	0.79	0.81	0.63	0.62	0.65
MSSB Negative	0.76	0.50	0.77	0.58	0.24	0.59
MSSB Disorganized	0.83	0.75	0.82	0.69	0.55	0.67
O-LIFE UE	0.93	0.89	0.64(O-LIFE)/0.28(Positive)	0.86	0.80	0.84
O-LIFE CD	0.86	0.71	-1.24(O-LIFE)/2.09(Disorganized)	0.74	0.50	0.98
O-LIFE IA	0.63	0.28	-0.08(O-LIFE)/0.67(Negative)	0.49	0.08	0.39
O-LIFE IN	N/A	0.53	0.52	N/A	0.28	0.27
WSS Perceptual	0.34	0.39	0.36	0.11	0.15	0.13
WSS Physical	0.50	0.15	0.51	0.25	0.02	0.26
WSS Social Anhedonia	0.93	0.54	0.93	0.83	0.29	0.87
WSS Magical Ideation	0.73	0.68	0.75	0.53	0.46	0.56
PQ-B Positive	0.87	0.93	0.87	0.76	0.87	0.75
PQ-B Disorganized	0.77	0.74	0.74	0.60	0.55	0.55

Chapter 5

Discussion

The schizophrenia-spectrum literature currently consists of many different theoretical camps conducting their own research separate of the others, much to the detriment of any chances for the field to become a cumulative science. This study examined the various measures of schizophrenia-spectrum risk used by these camps, as well as common correlates of schizophrenia-spectrum risk. This was accomplished via a quantitative literature review (QLR) as well as data collection.

There were two primary goals for this study. The first was to identify whether the various risk frameworks can be synthesized into one cohesive schizophrenia risk conceptualization. The second was to evaluate whether our QLR methodology would be able to estimate intercorrelations in the presence of a large quantity of missing correlations. We largely accomplished our first goal, with our analyses suggesting that it may be fruitful to condense some of the various schizophrenia-spectrum measures. With regards to our second goal, it is evident that our QLR methodology will not successfully estimate intercorrelations when confronted with a large amount of missing data. Implications for the schizophrenia-spectrum literature and quantitative literature are discussed in greater detail in the following paragraphs.

The present study found slight support in favor of a symptom-based model (where subscales of risk measures were proposed to load onto positive, negative, or disorganized symptoms) compared to a measure-based model (which proposed that each risk measure captured a unique element of overall risk). However, neither symptom nor measure-based

models were adequate. A modified model, a hybrid model of sorts between the symptom and measure-based models, provided the strongest fit of either of the three models to our data, although at the price of added complexity in comparison to the symptom-based model. Within this model, along with the symptom clusters, the SPQ-BR and O-LIFE emerged as unique latent variables.

Our findings would appear to provide support to a movement towards consolidating the various risk conceptualizations and accompanying measures employed in the literature, as many of these differing measures do not appear to be capturing unique variance. Based on our analysis, the SPQ-BR and O-LIFE are measures which capture some unique element of risk variance, with the subscales of other measures loading onto positive, negative, or disorganized symptoms. Measures included in this study such as the WSS and MSSB may be candidate measures for future consolidation as they do not appear to capture unique risk variance, although it should be noted that with an increased sample size more measures may have been found to account for unique variance. Based on factor loadings and variance explained metrics, the PQ-B, unusual experiences, and cognitive disorganization subscales of the O-LIFE, as well as the negative subscale of the MSSB are particularly promising measures of schizophrenia-spectrum risk symptom clusters (e.g., positive, negative, and disorganized) to consider in any future consolidation.

Of note, the present study found a trend in many of the risk measures. When visualized, the relationships in the data were frequently curvilinear in nature, increasing steadily until a threshold of sorts is reached, whereupon the relationship increases at a steeper rate (see Figures 5 and 6 for examples). This may provide further support towards

conceptualizing schizophrenia and schizophrenia risk as lying on a spectrum, where most of the population experience some level of risk symptoms but only a subset may experience schizotypy and even fewer experience schizophrenia (APA, 2013; Lenzenweger, 2006a; Meehl, 1962). Alternatively, the curvilinearity may be an artifact of distributional properties such as a floor effect in our data. These two explanations could be re-examined in future research.

With regards to our proposed quantitative literature review (QLR) methodology, the present study revealed grave limitations in the methodology when confronted with significant missing data. When estimates between variables of researcher interest are sparse in the literature, models produced by the QLR will frequently fail to converge. In instances where the models do converge, the models will likely produce estimates spanning the entire range of potential estimates, which are of minimal utility to researchers. This represents a significant obstacle for attempts at consolidating the archival risk literature. One potential solution for this may be to identify clusters, or portions, of the entire model of interest that can be fit and informative, rather than attempting to fit the entire model. This approach could allow researchers to use the QLR methodology as intended, integrating archival information regarding risk measures and risk correlates while attempting to consolidate the risk literature.

Perhaps the most straightforward approach to addressing this as a field is to more frequently include multiple measures of risk in the same study. When this is done, researchers should report the bivariate relationships between those measures and/or make their dataset publicly available for other researchers in an effort to foster a consolidated, cumulative science. These efforts may aid the field in building a cumulative science.

Hopefully, once more evidence has been gathered (both from our efforts as well as efforts of other researchers), we will have gathered enough evidence to form a comprehensive view of schizophrenia risk. Subsequently, *one* measure may be developed that adequately taps all relevant dimensions of schizophrenia without overlap. The importance of a consolidated, cumulative risk literature cannot be overstated. To reiterate the sentiment expressed by Henriques (2003), psychology cannot reach maturity as a science without shared theoretical underpinnings. The schizophrenia-spectrum area of research is no different, as currently the many different camps of risk research pull in separate directions instead of together. While consolidation is not without its risks, such as the potential for consolidation to oversimplify our understanding and assessment of risk, our study appears to provide initial support in favor of consolidation.

Limitations

One major limitation of the present study is the sample. Our sample was predominantly white and exclusively contained college students, potentially limiting generalizability. That being said, college student samples can be useful for risk research as the "typical" college student falls within an age range where development of schizophrenia-spectrum symptoms is relatively common (NIMH, 2018). Additionally, our small sample size (78 for the SEM analyses) may have impacted our ability to pick up on notable trends in our data. As noted by (Kline, 2016 p. 14-16), to be adequately powered SEM analyses typically require sample upwards of 200 participants or 20 participants per parameter estimated.

An additional limitation of the present study was the inability to include the UHR and CHR conceptualizations of risk in our analysis due to poor follow-up rates. This

limitation was partially mitigated by the presence of the PQ-B in our study, a measure commonly used to screen for individuals who may meet UHR/CHR risk criteria (Loewy et al., 2011).

Future Research

A seemingly obvious target for future research will be to successfully collect SIPS data within the same dataset as other measures of risk, allowing for a more complete comparison of the schizophrenia-spectrum risk conceptualizations. Additional future research may seek to develop a novel risk measure (or set of measures) that consolidates many of the risk measures evaluated in this study in an optimal way. This may take the form of a factor analysis on item level data from a dataset where researchers administer numerous risk measures to a large sample and identify the most consistently predictive items. Such an undertaking may be considered "carving nature at its joints" (Meehl, 1999, p. 1) in an attempt to identify groupings of items which consistently predict risk for developing a schizophrenia-spectrum disorder. As part of this undertaking, data on risk correlates (e.g., QOL, stress, social functioning, etc.) may be collected to aid researchers in understanding how measures of risk differentially correlate with various spheres of daily functioning. This information may be important when attempting to consolidate the risk literature in the form of developing a new risk measure. For example, researchers may be interested in developing a risk measure that strongly correlates with a worse QOL or greater impairment in social functioning.

An optimally consolidated risk measure may allow researchers from various risk camps to consolidate their efforts and contribute to the building of a cumulative risk literature. The most important potential byproduct of a novel, optimally consolidated risk

measure would be an improved ability to detect those at risk for developing schizophrenia-spectrum symptomology and allow for targeted prevention efforts. Such a measure would likely have to be studied longitudinally to properly evaluate its effectiveness at risk identification relative to other measures.

Conclusions

The schizophrenia-spectrum literature is currently divided into different theoretical camps, potentially hampering any effort to build a cumulative science in this area and ultimately harming prevention efforts. Our data indicate that many of the schizophrenia-spectrum risk measures load onto latent variables organized by symptom cluster, suggesting the potential for consolidation to take place without a meaningful loss in measuring schizophrenia-spectrum risk. According to our analysis, the only measures which captured unique variance were the SPQ-BR and O-LIFE, although future studies which include a greater quantity of measures and utilize a larger sample may identify more such measures. While much work remains to be done to consolidate the risk literature effectively, this study offers an initial glimpse into a potential consolidation. Future research may examine item-level data using factor analysis to develop a new risk measure which integrates items from previous measures. Once developed, this measure should be evaluated longitudinally to evaluate its effectiveness in accurately and reliability predicting who is at risk for transitioning to a schizophrenia-spectrum disorder, as well as establish that the measure has longitudinal invariance (meaning a stable factor structure over time).

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Appendix

List and Description of Studies Included in QLR

Study	Sampl	Sample Characteristics	Variables Included
Kwapil et al., 2020	9,366	College students	MSS
Herzig et al., 2013	58	College students	O-LIFE, Stress
Wuthrich et al., 2006	277	College students	SPQ, Chapman scales
Gross et al., 2018*	1,430	College students, MTurk	MSSB, SPQ-B
Gross et al., 2018*	1,289	College students, MTurk	MSSB, SPQ-B
Abbott et al., 2012	139	College students	SPQ, QOL
Henry et al., 2008	223	Community volunteers, college students	SPQ, SF
Alexopoulos et al., 2014	201	Greek police officers	QOL, Stress
Panayiotou et al., 2013	326	Greek adults	QOL, Stress
Delgado, 2007	181	People with COPD	QOL, Stress
Cicero et al., 2014	160	College students at psychometric risk	Chapman scales
Meyer, 2001	70	Inpatient psychiatric unit patients	QOL, SF
Lin et al., 2013	228	Help-seeking research participants	QOL, O-LIFE
Cohen et al., 2009	1395	College students	QOL, SPQ
McCleery et al., 2012	50	College students	QOL, O-LIFE
Barragan et al., 2011	72	Adolescents in Spain	O-LIFE
Cicero et al., 2010	295	College students	Chapman scales
Lewandowski et al., 2006	1254	College students	Chapman scales
Batey et al., 2008	140	College students	O-LIFE
Rawlings et al., 2001	100	College students	O-LIFE
Premkumar et al., 2018	318	Primarily college students	O-LIFE, QOL

*Note. * denotes a study which included multiple samples.*