DISSERTATION

LONGITUDINAL PANEL NETWORKS OF RISK AND PROTECTIVE FACTORS IN YOUTH SUICIDALITY

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ABSTRACT

LONGITUDINAL PANEL NETWORKS OF RISK AND PROTECTIVE FACTORS IN YOUTH SUICIDALITY

Rates of suicidal thoughts and behaviors (STBs) are increasing among youth in the United States. Younger age at onset for STBs confers higher vulnerability to lifetime mental health concerns, yet relatively few studies have investigated STBs during the critical developmental period as youth transition from childhood into early adolescence. Several domains of risk and protective factors have been identified, however accurate prediction of STBs remains poor. Network analyses that can examine pairwise associations between many variables may provide information about complex pathways of risk for STBs, thereby improving the timing and targets of interventions. The present study applied a longitudinal panel network approach to elucidate potential risk and protective pathways for STBs across early adolescence. Data came from 9,854 youth who participated in the population-based Adolescent Brain Cognitive Development Study (M_{age} = 9.90 ± .62 years, 63% white, 53% female at baseline). Youth and their caregivers completed an annual measurement battery from when participants were ages 9-10 through 11-12 years (i.e., three timepoints). 1,699 youth reported past or present STBs at one or more study timepoints. Panel Graphical Vector Autoregressive models evaluated temporal within-person, contemporaneous within-person, and between-person relations between several previously identified risk and protective factors for youth STBs, including mental health symptoms, socioenvironmental factors, life stressors, and substance use. An autoregressive effect was observed for STBs in the temporal network. In the contemporaneous and between-subjects networks, STBs had consistent direct associations with internalizing symptoms, low-level substance use, family conflict, lower parental monitoring, and lower school protective factors. Possible indirect pathways were also observed, in which other mental health symptoms and stressful life events might contribute to STBs through internalizing. Results emphasize that family and school experiences are salient social risk factors for early adolescents. Age-specific interventions may benefit from prioritizing targeting internalizing symptoms and early substance use, as well as promoting positive school and family support. Results support the use of longitudinal network approaches to understand the complex interplay between STBs and different domains of risk and protective factors.

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TABLE OF CONTENTS

INTRODUCTION

Suicidal Thoughts and Behaviors Among Youth

Suicidal thoughts and behaviors (STBs) are a prominent public health concern among youth worldwide, and especially in the United States (National Institutes of Mental Health, 2023). Suicide is the second-leading cause of death among individuals aged 10-14 and 15-24 years (National Institutes of Mental Health, 2023), and the prevalence of youth STBs has increased in the past decade (Centers for Disease Control and Prevention, 2023). The rate of high school students in the United States who reported having attempted suicide increased from 8.0% to 10.0% between 2011-2021 (Centers for Disease Control and Prevention, 2023). Further, rates of death by suicide among adolescents (ages 15-19) alarmingly increased by 29% between 2014 and 2020, from 8.4 to 10.8 deaths per 100,000 individuals (United Health Foundation, 2023). STBs occur on a spectrum of severity, including passive suicidal ideation (e.g., thinking "it would be easier if I weren't here"), active suicidal ideation (e.g., thoughts about method, plan, and intent for suicide), non-lethal suicide attempts, and death by suicide (Harmer et al., 2021; Klonsky et al., 2016; Nock, 2012; Obegi et al., 2015). STBs are distinct from non-suicidal self-injury (NSSI), which is an associated behavior that does not involve intent to die (Nock, 2010). In addition to risk of death by suicide, individuals who experience STBs have reported greater overall distress compared to individuals without STBs, including those who also experienced psychopathology (Nyer et al., 2013; Stanley et al., 2018). STBs in childhood and adolescence may also have bidirectional associations with psychopathology, behavioral concerns, and poorer overall functioning that can persist into adulthood (Brunstein Klomek et al., 2019; Copeland et al., 2017; Herba et al., 2007; Reinherz et al., 2006).

STB presentations and risk profiles appear to vary across developmental stages (Goldston et al., 2009; Ong et al., 2021). This may be due to impacts of brain development, including changes in social cognition over time (Foulkes & Blakemore, 2018) and the dyssynchronous development of the cortical and limbic systems (de Sousa et al., 2017), or differences in salient experiences for children of different ages (Cha et al., 2018). Most youth STB research to date has utilized samples with participants aged 13-18, but rates of STBs begin to increase after approximately age 10 (Nock et al., 2013). Although recent studies have specifically investigated childhood STBs (DeVille et al., 2020; e.g., Harman et al., 2021; Janiri et al., 2020; Raffagnato et al., 2022), there is still a relative paucity of studies on STBs in early adolescence (ages 10-13) compared to older age groups (Ayer et al., 2020; de Sousa et al., 2017). Younger age at onset for STBs has importantly predicted increased vulnerability to subsequent severe suicidality and negative mental health outcomes (e.g., Thompson et al., 2012). Thus, improving understanding of risk for STBs in early adolescence could inform prevention and early intervention efforts that could have protective impacts across the lifespan (Cha et al., 2018; Copeland et al., 2017; Reinherz et al., 2006).

Risk and Protective Factors for Youth STBs

Thousands of studies have investigated risk and protective factors for youth STBs. See reviews by Fazel and Runeson (2020), Franklin et al. (2017), and Turecki and Brent (2016) for thorough discussions of previously identified correlates of STBs in general, and Carballo et al. (2020), Cha et al. (2018), and de Sousa et al. (2017) for reviews of STB correlates among youth specifically. For the purpose of this study, correlates are defined as constructs that have previously demonstrated salient associations with STBs. Within correlates, risk factors are constructs that have been found to precede and positively relate to STBs, while protective factors are constructs that precede and negatively relate to STBs. In alignment with the social-ecological perspective, salient risk and protective factors for suicidality have been identified from multiple life domains (Cramer & Kapusta, 2017). Mental health difficulties, socioenvironmental factors, life stressors, and substance use are among the most common domains of correlates of youth STBs (Carballo et al., 2020; Cha et al., 2018; de Sousa et al., 2017). Thus, it is valuable for researchers to consider constructs from each of these life domains to comprehensively understand risk for STBs (Cramer & Kapusta, 2017).

Mental health symptoms are among the most robust correlates of STBs. Depressive and other internalizing symptoms (e.g., anxiety, hopelessness, anhedonia, negative cognitions) are considered core risk factors for STBs across age groups (Carballo et al., 2020; Cha et al., 2018). However, STBs are a transdiagnostic feature of several mental health concerns, and STBs have also been associated with externalizing, attention, thought, social, and other mental health symptoms (American Psychiatric Association, 2013). Socioenvironmental factors have also been identified as robust correlates of STBs. During early adolescence, family and school environment factors appear to be the most important socioenvironmental correlates of STBs, with lower family conflict, higher parental monitoring, and school engagement and support protecting against STBs (Carballo et al., 2020; Cha et al., 2018; de Sousa et al., 2017; Fotti et al., 2006; Janiri et al., 2020; Miller et al., 2015; Sedgwick et al., 2019). Peer and friendship factors appear to become more important as youth transition into adolescence (Telzer et al., 2018).

Adverse life events, such as child maltreatment, trauma and stressful events, poverty and material hardship, exposure to neighborhood crime and/or violence, and bullying, have been identified as experiences that often precede STBs (e.g., Cha et al., 2018; King et al., 2001; Pan & Spittal, 2013). Additionally, adolescent substance use has been frequently identified as a risk factor for youth STBs (see review by Carballo et al. (2020)). STBs are also more prevalent among certain social identities and demographic groups. For example, gender and sexual minority youth report higher rates of STBs than youth who identify as cisgender and/or heterosexual, and American Indian, Aboriginal, and Alaska Native youth report higher rates of STBs than other racial and ethnic groups (Cha et al., 2018). The intersection of multiple non-dominant identities can also increase risk for STBs (Assari et al., 2021; Standley, 2020).

Challenges in Studying Suicidal Thoughts and Behaviors

Despite the large number of studies investigating STBs, the etiological mechanisms underlying STBs continue to be unclear (Cha et al., 2018), and accurate prediction of STBs remains poor (Belsher et al., 2019; Franklin et al., 2017; Millner et al., 2020). This may be related to constraints of common study designs in psychiatric research that can obfuscate important information, including cross-sectional data (Cha et al., 2018; Guzmán et al., 2019), case-control frameworks (Caspi et al., 2020), only examining a limited number of variables (Dwyer et al., 2018; Linthicum et al., 2019), and use of predictive models that cannot account for dynamic relations between many risk and protective factors (de Beurs, 2017). In alignment with the developmental psychopathology perspective, not all individuals who experience STBs have the same risk factors (i.e., equifinality), and not all individuals with the same risk factors experience STBs (i.e., multifinality) (Cicchetti & Rogosch, 1996). For example, while depression is a salient correlate, only a subset of individuals with depression experience STBs (e.g., Nyer et al., 2013). STBs appear to result not from one or a few predisposing factors, but from complex interactions between many risk and protective factors (Carballo et al., 2020; Cha et al., 2018; de Beurs, 2017; Fazel & Runeson, 2020; Millner et al., 2020).

Given this complexity, data-driven approaches that can account for high-dimensional data have been increasingly employed in STB research. In particular, machine learning has been used in numerous recent STB studies (see reviews by Burke et al., 2019; McHugh & Large, 2020). Machine learning studies on mental health are often centered on the argument that highly complex phenomena, such as STBs, can be better predicted by models that can handle a larger number of variables than traditional *a priori* models (Burke et al., 2019; Linthicum et al., 2019; Su et al., 2020). Machine learning approaches have successfully identified novel predictors of STBs and may be useful for identifying unique predictors among certain high-risk populations (e.g., García de la Garza et al., 2021; Wallace et al., 2021). However, thus far, machine learning models do not appear to outperform traditional statistical analyses in their predictive utility for STBs (Brunstein Klomek et al., 2019; Fazel & O'Reilly, 2020; Jacobucci et al., 2021; McHugh & Large, 2020), and their accuracy in predicting future suicidal behaviors has been very low (Belsher et al., 2019). Machine learning predictive models also provide little information about the causal mechanisms by which risk and protective factors may contribute to STBs. Thus, while there is need to account for many potential risk and protective factors, additional studies that simply identify salient correlates are unlikely to elucidate the pathogenesis of STBs (Fazel & O'Reilly, 2020).

Transdiagnostic and Temporal Features of Mental Health Phenomena

Much of the existing research on mental health etiology has attempted to identify distinct factors that increase risk for distinct outcomes (Kendler, 2019). However, the search for unique risk and protective factors for different mental health concerns has remained elusive (Kendler, 2019). For example, STBs share correlates with substance misuse, disordered eating, and many psychiatric disorders (e.g., Conway, Mansolf, et al., 2019; Logan et al., 2020; Smith et al., 2018).

This lack of causal specificity for different mental health phenomena is likely related to transdiagnostic processes and dynamic changes in mental health phenomena over time (Caspi et al., 2020). Transdiagnostic, shared risk processes underlie many mental health concerns, and this has been extensively studied through the Research Domain Criteria (RDoC) and Hierarchical Taxonomy of Psychopathology (HiTOP) frameworks (Conway, Forbes, et al., 2019; Cuthbert, 2014; Cuthbert & Insel, 2013; Hyman, 2019; Kotov et al., 2017; Krueger & Eaton, 2015; Michelini et al., 2021). For example, negative cognitions and difficulties with emotion regulation are common features of many psychiatric disorders (Cludius et al., 2020; McEvoy et al., 2019). Further, early life stressors appear to increase risk for many types of mental health concerns; specific types of stress have not been uniquely associated with the development of specific mental health concerns (e.g., McMahon et al., 2003). STBs are associated with numerous types of psychiatric symptoms and health-risk behaviors (American Psychiatric Association, 2013; Nock et al., 2009; Turecki & Brent, 2016), suggesting STBs may be a transdiagnostic risk factor for and/or a result of a wide range of mental health concerns.

Moreover, many individuals who experience one type of mental health concern are likely to experience additional mental health concerns, either co-occurring at the same time (i.e., comorbidity) or at different points in their life (Caspi et al., 2020; Kotov et al., 2017; Plana-Ripoll et al., 2019). Recent landmark studies have demonstrated that individuals often shift between internalizing, externalizing, and thought disorder symptoms across the life-course, and the presence of one type of mental health concern at one timepoint increases risk for the presence of any other type of mental health concern at a later timepoint (Caspi et al., 2020; Plana-Ripoll et al., 2019). Similarly, individuals who present with STBs often also present with comorbid, previous, and/or subsequent health-risk behaviors and psychopathology (Nock et al., 2009; e.g., Ortiz & Smith, 2020; Sellers et al., 2021; Turecki & Brent, 2016; Yuodelis-Flores & Ries, 2015). Cross-sectional designs that only consider one timepoint may therefore conceal important information about individuals' lived experiences of comorbid and shifting mental health concerns (Caspi et al., 2020; Plana-Ripoll et al., 2019). Indeed, many researchers have suggested that the continued use of cross-sectional designs has diminishing returns for mental health research (e.g., Wilson & Olino, 2021).

Within longitudinal frameworks, additional considerations apply to STB and mental health research. Longitudinal effects can be conceptualized as between-person, evaluating how relations between variables vary over time *across* individuals, or within-person, evaluating how relations between variables may fluctuate over time *within* an individual (Curran & Bauer, 2011). Longitudinal life-course studies indicate heterogeneity, in which trajectories of mental health presentations are often highly unique to individual participants (e.g., Caspi et al., 2020). It is therefore beneficial to account for both between- and within-person effects in longitudinal mental health research (e.g., Hamaker et al., 2015), but relatively few longitudinal studies of youth STBs have employed multi-level designs that can evaluate within-person effects (e.g., Miller et al., 2017). Taken together, studies on transdiagnostic and comorbid features of mental health phenomena suggest that STBs should be studied in the context of other mental health constructs and within a longitudinal framework that can account for both temporal and within-person effects (Conway, Forbes, et al., 2019; Ram & Diehl, 2014).

Network Approach to Psychopathology

Modern research approaches to conceptualizing mental health provide a valuable framework for addressing the aforementioned methodological challenges to studying STBs. Traditional nosology (i.e., diagnostic classification) systems for mental health, such as the

Diagnostic and Statistical Manual of Mental Disorders (DSM) and International Classification of Diseases (ICD) (American Psychiatric Association, 2013; World Health Organization, 2004), conceptualize mental health phenomena as categorical diseases (Borsboom, 2017; Conway, Forbes, et al., 2019; Kotov et al., 2017; Lin & Eaton, 2020). These systems classify mental health concerns into discrete categories of diagnoses, and the presence of a specific diagnosis often guides the specific treatment plan. Diagnostic criteria are typically met when an individual has a certain number of symptoms for a certain length of time and/or severity; the specific symptoms involved are generally interchangeable as long as the required number of symptoms is met (American Psychiatric Association, 2013; Lin & Eaton, 2020; World Health Organization, 2004). For example, suicidality is one of nine listed symptoms for Major Depressive Disorder, and individuals meet criteria for this diagnosis if they endorse five or more of these symptoms (American Psychiatric Association, 2013). Thus, categorical systems create a dichotomous boundary between normal and abnormal mental health. While diagnostic categories are convenient for treatment planning, medical billing, and research designs (e.g., case-control studies) (Lin & Eaton, 2020), the cut-off criteria for mental health diagnoses were created somewhat arbitrarily and often without robust supporting research evidence (Kendler, 2012; Kotov et al., 2017; Lin & Eaton, 2020).

Recent quantitative research on the structure of psychopathology provides limited support for categorical diagnostic systems (Conway, Forbes, et al., 2019; Forbes et al., 2021; Kendler, 2012; Kotov et al., 2017; Ruggero et al., 2019; The HiTOP Neurobiological Foundations Workgroup et al., 2020). Instead of being categorical, mental health phenomena appear to exist on a continuum from normal to atypical functioning, and mental health phenomena can shift over time (Conway, Mansolf, et al., 2019; Kotov et al., 2017; Ruggero et al., 2019). By making symptoms interchangeable, diagnoses that rely on symptom checklists conceptualize mental health concerns as latent constructs, in which all the pertinent symptoms are caused by a shared underlying mechanism (i.e., an underlying disease). Many medical diagnoses have specific and identifiable causes, such as a viral infection causing a specific constellation of symptoms. However, most mental health concerns do not appear to have unique and single-origin causes (Borsboom, 2017; Kendler, 2019; Kendler et al., 2011). As discussed previously, comorbidity and transdiagnostic processes are abundant across mental health concerns, and mental health outcomes appear to result from dynamic interactions between numerous factors. While it can still be important to account for underlying latent structures among symptoms (Bringmann & Eronen, 2018; Hallquist et al., 2021), mental health phenomena may be better conceptualized as manifestations of complex relations between symptoms (Bringmann, 2021).

The network approach to psychopathology, also called the psychosystems approach, posits that instead of resulting from *one shared cause*, mental health symptoms may have causal relations *with each other* (Borsboom, 2017; Fried et al., 2017). Thus, the network approach to psychopathology conceptualizes mental health phenomena as interactive and dynamic systems of psychological factors. For example, within depressive symptoms, sleep difficulties may contribute to fatigue, which may activate feelings of inadequacy, leading to ruminating thoughts, negative mood, and suicidal ideation, which may further exacerbate sleep difficulties, creating a self-perpetuating system of symptoms (Borsboom, 2017; Fried et al., 2017). These feedback loops between symptoms may cause individuals to shift between levels of normal and abnormal functioning, and to sometimes become trapped in a state of highly activated symptoms (Borsboom, 2017; Dablander et al., 2020). Network models allow for empirical estimation of interactive systems of psychological factors (Fried et al., 2017), which may identify early warning signs that an individual is starting to shift into instability and distress (Dablander et al., 2020). While network models are not causal (i.e., mediation is not explicitly tested), they can be used to generate causal hypotheses about complex interrelations between several variables of interest (Borsboom & Cramer, 2013).

The network approach is based on graph theory, in which psychological variables represent *nodes*, and the pairwise connections between all of the nodes (i.e., the association between each pair of variables) represent *edges* (Menczer et al., 2020). The strength of the edge between two nodes indicates the strength of the association between those variables. The network structure can be visualized graphically and statistically analyzed to identify patterns among the nodes (Epskamp et al., 2018; Hevey, 2018; Menczer et al., 2020). This can identify nodes that are highly or sparsely associated with the other nodes in the network (Epskamp et al., 2018; Menczer et al., 2020). For example, certain nodes may have strong connections with many other nodes, suggesting they may have the ability to activate the network as a whole. Other nodes may have only a few connections with other nodes and may peripherally influence or be influenced by the network (Borgatti, 2005).

While the network approach to psychopathology is relatively recent (Borgatti, 2005), network science has been extensively employed in other behavioral disciplines, such as social network analysis. All network analyses rely on graph theory, but the network approach to psychopathology is unique from many other common applications of network modeling. In most other network approaches, nodes are distinct entities (e.g., people) and edges between nodes are *observed* (e.g., the reported strength of an interpersonal relationship) (Menczer et al., 2020). In contrast, nodes in psychopathology networks represent constructs and the edges between them need to be *estimated* (e.g., the correlation between two constructs) (Epskamp et al., 2018). Thus, methodologies for the network approach to psychopathology are often distinct from the techniques used in other, related disciplines.

The network approach to psychopathology may help to bridge the gap between clinical research and practice. Clinical case conceptualizations in many therapy modalities (e.g., Cognitive Behavioral Therapy) generally consider dynamic interactions between many variables in a client's life that may contribute to their presenting concern(s); case conceptualizations for individual clients are essentially networks (Lin & Eaton, 2020). Integrating this approach into clinical research may better capture the complexity of individuals' lived experiences by accounting for the interplay between numerous factors (Lin & Eaton, 2020). Further, psychological networks may shed light on the comorbid and transdiagnostic nature of mental health phenomena (Boschloo et al., 2015; Cramer et al., 2010; Fried et al., 2017).

Most network studies to date have primarily focused on specific domains of mental health symptoms (e.g., networks of depression symptoms) (Borsboom, 2017; Boschloo et al., 2015; Contreras et al., 2019), and have less commonly been expanded to include other domains of constructs, such as socioenvironmental and behavioral factors (e.g., Contreras et al., 2019; Hevey, 2018). Accounting for many domains of risk and protective factors in addition to mental health symptoms could provide a more global understanding of the complex systems underlying mental health presentations (Goh & Martel, 2021; Lunansky et al., 2021). Further, longitudinal network designs may provide important information about how systems of symptoms and associated correlates shift between levels of normal and abnormal functioning over time (Borsboom, 2017; Dablander et al., 2020; Funkhouser et al., 2021; Goh & Martel, 2021; Jordan et al., 2020). Longitudinal network analysis techniques have recently become more accessible than in the past (Jordan et al., 2020). Nonetheless, most network studies to date have utilized cross-sectional designs, and a relatively small (though increasing) number of studies have accounted for temporal and within-person effects (e.g., Briganti et al., 2021; Bringmann, 2021; Funkhouser et al., 2021; Goh & Martel, 2021; Kroeze et al., 2017; O'Driscoll et al., 2022).

Approaching the study of STBs from a network perspective, in which multiple factors are examined as causal interactive systems, may elucidate complex risk and protective pathways (de Beurs, 2017). Specifically, the network approach may help to map the relations between previously identified risk and protective factors (de Beurs, 2017; Shiratori et al., 2014). Previous studies have applied network approaches to the study of STBs. These studies have generally focused on STBs' relations with psychological constructs, including mental health symptoms and cognitive and emotional experiences (Bloch-Elkouby et al., 2020; Fonseca-Pedrero et al., 2020; e.g., Gijzen et al., 2021; Rath et al., 2019). However, a small number of network analysis studies have examined broader sets of risk and protective factors for STBs.

An important 2014 study used network analysis to examine a wide range of psychological and socioenvironmental variables among a sample of primarily adult suicide victims in Japan (Shiratori et al., 2014). This study identified depressive symptoms, physical illness, family conflicts, and financial stress as central motives for suicide and indicated these constructs may uniquely influence broader systems of risk and protective factors for suicide (Shiratori et al., 2014). Other studies have similarly used network analysis to evaluate relations between suicidal ideation and several psychiatric symptoms and socioenvironmental risk factors in samples of combat veterans (Graziano et al., 2021; Simons et al., 2020). In these studies, STBs were included as nodes in the network and demonstrated strongest positive associations with depressive symptoms, anger, childhood trauma, substance misuse, and post-traumatic stress symptoms (Graziano et al., 2021; Simons et al., 2020). In another recent study on adults during the COVID-19 pandemic lockdown, psychological symptoms, loneliness and quality of relationships were also associated with suicidality (Delgadillo et al., 2023). Results from these studies substantiate that STBs involve complex systems of risk and protective factors (Graziano et al., 2021; Shiratori et al., 2014). However, these studies utilized adult samples, and their cross-sectional designs precluded evaluating how systems of correlates changed over time to influence risk for STBs.

Among early adolescents specifically, a recent innovative study evaluated temporal associations between psychological risk factors and suicidality in a Chinese sample of youth ages 9-15 years (Li & Kwok, 2023). These authors found that subjective happiness and hopelessness (moderated by self-efficacy) were prospectively associated with STBs at the subsequent timepoint (Li & Kwok, 2023). Nonetheless, this study had two measurement occasions, preventing examination of within-person and stable temporal effects, and did not evaluate risk and protective factors other than psychological constructs. To my knowledge, no previous studies have employed network analyses to investigate how mental health symptoms, socioenvironmental factors, stressors, and substance use relate to STBs among early adolescents at within- and between-person levels. Additionally, to my knowledge, no previous research has examined networks of risk and protective pathways for suicidality across the developmental transition from childhood into early adolescence (ages 9-12 years).

Present Study

The present study applied a network lens to the investigation of risk for STBs in early adolescence. Longitudinal panel network analyses were used to examine pairwise relations between several previously identified correlates of STBs among youth followed from ages 9-10 to 11-12 years. Thus, the present study aimed to extend the network approach to psychopathology to increase understanding of early onset STBs. Data came from the Adolescent Brain Cognitive Development (ABCD) study, a longitudinal population-based study of approximately 12,000 youth in the United States. The ABCD study aims to examine the development of risk for health and behavioral concerns across adolescence (Auchter et al., 2018; Garavan et al., 2018; Karcher & Barch, 2021). It includes wide-ranging and multimodal measures of health-related phenomena, including numerous previously identified correlates of STBs. Presently in its fifth year of data collection, the same cohort will be followed longitudinally for ten years, from ages 9-10 to 19-20 years. The large population-based sample of early adolescents, breadth of measures available, and longitudinal design make the ABCD data well-suited to answer the present research questions (Karcher & Barch, 2021).

The overall goal of the present study was to examine how risk and protective factors from multiple life domains relate to each other and to STBs during the transitional period from childhood into early adolescence. All the constructs examined in network models have been robustly identified as risk and protective factors for STBs by previous literature, including mental health symptoms (internalizing, externalizing, attention problems, social problems, thought problems, and sleep problems), socioenvironmental factors (family conflict, parental monitoring, and school protective factors), stressors (stressful life events, material hardship, and neighborhood safety), and low-level substance use (e.g., Carballo et al., 2020; Cha et al., 2018; de Sousa et al., 2017). Moreover, several of these constructs have been identified as risk and protective factors for STBs in cross-sectional studies of the ABCD sample specifically, including youth psychopathology (DeVille et al., 2020; Harman et al., 2021; Janiri et al., 2020; van Velzen et al., 2021), family conflict (DeVille et al., 2020; Janiri et al., 2020), lower parental monitoring (DeVille et al., 2020; Janiri et al., 2020), and higher school involvement (Janiri et al., 2020).

These studies bolster confidence in the risk and protective factors' theoretical relevance to the present study. Analyses investigated both within- and between-person effects to evaluate how the structure of relations between STBs and the risk and protective factors changed over time across the entire sample, as well as how these relations varied within individuals. Thus, analyses accounted for potential heterogeneity in the relations between STBs the other constructs in the networks.

While previous research has examined the study variables in various multivariate frameworks (Lehman et al., 2017), network structures of STBs and the risk and protective factors are unknown, and the network approach to psychopathology is largely data-driven (Borsboom, 2017; Contreras et al., 2019; Fried et al., 2017). Therefore, I did not propose detailed hypotheses about pairwise relations between specific study variables. I expected higher levels of mental health symptoms, socioenvironmental and life stressors, and substance use to associate with and predict higher level of STBs (Carballo et al., 2020; Cha et al., 2018; de Sousa et al., 2017). I also expected networks to identify potential indirect pathways of risk for STBs, such that higher levels of stressors may indirectly impact STBs through subsequent increases in mental health symptoms (Aas et al., 2017). To my knowledge, this study represents the first application of a longitudinal panel network approach to examining early adolescent suicidality and its relations to multiple salient domains of risk and protective factors. Illuminating systems of risk and protection for early onset STBs, including how these relations vary over time, could identify early warning signs and inform the timing and targets of specific interventions.

METHODS

Participants and Procedures

The ABCD study design and protocols have been described in detail elsewhere (Auchter et al., 2018; Feldstein Ewing et al., 2018; Garavan et al., 2018; Karcher & Barch, 2021; Saragosa-Harris et al., 2022). The ABCD study utilizes multimodal measurement methodologies, including biological, genetic, neuroimaging, behavioral, cognitive, and psychometric assessments (Karcher & Barch, 2021). A comprehensive measurement battery is conducted annually, with measures of mental and physical health, culture and environment, neurocognition, and substance use. Additionally, brief remote assessments (i.e., via telephone or teleconference) of youth self-reported substance use and mental health symptoms occur every six months (Karcher & Barch, 2021). Neuroimaging data (not examined in the current study) are acquired every two years and are the only mode of data collection that occurs less than annually. Psychometric data includes a mix of child and parent/caregiver-reported experiences, with select measures also including teacher report forms. Study protocols are provided at https://abcdstudy.org/scientists/protocols/. The complete study battery is publicly available and can be found in the National Institutes of Mental Health (NIMH) Data Archive at https://nda.nih.gov/data_dictionary.html?source=ABCD%2Brelease%2B3.0&submission=ALL.

The ABCD study employed a school-based probability sampling system in order to reduce convenience-sample bias. Study procedures occur at 21 nationally-distributed research sites in the United States (Auchter et al., 2018; Garavan et al., 2018; Karcher & Barch, 2021). Each study site had a specified recruitment catchment area that included demographically and economically diverse communities, and schools within each catchment area were selected and stratified based on demographic and economic characteristics of their student bodies (Garavan et al., 2018). Most participants (~90% of the total sample) were then recruited directly through their schools (Garavan et al., 2018). Probability sampling and recruitment monitoring were used to reduce systemic sampling biases and maximize representation of the broader U.S. population of same-aged youth (Garavan et al., 2018). To date, the ABCD study attrition rates have been fairly low (about 9%). Data collection is ongoing and will continue until youth are approximately 20 years old. Presently, three complete annual timepoints of data have been released: Baseline (participants aged 9-10 years, N = 11,878), Year 1 (participants aged 10-11 years, N = 11,235), and Year 2 (participants aged 11-12 years, N = 10,414). Only data from these first three annual timepoints were used in the current study, as these are the only measurement occasions that assessed STBs and key study variables in the full sample. The brief mid-year measurement battery does not include suicidality and other variables of interest. Data from ABCD Release 3.0 were accessed through the NIMH Data Archive Data Exploration Analysis Portal (DEAP; deap.nimhda.org), which provides an online portal for downloading ABCD measures.

Analytic Sample

The ABCD study oversampled siblings and twins (Garavan et al., 2018; Karcher & Barch, 2021), and the baseline sample included 8,150 singletons, 1,600 non-twin siblings, 2100 twins, and 30 triplets (Palmer et al., 2021). To avoid potential confounding effects of nested data within families, one sibling was randomly selected from each family such that participants from the same household were excluded from analyses (i.e., the sample consisted of unrelated participants). One additional participant was excluded due to a coding error in their data. This resulted in a full analytic sample of N = 9,854 at baseline, N = 9,286 at Year 1, and N = 8,629 at Year 2.

While it is important to understand risk and protective factors for STBs in the broader population, as represented by the full sample, there is also value in examining risk and protective factors among youth who have already experienced STBs, as this may provide insight into vulnerability pathways among those most at risk. Thus, two stages of analyses were conducted. The first set of models utilized the full analytic sample (*N* = 9,854) to evaluate associations between variables in the general population. The second set of models were estimated using only the subsample of youth who endorsed STBs at one or more study timepoints (*n* = 1,699; hereafter referred to as the "STB subsample"). The STB subsample models offer information about risk and protective pathways among youth with clinically elevated risk for future STBs. While different ages at onset and levels of severity for suicidality can have different implications for intervention (e.g., passive ideation versus an attempt) (Klonsky et al., 2017; Nock et al., 2013), any level of STBs in this age range is considered clinically concerning and confers vulnerability to long-term negative outcomes (Cha et al., 2018; Thompson et al., 2012). Thus, inclusion criteria for the STB subsample were self-report of any level of current or past suicidality, including passive and active ideation, method, plan, intent, or attempt.

Measures

The ABCD measurement battery has been described in previous publications. See Barch et al. (2017) for details on the mental and physical health measurement protocol, Lisdahl et al. (2018) for substance use measures, Zucker et al. (2018) for socioenvironmental measures, and Hoffman et al. (2019) for stress exposure measures. Inclusion criteria for variables in the current study were: (1) previous literature identifying a construct as a risk or protective factor for STBs and (2) available data for all three waves of data collection from a consistent reporter (parent or youth). While the ABCD battery includes a rich set of constructs that have been implicated in

STBs, some theoretically relevant constructs were not considered due to data not being available at all three timepoints (e.g., peer experiences measurement began at Year 2). Further, some measures had complete data for one reporter but incomplete data for the other reporter (e.g., parents completed dimensional measures of youth mental health symptoms all three years, and corresponding youth measurement began in Year 1). In these cases, only data for which there was a consistent reporter across all timepoints were used. The list of study variables and their corresponding measures are shown in Table 1.

Table 1

Measures and data availability of variables used in the current study

Variable	Measure	Reporter	Data availability
1. Suicidality	KSADS-COMP Suicide Module	Youth	Baseline, Year 1, Year 2
2. Internalizing	Child Behavior Checklist	Parent	Baseline, Year 1, Year 2
3. Social problems	Child Behavior Checklist	Parent	Baseline, Year 1, Year 2
4. Thought problems	Child Behavior Checklist	Parent	Baseline, Year 1, Year 2
5. Attention problems	Child Behavior Checklist	Parent	Baseline, Year 1, Year 2
6. Externalizing	Child Behavior Checklist	Parent	Baseline, Year 1, Year 2
7. Sleep problems	Sleep Disturbances Scale for Children	Parent	Baseline, Year 1, Year 2
8. Family conflict	PhenX Family Environment Scale–Family Conflict Subscale	Youth	Baseline, Year 1, Year 2
9. Parental monitoring	Parental Monitoring Survey	Youth	Baseline, Year 1, Year 2
10. Neighborhood safety	PhenX Neighborhood Safety/Crime Survey	Parent	Baseline, Year 1, Year 2
11. School protective factors	PhenX School Risk & Protective Factors Survey	Youth	Baseline, Year 1, Year 2
12. Stressful life events [1]	KSADS-COMP PTSD Module	Parent	Baseline, Year 2
	Life Events Scale	Parent	Year 1, Year 2
13. Material hardship	PhenX Demographics Survey	Parent	Baseline, Year 1, Year 2
14. Low-level substance use	Substance Use Timeline Follow-Back Survey	Youth	Baseline, Year 1, Year 2

Note: [1] Due to inconsistent data availability over time, stressful life events were coded as a composite score of items measuring traumatic and/or negative significant life events from the KSADS PTSD module and Life Events Scale (see Measures).

Suicidal Thoughts and Behaviors (STBs)

Youth report of STBs was measured with the Suicide Module of the Kiddie Schedule for Affective Disorders and Schizophrenia for the DSM-5 (KSADS). Youth completed a computerized, self-administered version of the KSADS (KSADS-COMP) (Kobak & Kaufman, 2015; Townsend et al., 2020). Participants responded to a series of binary items assessing the presence (1) or absence (0) of nine STBs: passive suicidal ideation, active but non-specific suicidal ideation, suicidal ideation with a specific method, active suicidal ideation with intent, active suicidal ideation with a plan, preparatory actions toward suicidal behavior, interrupted suicide attempt(s), aborted suicidal attempt(s), and suicide attempt(s). Youth responded to separate items for current (past 2-week) and past (ever at baseline, or since last measurement occasion at Years 1 and 2) STBs. Suicidality was modeled as a count of the number of STB items a youth endorsed having experienced at each measurement timepoint (i.e., ever or past-year), with higher values reflecting more severe suicidality. Previous research using the ABCD sample has used a similar coding scheme, in which suicidality was defined as endorsement of one or more KSADS STB items (Janiri et al., 2020). The current study only considered youth reports of STBs because the KSADS Suicide Module was not administered to parents/caregivers in Year 1 and interrater agreement was generally low (within $\rho = .12$, between $\rho = .36$).

Mental Health Symptoms

Parent/caregiver report of their child's dimensional mental health symptoms was measured with the ASEBA Child Behavior Checklist (CBCL) (Achenbach, 2009). The CBCL is an empirically derived 112-item measure that assesses several dimensions of mental health symptoms parents observed for their child over the past six months. Parents responded to each item on a 3-point scale of 0 = "not true (as far as you know)", 1 = "somewhat or sometimes true”, and 2 = “very true or often true.” CBCL items that directly overlapped with other study variables were omitted, including two STB items, three substance use items, and two sleep problem items. Coding schemes for the CBCL variables are provided in the Appendix. Raw scores were calculated for the following CBCL Syndrome Scales (Achenbach, 2009): Social Problems (11 items; within ω = .53, between ω = .85), Thought Problems (11 items; within ω = .44, between ω = .82), and Attention Problems (10 items; within ω = .69, between ω = .94). Internalizing was modeled as a sum of 12 items from the Anxious/Depressive syndrome scale, eight items from the Withdrawn/Depressed scale, and 10 items from the Somatic Complaints scale (30 items total; within ω = .80, between ω = .93) (Achenbach, 2009). Externalizing was modeled as a sum of 14 items from the Rule Breaking scale and 18 items from the Aggressive Behavior scale (32 items total; within ω = .85, between ω = .96) (Achenbach, 2009). Only parent-report data was used for mental health symptoms due to inconsistent youth-report data across the three measurement occasions. The ASEBA Brief Problem Monitor (BPM), a 22-item companion scale to the CBCL (Achenbach et al., 2011), was administered to youth in Years 1 and 2. The BPM measures internalizing, externalizing, and attention problems, and corresponding youth report data were not available at baseline (KSADS modules administered to youth at baseline had limited item overlap). Further, available youth-report data generally demonstrated low interrater agreement with the CBCL (within ρ = .04-.05, between ρ = .26-.40). Teachers also completed the BPM at all three timepoints, although these data were not used due to high rates of missingness (55.37-58.40% missing) and generally low interrater agreement with youth and parent-report data (within ρ = .01-.05, between ρ = .24-.50).

Parent/caregiver report of their child’s sleep problems were measured using Sleep Disturbances Scale for Children (SDSC) (Bruni et al., 1996). The SDSC is a 26-item scale that assesses six domains of sleep-related problems: initiating and maintaining sleep (7 items; e.g., “the child has difficulty getting to sleep at night”), sleep breathing (3 items; e.g., “the child snores”), arousal/nightmares (3 items; e.g., “you have observed the child sleepwalking”), sleep-wake transition (6 items; e.g., “the child startles or jerks parts of the body while falling asleep”), excessive somnolence (5 items; “e.g., the child is unusually difficult to wake up in the morning”), and sleep hyperhidrosis (nighttime sweating) (2 items; e.g., “the child sweats excessively during the night”). Parents responded to items on a 5-point scale of 1 = “never” to 5 = “always (daily)”, where higher values reflected more sleep difficulties for their child. A total score can be calculated to represent overall sleep concerns (Bruni et al., 1996), and <u>sleep problems</u> was modeled as a sum score of the 26 SDSC items (within $\omega = .82$, between $\omega = .85$).

Socioenvironmental Factors

Youth report of perceived family conflict was assessed with the PhenX Family Conflict subscale of the Family Environment Subscale (Moos & Moos, 1994). Nine items assessed the amount of expressed conflict in the family environment (e.g., “family members sometimes get so angry they throw things”). Youth responded on a binary scale where 0 = “false” and 1 = “true.” <u>Family conflict</u> was modeled as a sum score of the nine items (within $\omega = .51$, between $\omega = .90$), with higher scores representing higher levels of family conflict. Although parents/caregivers also completed the Family Conflict subscale, parent-report data for this measure were not available in the NIMH data archive. Thus, only youth report items were used for this variable.

Youth report of perceived parental monitoring was measured with the Parental Monitoring Survey. This scale was adapted from two other measures for the ABCD study (Karoly et al., 2016; Stattin & Kerr, 2003). Five items assessed parent/caregiver tendency to be aware of their child’s activities and location (e.g., “How often do your parents know who you are with when you are not at school and away from home?"). Youth responded on a 5-point Likert-style scale of 1 = "never" to 5 = "always or almost always." Parental monitoring was modeled as a sum score of the five items, where higher values reflected lower parental monitoring (within ω = .35, between ω = .75).

Youth report of school protective factors was measured using the PhenX School Risk and Protective Factors Survey (SRPF), which was adapted for the ABCD study from the Communities That Care Youth Survey (Arthur et al., 2007). The SRPF includes three subscales that measure youth's perception of their school environment (6 items, e.g., "I get along with my teachers"), school involvement (4 items, e.g., "In general, I like school a lot"), and school disengagement (2 items, e.g., "Usually, school bores me"). Youth were provided the following instructions to respond on a 4-point scale: "*1 = NO!, 2 = no, 3 = yes; 4 = YES! – Mark (the BIG) YES! If you think the statement is definitely true for you. Mark (the little) yes if you think the statement is mostly true for you. Mark (the little) no if you think the statement is mostly not true for you. Mark (the BIG) NO! if you think the statement is definitely not true for you."* School protective factors was modeled as a sum score of the 12 SRPF items, where higher values represented higher levels of school protective factors (school disengagement items were reverse coded; within ω = .77, between ω = .89).

Stressors

Parent/caregiver report of neighborhood safety was assessed using the PhenX Neighborhood Safety/Crime Survey, which was adapted from previous studies on measurement reliability for self-reported neighborhood characteristics (Echeverria et al., 2004; Mujahid et al., 2007). Parents responded to three items assessing perceptions of safety and crime presence in their neighborhood (e.g., "I feel safe walking in my neighborhood, day or night"). Parents responded on a 5-point Likert-style scale where 1 = "strongly disagree" and 5 = "strongly agree." Neighborhood safety was modeled as a sum score of these three items (within $\omega = .77$, between $\omega = .95$); items were reverse coded such that higher scores represented lower neighborhood safety. Although youth were also asked one item from the neighborhood safety scale, only parent-report data was used for this variable due to the use of single-item measurement for youth and low interrater agreement (within $\rho = .07$, between $\rho = .39$).

Parent/caregiver report of family material hardship was measured in the PhenX Demographics Survey (Barch et al., 2017). Parents were asked seven binary items about types of material hardship their family had experienced in the past 12 months due to financial difficulties (e.g., "In the past 12 months, has there been a time when you and your immediate family experienced the following: Needed food but couldn't afford to buy it or couldn't afford to go out to get it?"). Parents responded 0 for "no" and 1 for "yes." Material hardship was modeled as a count of the number of material hardship items parents/caregivers endorsed, where higher values reflected greater material hardship.

Parent/caregiver report of stressful life events their child had experienced was measured as a composite of items from the KSADS-COMP Post Traumatic Stress Disorder (PTSD) module (Kobak & Kaufman, 2015; Townsend et al., 2020) and the Life Events Scale (LES) (Grant et al., 2004; Hoffman et al., 2019). The KSADS PTSD module asked parents if their child had experienced 17 types of potentially traumatic events (e.g., "Learned about the sudden unexpected death of a loved one"). Parents responded with 0 = "no" and 1 = "yes" for the binary presence of each item. The KSADS PTSD module was scored as a count of the number of events parents endorsed. The LES similarly assessed parents' knowledge about 26 significant life experiences their child may have experienced. If an item was endorsed (0 = "no", 1 = "yes"), parents were then asked if their child experienced the event as “mostly good” or “mostly bad.” The LES was scored as a count of the number of “mostly bad” events parents endorsed for their child. The KSADS PTSD module was administered to parents at Baseline and Year 2 (i.e., not available for Year 1). The Life Events Scale was administered to parents at Years 1-2 (i.e., not available at baseline). Given that stressful life events are salient risk factors for STBs, these measures were integrated to provide a proxy for youth’s stressful life events at all three timepoints. Stressful life events were modeled as the KSADS PTSD score at baseline, the LES score at Year 1, and the mean of the KSADS PTSD and LES scores at Year 2. The KSADS and LES were standardized (i.e., *z*-scored) prior to combining them to account for different response scales. While the KSADS PTSD module and LES have content overlap for several items, they do not assess identical life stressors. This variable should be interpreted with these considerations in mind. Further, while youth completed the LES in Years 1-2, these data were not used due to unavailable youth report from all three years and low interrater agreement (within $\rho = .06$, between $\rho = .31$).

Low-Level Substance Use

Youth report of low-level substance use was measured by the ABCD Timeline Follow-back Interview (TLFB), which assesses lifetime and recent use of a wide range of substances (Lisdahl et al., 2018). The young age of the sample between baseline and Year 2 (approximately ages 10-12) is before age at onset for most substance use, and rates of engagement in moderate to high substance use were low in the ABCD cohort (Lisdahl et al., 2018; Martz et al., 2022). Thus, the present study focused on low-level use (e.g., a sip or puff) of the three most used substances: alcohol, nicotine, and marijuana (Lisdahl et al., 2021; Martz et al., 2022). Early low-level substance use is clinically important to understand because it can increase the risk of harmful substance use later in life (Donovan & Molina, 2011). Youth were first asked if they had ever heard of several substances. If they responded yes, they were then asked if they had tried each substance. Alcohol use was assessed with "Have you ever tried a sip of alcohol such as beer, wine or liquor (rum, vodka, gin, whiskey)?" Nicotine use was assessed with "Have you ever tried a puff from a tobacco or electronic cigarette, Juul, vape pens, e-hookah, cigar or pipe?" Marijuana use was assessed with "Have you ever tried a puff or eaten any marijuana, also called pot, grass, weed or ganja?" At baseline, youth were asked if they had *ever* tried each substance, and at Years 1-2 they were asked if they had tried each substance *since the last measurement occasion*. Participants responded 0 for "no" and 1 for "yes." Low-level substance use was modeled as a count of the number of the three substances youth reported having tried.

Measures Not Included in Analyses

Additional theoretically relevant risk and protective factors were considered in initial analyses, but were not included in presented models due to negligible associations with other variables after controlling for other pairwise relations in the networks, and poorer model fit when included. These included prosocial behavior, peer deviance, screen time, and activities and hobbies.

Statistical Analyses

All data wrangling and analyses were conducted in R version 4.3.0 (R Core Team, 2023). Variable distributions were assessed for normality assumptions and multilevel omegas were calculated for sum-scored variables (Wiley, 2020). Within-person omegas are typically lower than between-person omegas in multilevel data, especially when the number of measurement occasions is small (three in the present study) (Geldhof et al., 2014; Rush & Hofer, 2017). To interpret statistical effects on the same scale, variables were standardized (i.e., *z*-scored) prior to analysis. To account for possible latent confounding, in which underlying latent factor structures of nodes in a network can lead to spurious results (Hallquist et al., 2021), exploratory and confirmatory factor analyses (EFA and CFA) were conducted on model variables to determine if they had an underlying latent structure. Measurement models were estimated in *lavaan* (Rosseel, 2012) and were evaluated by examining factor loadings (values ≥ .33 preferred), cross-loadings (values < .40 preferred), and multiple fit indices: root mean square error of approximation (RMSEA), comparative fit index (CFI), Tucker Lewis index (TLI), and Bayesian information criterion (BIC). Values < .06 represent good fit for RMSEA, while values ≥ .90 indicate good fit and values ≥ .95 indicate excellent fit for CFI and TLI (Hu & Bentler, 1999; Tabachnick & Fidell, 2013). Smaller BIC values indicate better comparative fit between models (Tabachnick & Fidell, 2013).

Network analyses were conducted using Panel Graphical Vector Autoregressive (Panel GVAR) models via the *psychonetrics* package (Epskamp, 2020, 2022). *Psychonetrics* is a relatively new package that enables estimation of temporal network models in panel data with three or more timepoints. The *psychonetrics* package builds on the *lavaan* package for structural equation modeling and integrates multivariate modeling with Gaussian Graphical Models, a type of network model for continuous data, and Graphical Vector Autoregressive Models, a type of model for estimating dynamic temporal effects (Epskamp, 2020). Panel GVAR models can account for potential latent structures in data, estimate contemporaneous and cross-lagged relations between nodes, and evaluate both within and between-person effects.

Network edges were estimated as partial correlations between each pair of nodes (Epskamp & Fried, 2018). Undirected edges represent bidirectional associations between variables (typically within the same timepoint), while directed edges represent predictive effects of one node on another (typically across timepoints) (Hevey, 2018). Panel GVAR models estimate three network structures: temporal, contemporaneous, and between-subject networks (Epskamp, 2020; Jordan et al., 2020). The temporal network provides within-person lagged correlations and autocorrelations for nodes across timepoints via directed partial correlations. The contemporaneous network provides within-person undirected partial correlations between each pair of nodes within the same timepoint, after controlling for temporal effects. Lastly, the between-subject network provides undirected partial correlations that reflect how overall variable means relate while controlling for other variables in the model. See the *psychonetrics* tutorial by Epskamp (2020) for detailed discussion of the three network structures.

Panel GVAR models used the nlminb optimizer (Epskamp, 2022) and were estimated using Full Information Maximum Likelihood (FIML). FIML handles missing data by using all available data to estimate each parameter (Allison, 2003; Rosseel, 2012). Two network models were estimated using the same set of study variables (i.e., nodes): Model 1 used the full analytic sample (N = 9,854), and Model 2 used the STB subsample (n =1,699). Network structures were visualized using the *qgraph* package (Epskamp et al., 2012, 2023).

Model Assumptions

Panel GVAR models assume equidistant measurement occasions, multivariate normality, and stationarity. Stationarity assumes that modeled processes are independent of time, such that the model parameters and variable means, variances, and autovariances are stable across measurement occasions (Burger et al., 2022; Epskamp, 2020; Ram et al., 2013). However, many psychological and developmental processes do not adhere to stationarity (Jordan et al., 2020). In the current study, youth age (also a proxy for time) is a theoretically relevant predictor of STBs and other study variables. Age may also influence how variables in the network relate over time.

For example, older youth age is associated with increased prevalence of STBs, substance use, and mental health symptoms (UNICEF, 2021), and parental monitoring generally changes as children transition into adolescence (Smetana & Rote, 2019). Because age increases linearly with time, including age directly in models would violate the stationarity assumption. Multiple options exist for addressing non-stationarity, and while best practices are not well-established for these data processing decisions (Ram et al., 2013), it is typically recommended that data are detrended prior to conducting network analyses (Mansueto et al., 2022). Thus, age was accounted for by detrending each variable for the linear effects of age (Ram et al., 2013). A series of bivariate linear regressions were conducted in which each variable was regressed on age, and the resulting residuals for each variable were modeled as nodes in the networks (Burger et al., 2022; Fried et al., 2022). Regression coefficients for age predicting each variable are shown in Supplemental Table S1. To ensure detrending did not confound results, corresponding supplemental models were estimated using the original (non-detrended) versions of the study variables (O'Driscoll et al., 2022). Supplemental Models 1 and 2 used non-detrended data for the full analytic sample (N = 9,854) and STB subsample (n = 1,699), respectively.

Model Selection and Evaluation

Overall model fit was evaluated using the following indices: RMSEA, CFI, TLI, and BIC. Model χ^2 was also reported but not interpreted due to sample size sensitivity (Tabachnick & Fidell, 2013). Panel VGAR models are relatively new techniques and there are not well-established criteria for evaluating model fit, but recommendations for structural equation models can be used as guidelines (described above) (Epskamp, 2020; O'Driscoll et al., 2022). Edge selection was conducted via recursive step-down and step-up model searches. In the step-down pruning step, edges not significant at $p < .01$. were iteratively removed and the model was re-fit with these edges fixed at 0 (Blanken et al., 2022). In the subsequent step-up search, edges were iteratively added until the best-performing BIC was obtained (Blanken et al., 2022; Epskamp, 2020). While regularization and thresholding approaches for edge selection are popular in the network analysis literature (e.g., Epskamp & Fried, 2018), model searches appear to produce more accurate results (Blanken et al., 2022). Edge stability was assessed using a 25% case-drop bootstrap resampling procedure (Epskamp, 2020), in which 100 models were refit using a random 75% of the sample. The number of times each edge was retained across the estimated bootstrapped models was then evaluated; edges retained in higher proportions of bootstrapped models are considered more stable (Epskamp et al., 2018).

Node importance was evaluated via centrality metrics, including node strength, betweenness, and closeness (Epskamp et al., 2018; Epskamp & Fried, 2018; Hevey, 2018). Node strength represents how strongly a node directly relates to other nodes in the network. In the temporal network structures, *in-strength* represents the sum of all incoming absolute edge weights to a node, while *out-strength* represents the sum of all outgoing absolute edge weights from a node. In the contemporaneous and between-subjects network structures, *strength* represents the sum of all absolute edge weights connected to a node. High strength suggests a node has strong relations with other variables in the network. Closeness and betweenness quantify a node's indirect associations with all other nodes in the network. *Closeness* represents the average shortest path (measured by geodesic distance) between a specific node and all other nodes. *Betweenness* represents the number of times a node is on the shortest path between other nodes. High closeness and betweenness suggest nodes can indirectly influence and be influenced by other nodes in the model (Deserno et al., 2022; Hevey, 2018).

RESULTS

Sample Characteristics

Demographic characteristics and rates of STBs for the full analytic sample and STB subsample across timepoints are shown in Table 2. Corresponding information for the original ABCD sample, before dropping sibling participants, is shown in Supplemental Table S2. Sample characteristics and rates of STBs were highly consistent across the original and analytic samples. 8.0-8.7% of youth reported STBs at each timepoint in the full analytic sample. 40-50% of the STB subsample endorsed STBs at each timepoint, representing variability in the age at onset and persistence of STBs over time. Among youth who reported any STBs, rates for the number of STB items endorsed across all timepoints were as follows: 53.4% of observations reported one STB (n = 1,222; mostly passive suicidal ideation), 18.5% (n = 423) reported two, 13.8% (n = 317) reported three, 5.5% (n = 125) reported four, 2.8% (n = 64) reported five, 2.4% (n = 56) reported six, and 3.5% (n = 83) reported seven or more STBs. The count variable representing the number of STBs endorsed was used to represent suicidality in the network models.

Table 2
Sample demographic characteristics and STB endorsement across study timepoints

	Full Sample: Baseline [1]	Full Sample: Year 1	Full Sample: Year 2	STB Subsample: Baseline [2]	STB Subsample: Year 1	STB Subsample: Year 2
	Mean (*SD*) or *n* (%)	Mean (*SD*) or *n* (%)	Mean (*SD*) or *n* (%)	Mean (*SD*) or *n* (%)	Mean (*SD*) or *n* (%)	Mean (*SD*) or *n* (%)
Age (in years)	9.90 (0.62)	10.91 (0.63)	11.99 (0.66)	9.92 (0.62)	10.92 (0.63)	12.00 (0.66)
n unknown	0	582	1,250	0	70	159
Race						
AIAN/NHPI	66 (0.7%)	60 (0.7%)	55 (0.6%)	7 (0.4%)	6 (0.4%)	6 (0.4%)
Asian	249 (2.6%)	236 (2.6%)	215 (2.5%)	37 (2.2%)	36 (2.2%)	33 (2.2%)
Black	1,576 (16%)	1,398 (15%)	1,242 (15%)	286 (17%)	270 (17%)	242 (16%)
Mixed	1,194 (12%)	1,116 (12%)	1,046 (12%)	245 (15%)	229 (14%)	224 (15%)
Other	467 (4.8%)	424 (4.6%)	393 (4.6%)	80 (4.8%)	75 (4.7%)	72 (4.7%)
White	6,160 (63%)	5,913 (65%)	5,535 (65%)	1,021 (61%)	993 (62%)	940 (62%)
n unknown	142	707	1,368	24	91	183
Annual household income [3]						
< 50K	2,746 (31%)	–	–	522 (34%)	–	–

≥ 50 & < 100K	2,535 (28%)	–	–	463 (30%)	–	–
≥ 100K	3,707 (41%)	–	–	570 (37%)	–	–
n unknown	866	–	–	144	–	–
Highest education of parent [3]						
< HS Diploma	510 (5.2%)	–	–	78 (4.6%)	–	–
HS Diploma or GED	975 (9.9%)	–	–	162 (9.6%)	–	–
Some College	2,569 (26%)	–	–	504 (30%)	–	–
Bachelor	2,443 (25%)	–	–	417 (25%)	–	–
Post Graduate Degree	3,346 (34%)	–	–	535 (32%)	–	–
n unknown	11	–	–	3	–	–
Sex assigned at birth						
Female	4,671 (47%)	4,376 (47%)	4,054 (47%)	807 (47%)	776 (48%)	739 (48%)
Male	5,183 (53%)	4,896 (53%)	4,550 (53%)	892 (53%)	853 (52%)	801 (52%)
n unknown	0	582	1,250	0	70	159
"Are you gay or bisexual?"						
Yes	29 (0.3%)	127 (1.4%)	382 (4.5%)	20 (1.2%)	70 (4.3%)	174 (12%)
Maybe	94 (1.0%)	223 (2.4%)	337 (4.0%)	41 (2.4%)	89 (5.5%)	112 (7.5%)
No	7,276 (74%)	8,044 (87%)	7,475 (88%)	1,208 (71%)	1,313 (81%)	1,164 (78%)
I do not understand this question	2,440 (25%)	842 (9.1%)	275 (3.2%)	429 (25%)	145 (9.0%)	50 (3.3%)
n unknown	15	618	1,385	1	82	199
"Are you transgender?"						
Yes	11 (0.1%)	15 (0.2%)	37 (0.4%)	6 (0.4%)	10 (0.6%)	15 (1.0%)
Maybe	43 (0.4%)	80 (0.9%)	57 (0.7%)	18 (1.1%)	31 (1.9%)	30 (2.0%)
No	5,959 (61%)	7,477 (81%)	7,963 (93%)	971 (57%)	1,260 (78%)	1,363 (90%)
I do not understand this question	3,830 (39%)	1,680 (18%)	483 (5.7%)	703 (41%)	323 (20%)	113 (7.4%)
n unknown	11	602	1,314	1	75	178
Endorsed STBs since last measurement occasion						
Never	8,933 (91%)	8,404 (92%)	7,842 (92%)	826 (49%)	850 (53%)	843 (55%)
Ever	856 (8.7%)	759 (8.3%)	680 (8.0%)	856 (51%)	759 (47%)	680 (45%)
n unknown	65	691	1,332	17	90	176

Note: [1] The full sample is the analytic sample after randomly dropping sibling participants from the same household (N = 9,854). [2] The STB subsample includes all participants who self-reported lifetime history of STBs at baseline or past-year STBs at years 1 and 2 (n = 1,699). [3] Annual household income and parental level of education were only measured at baseline. Gender and sexual identities were self-reported by youth; all other demographics items were assessed by parent/caregiver report. Rates of missingness increased over time due to study attrition. STBs = suicidal thoughts and behaviors, *SD* = standard deviation, AIAN/NHPI = American Indian/Alaska Native or Native Hawaiian and other Pacific Islander, HS = high school.

Variable Descriptive Statistics

EFA and CFA of the study variables did not support a clear underlying latent structure, and nodes were therefore modeled as observed variables. Thus, nodes were the 14 study variables in all network models, including suicidality and the 13 risk and protective factors (Table 1). Descriptive statistics and rates of missingness for all study variables are presented in Table 3. Multilevel bivariate correlations and intraclass correlations for study variables are shown in Table 4. Variables had missing data for 6.41-8.60% of cases (Table 3), and missing data was handled via FIML estimation. Most variables followed a non-normal distribution (Table 3). Although FIML assumes multivariate normality of continuous variables, simulation studies suggest it can be robust to non-normality, particularly in large sample sizes (Jobst et al., 2021). Nonetheless, sensitivity analyses were conducted to examine the possible influence of non-normality by refitting models with log-transformed (closer to normal) versions of study variables; this resulted in negligible changes to model fit and network structures. Thus, presented models used un-transformed versions of the standardized variables. Although there are not established guidelines for handling non-normality in network models, the bootstrapping procedure can be used to evaluate the stability of results when variables are non-normal (Epskamp, 2020).

Table 3

Standardized descriptive statistics for variables across study timepoints

Variable	Baseline Full Sample (N = 9,854) Mean (SD)	Year 1 Full Sample (N = 9,854) Mean (SD)	Year 2 Full Sample (N = 9,854) Mean (SD)	Baseline STB Subsample (n = 1,699) Mean (SD)	Year 1 STB Subsample (n = 1,699) Mean (SD)	Year 2 STB Subsample (n = 1,699) Mean (SD)
Suicidality	0.00 (0.95)	0.00 (1.03)	0.00 (1.02)	0.00 (0.94)	0.00 (1.04)	-0.01 (1.02)
n missing	71	694	1,337	20	90	178
Internalizing	0.00 (0.99)	0.02 (1.00)	-0.02 (1.01)	-0.02 (0.99)	0.02 (0.99)	0.00 (1.02)
n missing	8	601	1,300	0	75	168
Social problems	0.06 (1.04)	0.01 (1.00)	-0.08 (0.94)	0.04 (1.03)	0.03 (0.99)	-0.07 (0.98)
n missing	8	601	1,300	0	75	168
Thought problems	0.04 (1.02)	0.02 (1.02)	-0.07 (0.96)	0.02 (1.00)	0.02 (1.00)	-0.05 (1.00)
n missing	8	601	1,300	0	75	168
Attention problems	0.03 (1.02)	0.00 (1.00)	-0.04 (0.97)	0.02 (1.01)	0.01 (1.01)	-0.03 (0.98)
n missing	8	601	1,300	0	75	168
Externalizing	0.05 (1.03)	0.00 (1.00)	-0.05 (0.96)	0.04 (1.02)	0.00 (0.97)	-0.04 (1.00)
n missing	8	601	1,300	0	75	168
Sleep problems	0.00 (1.01)	0.02 (1.00)	-0.03 (0.99)	0.01 (1.03)	0.01 (0.99)	-0.02 (0.98)
n missing	26	617	1,315	2	78	173
Family conflict	0.05 (1.04)	-0.03 (0.99)	-0.03 (0.96)	0.04 (1.02)	-0.03 (0.99)	-0.01 (0.98)
n missing	29	598	1,284	5	75	167
Parental monitoring	0.13 (1.07)	-0.07 (0.94)	-0.07 (0.97)	0.12 (1.08)	-0.07 (0.94)	-0.06 (0.96)
n missing	24	591	1,281	5	72	165
Neighborhood safety	0.00 (1.02)	-0.01 (1.00)	0.01 (0.98)	-0.02 (1.00)	0.01 (1.02)	0.01 (0.97)
n missing	45	625	1,352	4	78	177
School protective factors	0.01 (1.01)	0.13 (0.97)	-0.16 (1.00)	0.06 (1.02)	0.07 (0.98)	-0.14 (0.99)
n missing	29	592	1,283	6	72	166
Stressful life events	0.02 (1.11)	-0.01 (1.02)	-0.01 (0.81)	0.00 (1.14)	0.01 (1.01)	-0.01 (0.79)
n missing	242	585	1,717	33	70	262
Material hardship	0.03 (1.04)	0.02 (1.04)	-0.06 (0.09)	0.06 (1.06)	0.02 (1.04)	-0.08 (0.88)
n missing	115	677	1,379	20	84	180
Low-level substance use	0.22 (1.17)	-0.14 (0.83)	-0.10 (0.91)	0.23 (1.10)	-0.18 (0.82)	-0.07 (1.00)
n missing	23	621	1,295	5	76	171

Note: Values represent descriptive statistics for variables after standardization (i.e., *z*-scoring). Rates of missingness increased over time due to study attrition. *SD* = standard deviation.

Table 4

Multilevel correlations and intraclass correlations for study variables in the full sample (N = 9,854)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Between-subject correlations														
1. Suicidality	1.00													
2. Internalizing	0.19	1.00												
3. Social problems	0.19	0.65	1.00											
4. Thought problems	0.16	0.58	0.59	1.00										
5. Attention problems	0.17	0.52	0.63	0.62	1.00									
6. Externalizing	0.19	0.58	0.66	0.57	0.66	1.00								
7. Sleep problems	0.13	0.54	0.47	0.48	0.48	0.48	1.00							
8. Family conflict	0.20	0.11	0.19	0.14	0.19	0.24	0.11	1.00						
9. Parental monitoring	0.19	0.10	0.16	0.14	0.23	0.16	0.09	0.35	1.00					
10. Neighborhood safety	0.03	0.12	0.17	0.09	0.12	0.15	0.14	0.11	0.09	1.00				
11. School protective factors	-0.21	-0.13	-0.14	-0.13	-0.22	-0.18	-0.14	-0.30	-0.45	-0.03	1.00			
12. Stressful life events	0.11	0.31	0.29	0.25	0.25	0.30	0.27	0.12	0.07	0.13	-0.07	1.00		
13. Material hardship	0.09	0.18	0.25	0.15	0.19	0.22	0.20	0.18	0.14	0.31	-0.04	0.29	1.00	
14. Low-level substance use	0.12	0.02	0.00	0.05	0.06	0.06	0.05	0.04	0.05	-0.07	-0.14	0.02	-0.06	1.00
Within-subject correlations														
1. Suicidality	1.00													
2. Internalizing	0.04	1.00												
3. Social problems	0.02	0.40	1.00											
4. Thought problems	0.01	0.34	0.30	1.00										
5. Attention problems	0.02	0.35	0.35	0.32	1.00									
6. Externalizing	0.04	0.42	0.41	0.34	0.44	1.00								
7. Sleep problems	0.01	0.23	0.17	0.17	0.19	0.20	1.00							
8. Family conflict	0.07	0.03	0.02	0.02	0.04	0.04	0.02	1.00						
9. Parental monitoring	0.05	0.03	0.03	0.02	0.04	0.05	0.02	0.13	1.00					
10. Neighborhood safety	0.00	0.03	0.02	0.02	0.03	0.03	0.05	0.00	-0.01	1.00				
11. School protective factors	-0.05	-0.05	-0.03	-0.02	-0.05	-0.06	-0.03	-0.13	-0.19	0.00	1.00			
12. Stressful life events	0.01	0.10	0.08	0.05	0.06	0.07	0.06	0.01	0.00	0.01	-0.02	1.00		
13. Material hardship	-0.01	0.08	0.06	0.05	0.06	0.07	0.04	0.00	-0.01	0.01	0.01	0.03	1.00	
14. Low-level substance use	0.05	0.00	0.02	0.02	0.01	0.02	-0.02	0.04	0.07	-0.01	-0.04	0.01	0.01	1.00
Intraclass correlation 1														
	0.28	0.67	0.66	0.63	0.75	0.72	0.66	0.44	0.41	0.62	0.46	0.37	0.57	0.30
Intraclass correlation 2														
	0.51	0.85	0.84	0.83	0.89	0.88	0.84	0.68	0.66	0.82	0.70	0.61	0.79	0.54

Note: Correlations represent spearman's rho coefficients, estimated via the psych package (Revelle, 2023). Intraclass correlation 1 represents the percentage of variance due to groups. Intraclass correlation 2 represents the reliability of group differences.

Model 1 Results: Full Analytic Sample

Model fit indices are shown in Table 5, and all models demonstrated excellent fit to the data. Network structures for Model 1, using detrended data for the full analytic sample (*N* = 9,854), are shown in Figure 1. Corresponding correlation coefficients for the temporal, contemporaneous, and between-subjects networks are presented in Tables 6-8, respectively. The bootstrap inclusion probabilities for each edge in Model 1 are shown in Table 9. Centrality indices for Model 1, including strength, betweenness, and closeness, are shown in Figure 2. Given the focus of the present study, most interpretation focused on direct and potential indirect associations between STBs and other nodes in the networks.

In the temporal network, directed edges represent within-person partial autocorrelations and lagged correlations between each pair of nodes from one timepoint to the next. In the pruned, estimated temporal network, autocorrelations were observed for all nodes in the network, including a negative autocorrelation for stressful life events and positive autocorrelations for STBs and the other 12 nodes (Figure 1A; Table 6). The bootstrapping procedure indicated high stability of all autoregressive effects (included in ≥ 92 out of 100 bootstrapped models; Table 9). Thus, higher STBs at an earlier timepoint was associated with higher STBs at a later timepoint. Several lagged correlations were also observed between the mental health symptom, socioenvironmental, and stressor nodes. STBs were not directly associated with other nodes in the temporal network. Attention problems, social problems, and thought problems had highest out-strength centrality, indicating relatively strong predictive effects on other nodes in the model (Figure 2A). Externalizing, family conflict, and material hardship had highest values for both in-strength and betweenness centrality, indicating they were most predicted by other nodes and had relatively strong indirect associations with other nodes in the network.

Table 5

Fit indices for panel vector autoregressive models

Model	DF	AIC	BIC	RMSEA	CFI	TLI	χ^2
Model 1: Full sample	764	902668.49	903970.85	0.03	0.97	0.96	7304.65*
Supplemental Model 1: Full sample (not detrended)	757	904088.44	905441.17	0.03	0.96	0.95	8730.41*
Model 2: STB subsample	824	158485.90	159143.87	0.03	0.96	0.96	2280.43*
Supplemental Model 2: STB subsample (not detrended)	819	158697.22	159382.38	0.03	0.95	0.95	2465.06*

Note: BIC and AIC should not be directly compared between Models 1 and 2 due to use of different samples. Supplemental models included variables that were not detrended for age effects. DF = model degrees of freedom, AIC = Akaike information criterion, BIC = Bayesian information criterion, RMSEA = root mean square error of approximation, CFI = comparative fit index, TLI = Tucker-Lewis index. * $p < 0.05$.

Table 6

Estimated directed partial correlations for the temporal network in the full sample (Model 1, N = 9,854)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Suicidality	0.087	–	–	–	–	–	–	–	–	–	–	–	–	–
2. Internalizing	–	0.085	–	–	-0.023	-0.023	–	–	–	–	–	–	–	–
3. Social problems	–	–	0.077	–	–	0.012	–	–	–	–	–	–	–	–
4. Thought problems	–	–	–	0.082	–	0.025	–	–	–	–	–	–	-0.035	–
5. Attention problems	–	–	–	–	0.132	–	–	–	–	–	–	–	0.047	–
6. Externalizing	–	0.036	0.068	0.059	0.054	0.156	–	–	–	–	–	–	–	–
7. Sleep problems	–	0.024	0.021	0.030	0.030	–	0.193	–	–	–	–	–	–	–
8. Family conflict	–	0.014	–	–	–	0.022	–	0.142	0.049	–	-0.039	–	–	–
9. Parental monitoring	–	–	–	–	–	–	–	0.037	0.155	–	–	–	–	–
10. Neighborhood safety	–	–	–	–	–	–	–	–	–	0.116	–	–	–	–
11. School protective factors	–	-0.012	-0.033	–	-0.022	–	–	-0.029	–	–	0.160	–	–	–
12. Stressful life events	–	–	–	–	–	–	–	–	–	–	–	-0.057	–	–
13. Material hardship	–	–	–	-0.027	0.036	–	–	–	–	–	–	0.057	0.130	–
14. Low-level substance use	–	–	–	–	–	–	–	–	–	–	–	–	–	0.112

Note: Values represent lagged and autoregressive (i.e., across timepoints) directed partial correlations at the within-person level. Values on the diagonal are autocorrelations. The *psychonetrics* package does not currently provide standard errors for partial directed correlations (Epskamp, 2022). See Figure 1A for graphical representation of the temporal network structure in the full sample.

Table 7

Estimated undirected partial correlations for the contemporaneous network in the full sample (Model 1, N = 9,854)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Suicidality	NA													
2. Internalizing	0.052 (0.006)	NA												
3. Social problems	–	0.266 (0.007)	NA											
4. Thought problems	–	0.188 (0.007)	0.106 (0.008)	NA										
5. Attention problems	–	0.091 (0.008)	0.145 (0.007)	0.158 (0.007)	NA									
6. Externalizing	–	0.186 (0.009)	0.261 (0.009)	0.199 (0.009)	0.289 (0.008)	NA								
7. Sleep problems	–	0.137 (0.008)	0.026 (0.008)	0.052 (0.008)	0.074 (0.008)	0.037 (0.008)	NA							
8. Family conflict	0.060 (0.007)	–	–	–	–	0.026 (0.006)	–	NA						
9. Parental monitoring	0.040 (0.007)	–	–	–	–	0.017 (0.006)	–	0.122 (0.010)	NA					
10. Neighborhood safety	–	–	0.024 (0.006)	–	–	–	0.041 (0.007)	–	–	NA				
11. School protective factors	-0.038 (0.007)	–	-0.019 (0.007)	0.029 (0.007)	-0.041 (0.007)	-0.026 (0.007)	–	-0.134 (0.010)	-0.193 (0.007)	–	NA			
12. Stressful life events	–	0.069 (0.007)	0.031 (0.007)	–	–	–	0.036 (0.008)	–	–	–	–	NA		
13. Material hardship	–	0.051 (0.007)	–	–	0.051 (0.008)	–	–	–	-0.031 (0.007)	–	–	0.055 (0.008)	NA	
14. Low-level substance use	0.039 (0.007)	–	–	–	–	–	–	0.023 (0.007)	0.031 (0.007)	–	-0.054 (0.007)	–	–	NA

Note: Values represent contemporaneous (i.e., same measurement occasion) undirected partial correlations at the within-person level after controlling for temporal effects. Standard errors are provided in parentheses. See Figure 1B for graphical representation of the contemporaneous network structure in the full sample.

Table 8

Estimated undirected partial correlations for the between-subjects network in the full sample (Model 1, N = 9,854)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Suicidality	NA													
2. Internalizing	0.133 (0.016)	NA												
3. Social problems	–	0.413 (0.012)	NA											
4. Thought problems	–	0.212 (0.015)	0.190 (0.016)	NA										
5. Attention problems	–	-0.123 (0.015)	0.257 (0.014)	0.381 (0.013)	NA									
6. Externalizing	–	–	0.287 (0.013)	0.092 (0.016)	0.261 (0.014)	NA								
7. Sleep problems	–	0.334 (0.014)	-0.080 (0.017)	0.109 (0.018)	0.142 (0.016)	0.114 (0.014)	NA							
8. Family conflict	0.144 (0.023)	-0.094 (0.016)	0.055 (0.017)	–	-0.077 (0.017)	0.190 (0.016)	–	NA						
9. Parental monitoring	0.117 (0.030)	-0.078 (0.015)	–	–	0.214 (0.013)	-0.077 (0.014)	–	0.221 (0.034)	NA					
10. Neighborhood safety	–	–	0.063 (0.012)	-0.052 (0.012)	–	–	0.026 (0.014)	0.065 (0.014)	–	NA				
11. School protective factors	-0.102 (0.029)	-0.107 (0.016)	0.064 (0.013)	–	–	–	–	-0.141 (0.032)	-0.531 (0.020)	–	NA			
12. Stressful life events	0.094 (0.020)	0.102 (0.014)	–	–	–	0.134 (0.012)	0.083 (0.017)	–	-0.117 (0.020)	0.037 (0.016)	-0.069 (0.020)	NA		
13. Material hardship	–	-0.051 (0.015)	0.102 (0.014)	–	-0.096 (0.013)	–	0.117 (0.015)	0.091 (0.017)	0.196 (0.021)	0.296 (0.014)	0.128 (0.020)	0.318 (0.017)	NA	
14. Low-level substance use	0.160 (0.027)	-0.064 (0.013)	–	–	–	0.089 (0.013)	–	–	-0.111 (0.025)	-0.109 (0.017)	-0.185 (0.024)	–	-0.049 (0.018)	NA

Note: Values represent undirected partial correlations at the between-person level (i.e., associations between overall variable means) after controlling for other variables in the model. Standard errors are provided in parentheses. See Figure 1C for graphical representation of the between-person network structure in the full sample.

Table 9

Number of times (out of 100) each edge was included in the case-drop bootstrap resampling procedure for Model 1

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Temporal network structure														
1. Suicidality	**92**	8	0	7	17	5	0	4	1	0	1	2	0	0
2. Internalizing	0	**100**	3	21	**38**	**47**	1	1	0	0	0	6	1	0
3. Social problems	0	23	**100**	37	24	**53**	26	0	1	0	6	1	1	0
4. Thought problems	3	15	16	**100**	23	**62**	11	0	0	0	1	0	**66**	0
5. Attention problems	1	0	5	12	**100**	0	1	0	0	0	0	7	**36**	0
6. Externalizing	0	**9**	**64**	**19**	**15**	**100**	13	2	2	0	2	35	0	0
7. Sleep problems	3	**85**	**77**	**82**	**64**	22	**100**	1	0	0	16	9	28	4
8. Family conflict	19	**44**	0	0	2	**68**	0	**100**	**76**	0	**57**	5	0	0
9. Parental monitoring	10	0	0	0	0	1	0	**27**	**100**	0	0	0	0	1
10. Neighborhood safety	15	0	0	6	3	22	5	1	0	**100**	3	0	1	0
11. School protective factors	0	**29**	**100**	1	**57**	11	7	**41**	13	0	**100**	6	2	0
12. Stressful life events	0	22	38	2	1	0	2	0	1	5	0	**94**	0	0
13. Material hardship	0	0	0	**70**	**19**	0	10	0	0	3	0	**99**	**100**	0
14. Low-level substance use	2	1	0	0	0	0	0	0	7	0	11	0	0	**100**
Contemporaneous (lower triangle) and between-subjects (upper triangle) network structures														
1. Suicidality	NA	**91**	22	18	36	14	6	**87**	**31**	13	**94**	**76**	8	**94**
2. Internalizing	**100**	NA	**100**	**100**	**100**	21	**100**	**100**	**46**	0	**100**	**100**	**63**	**75**
3. Social problems	1	**100**	NA	**100**	**100**	**100**	**76**	**61**	4	**83**	**92**	1	**94**	22
4. Thought problems	4	**100**	**100**	NA	**100**	**99**	**100**	0	6	**66**	23	13	34	2
5. Attention problems	11	**100**	**100**	**100**	NA	**100**	**100**	**95**	**100**	6	29	22	**67**	4
6. Externalizing	2	**100**	**100**	**100**	**100**	NA	**98**	**100**	**99**	7	0	**100**	1	**96**
7. Sleep problems	0	**100**	**69**	**100**	**100**	**95**	NA	3	35	**57**	27	**84**	**100**	17
8. Family conflict	**100**	0	0	2	0	**99**	1	NA	**100**	**67**	**95**	32	**80**	0
9. Parental monitoring	**99**	0	9	0	0	**54**	1	**100**	NA	31	**100**	**69**	**100**	**44**
10. Neighborhood safety	0	0	**44**	1	1	33	**97**	0	0	NA	2	**54**	**100**	**100**
11. School protective factors	**96**	14	**47**	**59**	**97**	**70**	5	**100**	**100**	0	NA	**24**	**95**	**100**
12. Stressful life events	3	**100**	**73**	0	9	8	**96**	0	1	0	0	NA	**100**	4
13. Material hardship	0	**100**	0	17	**86**	50	23	0	**85**	6	2	100	NA	**85**
14. Low-level substance use	**100**	0	0	0	0	0	23	**54**	**55**	0	**100**	0	0	NA

Note: Bold values represent edges that were included in the original analysis (Tables 6-8, Figure 1). Each of the 100 bootstrapped models used a random 75% of the full analytic sample (n = 7,388).

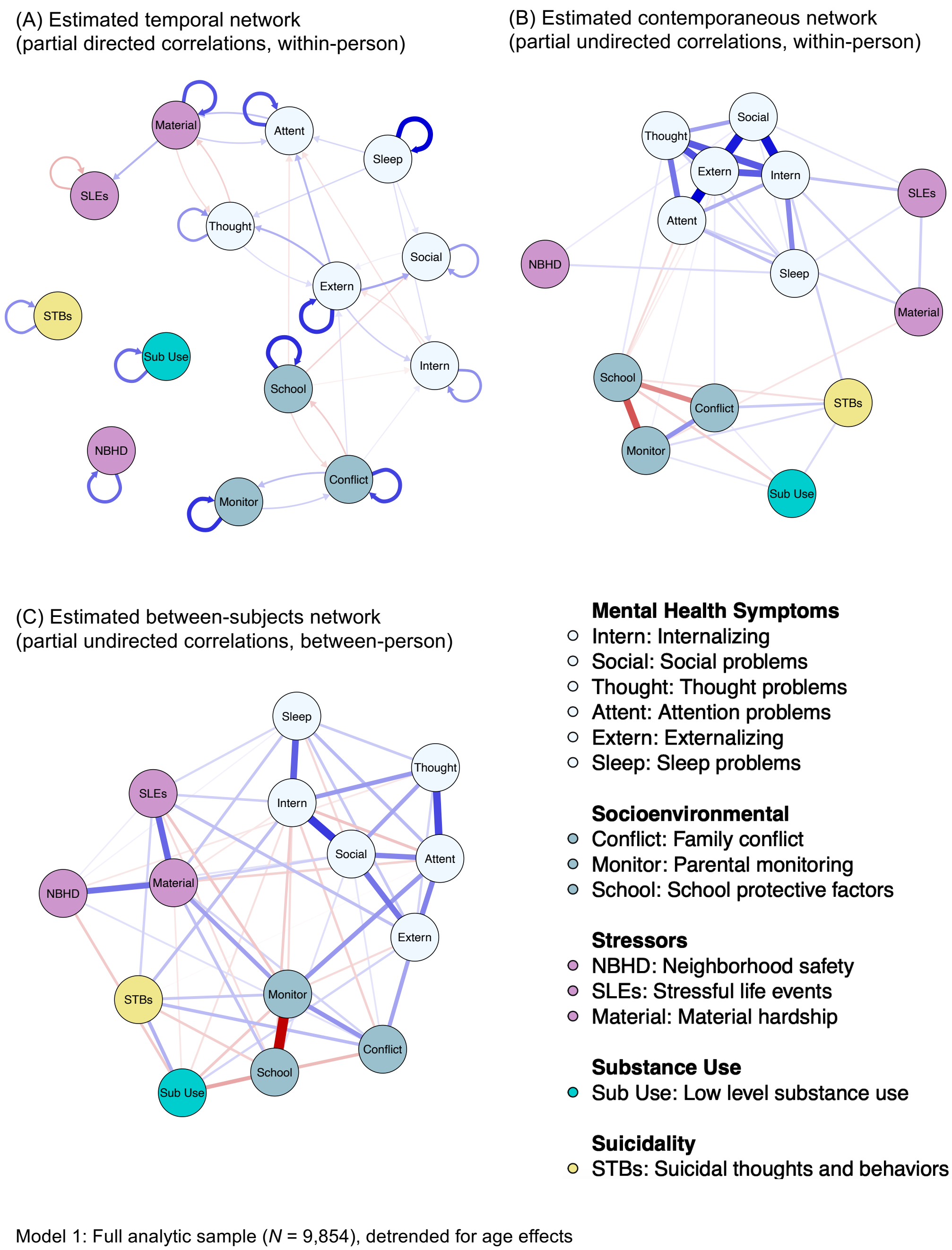

Figure 1: *Pruned network structures for the panel GVAR model in the full sample (N = 9,854)*
Note: Edge color represents effect direction (blue = positive, red = negative), while edge thickness represents effect strength (darker, thicker edges denote larger effects). Edges not shown were pruned during model selection. (A) Arrows represent lagged directed partial correlations and autocorrelations in the temporal network. (B) Lines represent undirected partial correlations in the contemporaneous network. (C) Lines represent undirected partial correlations in the between-subjects network. Corresponding numeric results are presented in Tables 6-8.

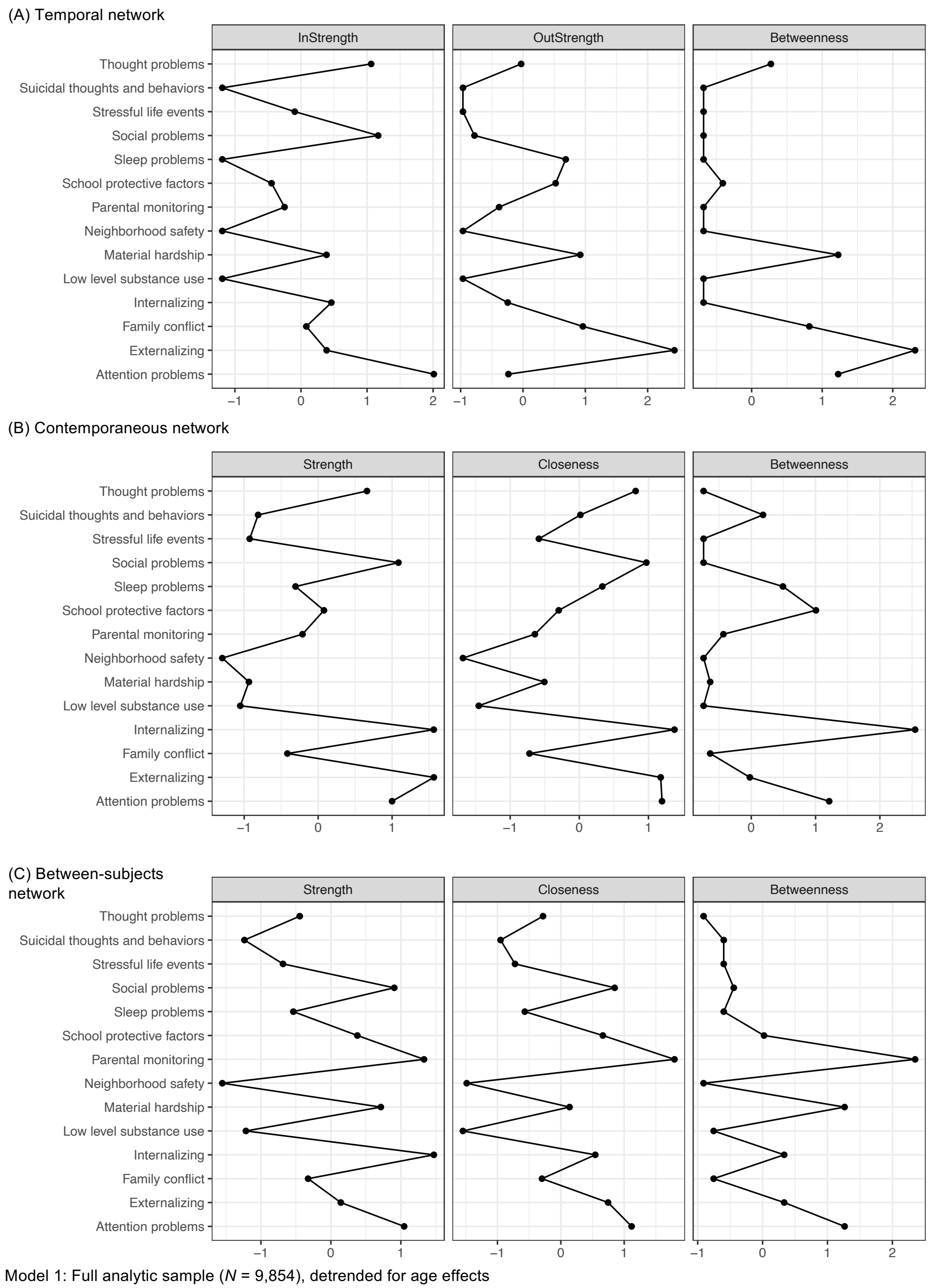

Figure 2: *Node centrality metrics for the panel GVAR model in the full sample (N = 9,854)*
Note: (A) In the temporal network, In-Strength centrality represents the sum of all incoming absolute edge weights to a node, while Out-Strength centrality represents the sum of outgoing absolute edge weights from a node. (B-C) In the contemporaneous and between-subjects networks, Strength centrality represents the sum of all absolute edge weights connected to a node. Closeness represents the average shortest path between a specific node and all other nodes. Betweenness represents the number of times a node is on the shortest path between other nodes (Hevey, 2018). Centrality is shown in the metric of *z*-scores.

In the contemporaneous network, undirected edges represent within-person partial correlations between each pair of nodes within the same measurement occasion, after controlling for all effects in the temporal model (i.e., the contemporaneous effects are residuals of the temporal network). In the pruned, estimated contemporaneous network, direct associations were observed between STBs and five other nodes: internalizing symptoms, low-level substance use, family conflict, lower parental monitoring, and lower school protective factors (Figure 1B; Table 7). The bootstrapping procedure indicated high stability of these direct effects (included in ≥ 89 out of 100 bootstrapped models; Table 9). Potential indirect pathways to STBs were also observed. Internalizing was associated with the other five mental health symptom dimensions (externalizing, thought problems, attention problems, sleep problems, and social problems), material hardship, and stressful life events. Each of these internalizing edges was included in 100% of the bootstrapped models, indicating internalizing may potentially be a pathway through which other mental health symptoms, material hardship, and stressful life events influence suicidality. Further, pairwise edges were observed between family conflict, parental monitoring, school protective factors, and substance use, indicating risk for STBs may be higher when more than one of these nodes is elevated. Mental health symptom nodes had highest strength and closeness centrality, including internalizing, externalizing, attention problems, and social problems (Figure 2B). Internalizing, attention problems, and school protective factors displayed highest betweenness centrality.

In the between-subjects network, undirected edges represent partial correlations between overall variable means. The overall structure of the between-subjects network was similar to the contemporaneous network, although several additional edges were observed and the bootstrapping procedure indicated lower stability for some edges (Tables 8 and 9). STBs again had direct associations with internalizing symptoms, low-level substance use, family conflict, lower parental monitoring, and lower school protective factors. An additional direct association was observed between STBs and stressful life events (Figure 1C; Table 8). The bootstrapping procedure generally indicated stability of these effects, although the edge between STBs and parental monitoring was only observed in 31 of the bootstrapped models (Table 9). Potential indirect pathways to STBs through internalizing were again observed for other mental health symptoms. Internalizing, parental monitoring, and attention problems had highest strength centrality (Figure 2C). Parental monitoring and attention problems displayed highest closeness centrality, while parental monitoring, material hardship, and attention problems had highest betweenness centrality. Effect sizes for all three Model 1 network structures were generally small ($r < .30$ for most edges).

Supplemental Model 1

Supplemental Model 1 estimated the same network structures using non-trended data for the full sample ($N = 9{,}854$). Supplemental Model 1 demonstrated excellent fit (Table 5). Network structures and centrality indices for Supplemental Model 1 are visualized in Supplemental Figures S1-2, respectively. Correlation coefficients for the temporal, contemporaneous, and between-subjects networks are presented in Supplemental Tables S3-5. Reassuringly, there were few substantial differences between the network structures estimated with detrended versus non-detrended data. In the temporal network, autoregressive effects were again observed between all nodes, and STBs did not directly associate with other variables. In the contemporaneous network, STBs again exhibited direct associations with internalizing symptoms, low-level substance use, family conflict, lower parental monitoring, and lower school protective factors. The between-subjects network for Supplemental Model 1 included a larger number of edges compared to Model 1, possibly due to not controlling for the linear effects of age in this model.

Model 2 Results: STB Subsample

Model 2 demonstrated excellent fit (Table 5). Network structures for Model 2, using detrended data for the STB subsample (*n* = 1,699), are shown in Figure 3. Correlation coefficients for the temporal, contemporaneous, and between-subjects networks are presented in Tables 10-12, respectively. The bootstrap inclusion probabilities for Model 2 edges are shown in Table 13. Centrality indices for Model 2 are shown in Figure 4. Overall, the network structures for Model 2 were sparser than in Model 1, possibly reflecting different experiences of youth who endorsed STBs compared to the general sample, as well as potential power limitations due to use of the much smaller STB subsample to estimate effects.

In the pruned, estimated temporal network, social problems positively predicted subsequent STBs (Figure 3A; Table 10). However, this effect was small (*r* = .03) and was only observed in 33 out of 100 bootstrapping procedures, decreasing confidence in its stability. Mental health symptoms again had highest centrality in the temporal network (Figure 3). Externalizing, thought problems, and social problems displayed highest in-strength centrality; attention problems, internalizing, and social problems had highest out-strength centrality; and internalizing, thought problems, and social problems had highest betweenness centrality.

In the pruned, estimated contemporaneous network, STBs had direct observed associations with the same five nodes as Model 1: internalizing symptoms, low-level substance use, family conflict, lower parental monitoring, and lower school protective factors (Figure 3B; Table 11). The bootstrapping procedure indicated high stability of these effects (edges were included in ≥ 89 out of 100 case-drop models). Also similar to Model 1, potential indirect

Table 10

Estimated directed partial correlations for the temporal network in the STB subsample (Model 2, n = 1,699)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Suicidality	–	–	–	–	–	–	–	–	–	–	–	–	–	–
2. Internalizing	–	0.224	0.118	0.098	–	0.077	0.082	–	–	–	–	0.162	0.076	–
3. Social problems	0.031	0.131	0.208	0.121	0.184	0.179	0.079	–	–	–	–	–	–	–
4. Thought problems	–	0.063	–	0.114	–	0.073	0.128	–	–	–	–	–	–	–
5. Attention problems	–	–	0.179	0.086	0.282	0.144	–	–	–	–	–	–	–	–
6. Externalizing	–	–	–	–	–	–	-0.072	–	–	–	–	–	–	–
7. Sleep problems	–	0.046	–	0.102	–	–	0.223	–	–	–	–	–	–	–
8. Family conflict	–	–	–	–	–	–	–	0.196	–	–	-0.078	–	–	–
9. Parental monitoring	–	–	–	–	–	–	–	–	0.119	–	–	–	–	–
10. Neighborhood safety	–	–	–	–	–	–	–	–	–	–	–	0.097	–	–
11. School protective factors	–	–	–	–	–	–	–	–	–	–	0.154	–	–	–
12. Stressful life events	–	–	–	–	–	–	–	–	–	–	–	-0.137	–	–
13. Material hardship	–	–	–	–	–	–	–	–	–	–	–	–	0.180	–
14. Low-level substance use	–	–	–	–	–	–	–	–	–	–	–	–	–	–

Note: Values represent lagged and autoregressive (i.e., across timepoints) directed partial correlations at the within-person level. Values on the diagonal are autocorrelations. The *psychonetrics* package does not currently provide standard errors for partial directed correlations (Epskamp, 2022). See Figure 3A for graphical representation of the temporal network structure in the STB subsample.

Table 11

Estimated undirected partial correlations for the contemporaneous network in the STB subsample (Model 2, n = 1,699)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Suicidality	NA													
2. Internalizing	0.089 (0.011)	NA												
3. Social problems	–	0.326 (0.017)	NA											
4. Thought problems	–	0.236 (0.019)	0.057 (0.019)	NA										
5. Attention problems	–	–	0.251 (0.019)	0.164 (0.018)	NA									
6. Externalizing	–	0.181 (0.017)	0.290 (0.017)	0.238 (0.017)	0.275 (0.018)	NA								
7. Sleep problems	–	0.192 (0.018)	–	0.147 (0.019)	0.070 (0.016)	–	NA							
8. Family conflict	0.121 (0.016)	–	–	–	–	–	–	NA						
9. Parental monitoring	0.101 (0.016)	–	–	–	–	0.051 (0.011)	–	0.092 (0.017)	NA					
10. Neighborhood safety	–	–	–	–	–	–	–	–	–	NA				
11. School protective factors	-0.088 (0.016)	-0.056 (0.011)	–	–	–	–	–	-0.187 (0.017)	-0.173 (0.017)	–	NA			
12. Stressful life events	–	0.136 (014)	–	–	–	–	0.073 (0.018)	–	–	–	–	NA		
13. Material hardship	–	0.074 (0.014)	–	–	0.052 (0.015)	–	–	–	–	–	–	0.067 (0.018)	NA	
14. Low-level substance use	0.097 (0.016)	–	–	–	–	–	–	–	0.068 (0.016)	–	–	–	–	NA

Note: Values represent contemporaneous (i.e., same measurement occasion) undirected partial correlations at the within-person level after controlling for temporal effects. Standard errors are provided in parentheses. See Figure 3B for graphical representation of the contemporaneous network structure in the STB subsample.

Table 12

Estimated undirected partial correlations for the between-subjects network in the STB subsample (Model 2, n = 1,699)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Suicidality	NA													
2. Internalizing	–	NA												
3. Social problems	–	–	NA											
4. Thought problems	–	–	–	NA										
5. Attention problems	–	–	–	0.494 (0.035)	NA									
6. Externalizing	–	–	–	–	0.215 (0.030)	NA								
7. Sleep problems	–	0.275 (0.042)	–	–	0.213 (0.031)	0.165 (0.032)	NA							
8. Family conflict	–	–	0.359 (0.073)	–	–	0.264 (0.036)	–	NA						
9. Parental monitoring	–	–	–	–	0.210 (0.028)	-0.132 (0.034)	–	0.324 (0.038)	NA					
10. Neighborhood safety	–	–	0.317 (0.065)	–	–	0.102 (0.028)	–	-0.006 (0.053)	–	NA				
11. School protective factors	–	–	–	–	–	–	–	–	-0.490 (0.039)	–	NA			
12. Stressful life events	–	–	–	–	–	0.116 (0.028)	–	–	–	–	–	NA		
13. Material hardship	–	–	–	–	–	–	0.195 (0.029)	–	–	0.327 (0.028)	–	0.365 (0.030)	NA	
14. Low-level substance use	–	–	–	–	–	–	–	–	–	–	–	–	–	NA

Note: Values represent undirected partial correlations at the between-person level (i.e., associations between overall variable means) after controlling for other variables in the model. Standard errors are provided in parentheses. See Figure 3C for graphical representation of the between-person network structure in the STB subsample.

Table 13

Number of times (out of 100) each edge was included in the case-drop bootstrap resampling procedure for Model 2

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Temporal network structure														
1. Suicidality	7	0	0	0	0	0	0	0	0	0	0	0	3	0
2. Internalizing	24	**94**	**29**	**19**	23	**15**	**15**	7	0	5	0	**61**	**16**	1
3. Social problems	**33**	**64**	**90**	**63**	**72**	**78**	**31**	19	2	2	0	5	15	20
4. Thought problems	1	**46**	34	**75**	37	**78**	**94**	0	1	1	4	4	4	0
5. Attention problems	8	25	**85**	**76**	**100**	**75**	27	1	3	0	1	3	10	0
6. Externalizing	4	2	3	2	5	13	**56**	2	0	2	0	12	0	1
7. Sleep problems	0	**18**	3	**64**	15	5	**100**	0	0	1	0	2	21	1
8. Family conflict	8	1	3	0	0	11	0	**100**	0	0	**24**	0	0	2
9. Parental monitoring	4	1	0	0	0	0	0	0	**87**	0	0	0	8	0
10. Neighborhood safety	0	1	0	0	0	0	3	3	0	5	0	**48**	2	0
11. School protective factors	21	1	4	0	0	0	1	0	0	0	**100**	0	0	0
12. Stressful life events	0	13	1	0	0	0	3	2	0	0	0	**99**	0	0
13. Material hardship	0	4	3	26	0	0	2	0	4	0	3	4	**81**	1
14. Low-level substance use	0	0	4	0	1	0	0	0	0	0	0	0	0	0
Contemporaneous (lower triangle) and between-subjects (upper triangle) network structures														
1. Suicidality	NA	1	2	10	1	2	0	0	11	0	2	0	15	1
2. Internalizing	**100**	NA	29	28	10	8	**56**	1	1	1	6	6	0	1
3. Social problems	13	**100**	NA	15	12	36	17	**14**	12	**29**	2	9	18	0
4. Thought problems	0	**100**	**91**	NA	**44**	8	15	3	10	2	0	2	0	1
5. Attention problems	0	4	**100**	**100**	NA	**39**	**36**	7	**64**	5	0	2	4	0
6. Externalizing	0	**100**	**100**	**100**	**100**	NA	**38**	**52**	**14**	**14**	2	**31**	33	20
7. Sleep problems	0	**100**	1	**100**	**66**	4	NA	9	10	6	2	39	**60**	0
8. Family conflict	**100**	2	0	0	0	7	0	NA	**62**	**36**	28	1	24	1
9. Parental monitoring	**99**	0	0	1	1	**60**	0	**99**	NA	1	**73**	0	1	18
10. Neighborhood safety	0	0	0	0	19	6	4	0	0	NA	0	0	**95**	18
11. School protective factors	**93**	**68**	1	4	0	0	0	**100**	**100**	0	NA	0	7	24
12. Stressful life events	0	**91**	13	0	0	3	**39**	0	2	0	0	NA	**95**	0
13. Material hardship	0	**88**	0	20	**58**	7	0	0	15	0	4	**79**	NA	0
14. Low-level substance use	**89**	0	0	0	0	0	0	0	**95**	0	15	0	0	NA

Note: Bold values represent edges that were included in the original analysis (Tables 10-12, Figure 3). Each of the 100 bootstrapped models used a random 75% of the STB subsample (n = 1,274).

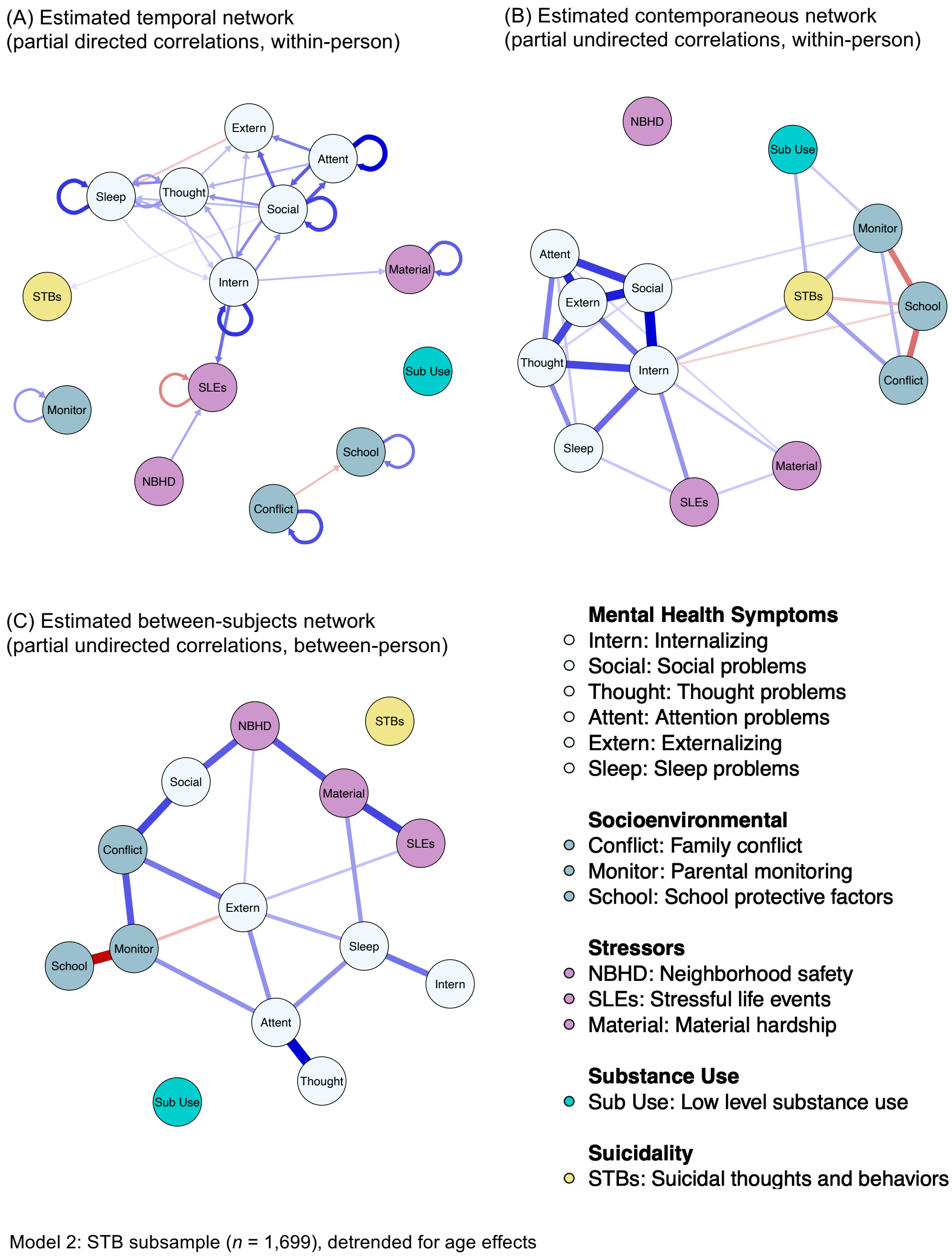

Figure 3: *Pruned network structures for the panel GVAR model in the STB subsample (n = 1,699)*
Note: Edge color represents effect direction (blue = positive, red = negative), while edge thickness represents effect strength (darker, thicker edges denote larger effects). Edges not shown were pruned during model selection. (A) Arrows represent lagged directed partial correlations and autocorrelations in the temporal network. (B) Lines represent undirected partial correlations in the contemporaneous network. (C) Lines represent undirected partial correlations in the between-subjects network. Corresponding numeric results are presented in Tables 9-11.

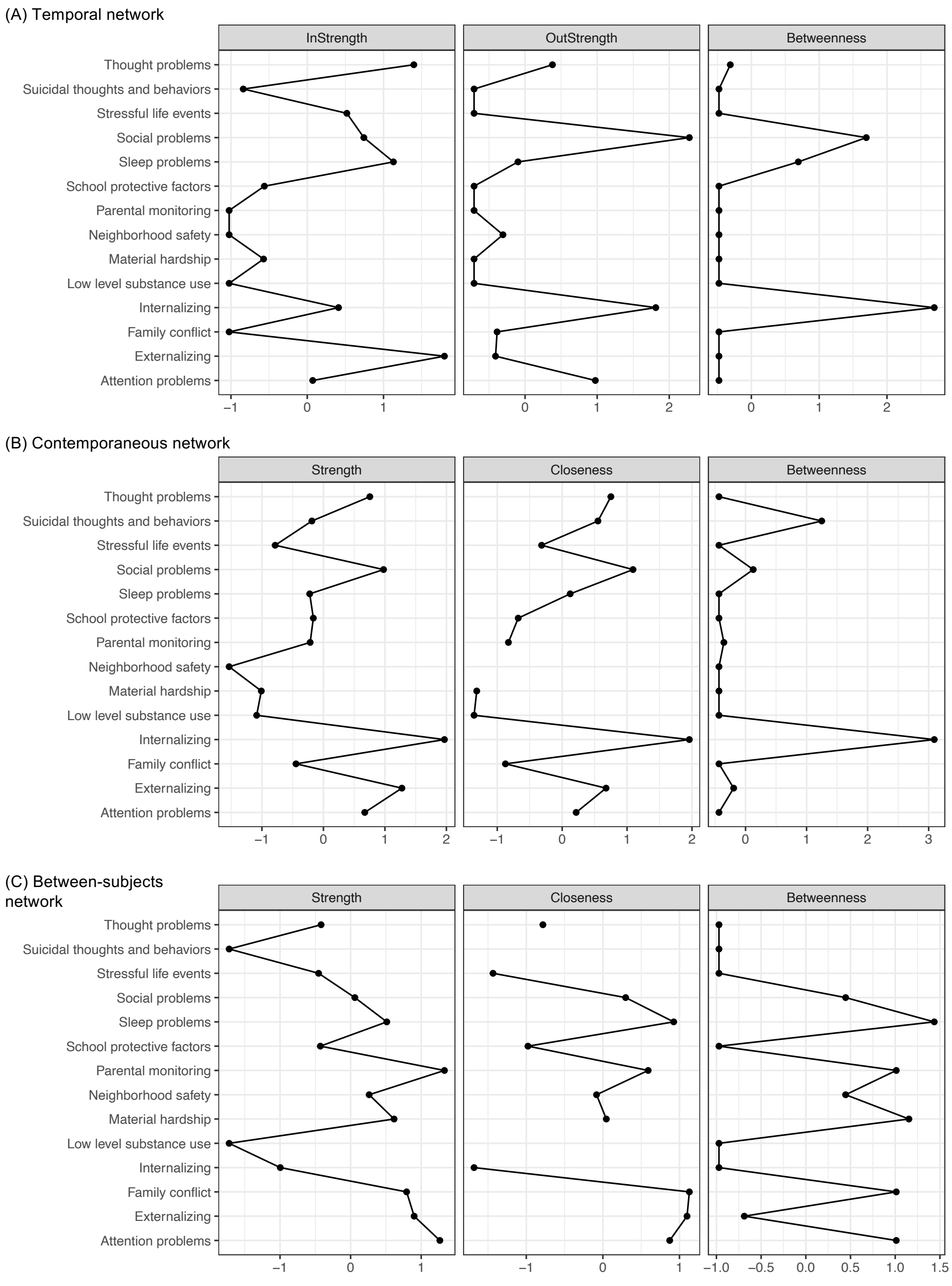

Figure 4: *Node centrality metrics for the panel GVAR model in the STB subsample (n = 1,699)*
Note: (A) In the temporal network, In-Strength centrality represents the sum of all incoming absolute edge weights to a node, while Out-Strength centrality represents the sum of outgoing absolute edge weights from a node. (B-C) In the contemporaneous and between-subjects networks, Strength centrality represents the sum of all absolute edge weights connected to a node. Closeness represents the average shortest path between a specific node and all other nodes. Betweenness represents the number of times a node is on the shortest path between other nodes (Hevey, 2018). Centrality is shown in the metric of *z*-scores.

pathways to STBs through internalizing were observed for other mental health symptoms, stressful life events, and material hardship. Pairwise edges were also observed again between family conflict, parental monitoring, school protective factors, and substance use, indicating these factors may conjointly elevate risk for STBs. An additional potential indirect pathway was observed, in which externalizing may possibly influence STBs through lower parental monitoring. The effect between externalizing and parental monitoring was observed in 60 out 100 case-drop bootstrapped models. Mental health symptoms, and internalizing in particular, had highest centrality indices, with STBs also demonstrating relatively high betweenness centrality. In the pruned, estimated between-subjects network, no direct effects were observed between STBs and the other nodes. Similar to Model 1, effect sizes for the three Model 2 network structures were generally small ($r < .35$ for most edges).

Supplemental Model 2

Supplemental Model 2 estimated the same network structures using non-detrended data for the STB subsample ($n = 1{,}699$). Supplemental Model 2 demonstrated excellent fit (Table 5). Network structures and centrality indices for Supplemental Model 2 are shown in Supplemental Figures S3-4, respectively. Correlation coefficients for the three network structures are presented in Supplemental Tables S6-8. Few substantive differences were observed between the network structures estimated using detrended versus the non-detrended data for the STB subsample. In the temporal network, a small, positive effect was again observed for social problems predicting subsequent STBs. In the contemporaneous network, STBs again had direct observed associations with internalizing symptoms, low-level substance use, family conflict, lower parental monitoring, and lower school protective factors. Observed potential indirect pathways to STBs were similar to the contemporaneous network in Model 2. In the between-subjects network, a positive direct association was observed between STBs and material hardship.

DISCUSSION

The present study applied a network analysis approach to elucidate potential pathways of risk and protection for suicidal thoughts and behaviors (STBs) during early adolescence. Models examined risk and protective factors for STBs from multiple salient life domains, including mental health symptoms, socioenvironmental factors, life stressors, and early onset substance use. Notably, models assessed longitudinal associations between STBs and each risk and protective factor during the critical developmental period as youth transition from late childhood into early adolescence, from approximately ages 10-12 years, an age range that has been relatively understudied in youth suicide research. To my knowledge, the present study represents a novel extension of the network approach to psychopathology by evaluating longitudinal panel networks of multiple domains of risk and protective factors for STBs. Additionally, to my knowledge, the present study is the first to examine longitudinal risk for STBs in the ABCD study cohort using data from the first three annual measurement occasions.

Study results largely supported initial hypotheses. Risk and protective factors representing multiple life domains were directly associated with STBs, highlighting the value of applying a social-ecological approach to STB research (Cramer & Kapusta, 2017). Socioenvironmental risk factors (higher family conflict, lower parental monitoring, and lower school protective factors), low-level substance use, and internalizing symptoms had consistent direct associations with STBs across network models. Moreover, observed potential indirect pathways supported the hypothesis that life stressors could indirectly impact STBs through subsequent increases in mental health symptoms (internalizing) (Aas et al., 2017). Network structures were similar for models estimated in the full sample (N = 9,854) versus the subsample of youth who endorsed STBs at one or more timepoints (*n* = 1,699). Thus, the same salient pathways of risk and protection for STBs may be identified in both population-based and clinically-focused studies.

Effect Timescales

It is important to consider timescales when interpreting longitudinal effects (Burger et al., 2022; Epskamp, 2020). Risk and protective factors for mental health phenomena can manifest at different timescales across development (Ram & Diehl, 2014). Some factors may be stable across the duration of a study, while others may change across the same period of data collection. STBs are often conceptualized as resulting from interactions between chronic, acute, and imminent risk factors (Cha et al., 2018; Obegi et al., 2015). For example, while family history of suicide is a chronic predisposing factor that increases risk across the lifespan, hopelessness can fluctuate rapidly and likely contributes to momentary, imminent risk for suicide (Obegi et al., 2015; Steele et al., 2018).

In the present study, measurement occasions were spaced approximately one year apart. However, the timescales for the causal effects of many risk and protective factors on STBs are likely shorter than one year (Berman & Silverman, 2014). For example, suicidality commonly co-occurs with internalizing symptoms (Goldston et al., 2009). Past-year STBs would hence be expected to have a stronger association with internalizing symptoms assessed during the same timepoint (in this case, the CBCL measured past six-month symptoms), compared to internalizing symptoms measured two years previously. Contemporaneous networks are therefore most likely to capture the putatively causal associations between variables in presented models (Burger et al., 2022). The lack of robust associations between STBs and other variables in the temporal networks indicates that the one-year time-lag between measurement occasions may be too long to capture meaningful impacts of the other variables on STBs. Moreover, the presence of several consistent contemporaneous effects with mostly null temporal effects suggests that the effects of other variables on STBs may diminish over time. Thus, while it is important to control for temporal lagged and autoregressive effects in the networks (Usami et al., 2019), interpretation will primarily focus on the contemporaneous network structures.

Direct Pathways of Risk and Protection for STBs

Across all the contemporaneous network models, STBs had direct, positive associations with the same five risk and protective factors: higher family conflict, lower parental monitoring, lower school protective factors, higher internalizing symptoms, and higher low-level substance use. While these risk and protective factors have been robustly identified in previous STB literature, observing these effects in network models bolsters confidence in their importance; these effects were consistent after controlling for all other pairwise associations in the networks. Thus, results emphasize that family and school environments serve as contexts for salient social experiences in this age range (Carballo et al., 2020; Cha et al., 2018; de Sousa et al., 2017; Fotti et al., 2006; Janiri et al., 2020; Miller et al., 2015; Sedgwick et al., 2019). Youth who perceived higher levels of expressed emotion and aggression in their family, and their caregivers being less involved in and aware of their daily activities, were more likely to report STBs. Additionally, youth who reported lower engagement and support in their schools were at greater risk for STBs.

It is interesting that internalizing symptoms were consistently predictive of STBs while other mental health symptom dimensions were not. Previous literature has emphasized the transdiagnostic and comorbid nature of STBs (American Psychiatric Association, 2013; Carballo et al., 2020; Cha et al., 2018), and other mental health symptom dimensions (e.g., externalizing) have been associated with STBs in the ABCD cohort (DeVille et al., 2020; Harman et al., 2021;

Janiri et al., 2020; van Velzen et al., 2021). However, these studies did not use a network approach, and thus did not control for other pairwise effects in models. Many individuals experience multiple types of mental health symptoms (Caspi et al., 2020; Plana-Ripoll et al., 2019). Among early adolescents, internalizing symptoms may be the primary causal pathway through which overall mental health concerns contribute to STBs.

The direct association between low-level substance use and STBs is also noteworthy. Similar to early onset STBs increasing the risk for subsequent severe suicidality (Thompson et al., 2012), early low-level substance use may increase the risk of harmful substance use later in life (Donovan & Molina, 2011). Both STBs and substance use can be harmful in this age range; the co-occurrence of STBs and substance use during early adolescence may compound risk for negative long-term outcomes (Effinger & Stewart, 2012). STBs also had a direct effect with stressful life events in the full sample between-subjects network, suggesting that, overall, youth with a lifetime history of stressful life events were more likely to report lifetime history of STBs. This is in line with previous research identifying adverse life events as correlates of STBs (Cha et al., 2018; King et al., 2001; Pan & Spittal, 2013). Lastly, the observed autoregressive effect for STBs in the full sample temporal network affirms that individuals with a history of STBs have elevated risk for future STBs, and risk assessment over time should account for this (Robinson et al., 2018).

Potential Indirect Pathways of Risk and Protection for STBs

Potential indirect pathways to STBs were also observed in the contemporaneous network structures. While internalizing was the only mental health variable that exhibited a direct association with STBs, internalizing generally had high centrality across models and was associated with the other five mental health symptom dimensions, stressful life events, and material hardship. Thus, internalizing may potentially provide a mechanism through which life stressors and other psychopathology symptoms contribute to risk of STBs. For example, externalizing problems could potentially lead to criticism from self and others, increasing lower self-worth and negative self-talk, thereby contributing to thoughts of suicide. Further, stressful life events may be more likely to impact STBs if youth experience resulting internalizing difficulties. This may partly explain why only some youth who experience significant adverse events present with subsequent STBs and other mental health concerns (e.g., Goldenson et al., 2021). Consistent pairwise associations were also observed between low-level substance use and all three of the socioenvironmental risk factors (family conflict, parental monitoring, and school protective factors). Because these factors all related to STBs and to each other, results suggest the potential for a feedback system in which these factors could conjointly increase risk for STBs.

A major strength of the network approach is the ability to visualize and analyze complex systems of variables (de Beurs, 2017; Epskamp et al., 2018). Nonetheless, network models with undirected edges do not evaluate causal direct effects (i.e., causal direction is not specified). Network models also do not test causal indirect effects, as mediation analysis is not explicitly conducted. Network analyses can therefore be used to generate causal hypotheses about complex pathways of risk and protection that may be obscured in traditional predictive models (Borsboom & Cramer, 2013). Future research could explicitly test potential causal, mediating effects of the indirect pathways identified in the present study (e.g., via path analysis).

Data Availability and Reliability

Results should be interpreted in the context of some features of the ABCD data. Small effect sizes (*r* generally < .3) were observed for most associations between study variables, and this occurred in both full and partial correlations. Previous research has documented that effect sizes in the currently available ABCD data are often smaller than expected given previous literature on associations between measured variables (Gonzalez et al., 2021; Owens et al., 2021). This may be partly due to rarity of mental health and behavioral concerns in the current sample, which makes sense given that STBs, substance use, and mental health symptoms often become more prevalent later in adolescence. It is also plausible that measurement error could have obscured the strength of some effects. While most measures demonstrated good or adequate internal consistency, reliability metrics for some study measures were low (Gonzalez et al., 2021), particularly at the within-person level. This may be related to the small number of measurement occasions examined in the present study (three annual timepoints). Ongoing rigorous evaluation of the psychometric properties of the ABCD data will be important as additional waves of data are released.

In particular, it will be interesting to evaluate if interrater reliability changes as the ABCD cohort gets older. Interrater agreement between self- and parent-report measures of youth experiences was often low. Given this, along with inconsistent data availability across timepoints, the present study only used data from a single reporter (parent or youth) for each variable. Despite low interrater reliability, parent and youth reports for the same measures statistically differentiated between risk levels for youth in the ABCD study (Gonzalez et al., 2021). Additionally, several of the same risk factors were predictive of both self- and parent-report of youth STBs in the ABCD sample, despite low interrater agreement for the STBs variable (Janiri et al., 2020). Nevertheless, the low interrater agreement suggests parents/caregivers may not be aware of some of their child’s experiences. Younger youth may also not fully understand some items on psychometric measures, and interrater agreement between parents and youth often improves as children become older (e.g., Ebesutani et al., 2011).

Most of the direct associations observed for STBs (self-reported by youth) in the network models were with other variables youth self-reported on (family conflict, parental monitoring, school protective factors, and substance use). Internalizing was the only parent-report variable that directly associated with STBs in most network models, although stressful life events (parent report) was associated with STBs in the full sample between-subjects network. Similarly, many of the parent-report variables had strongest associations with other parent-report variables in the networks (mental health symptoms and life stressors). All the examined risk and protective factors have been robustly associated with youth STBs in previous research regardless of measure reporter (Carballo et al., 2020; Cha et al., 2018; de Sousa et al., 2017). Nonetheless, it is possible that bias for larger effects among variables from the same reporter could have influenced some of the observed network structures. Replicating the present study using data from both parent and youth reports for each variable would increase confidence in study results.

Study Implications

Several implications can be drawn from the study results. Results highlight the complexity of STBs, in which STBs may result from direct and indirect pathways between several types of risk and protective factors (Graziano et al., 2021; Shiratori et al., 2014). Thus, considering risk and protective factors from multiple life domains is recommended for understanding a youth's overall risk for STBs (Carballo et al., 2020). While every risk and protective factor examined in networks has previously been associated with STBs, pairwise associations were not observed between all variables. STBs also had fairly low centrality in the network models, and a relatively small number of variables exhibited consistent direct associations with STBs. Taken together, results suggest the development of risk for STBs is not a uniform process; risk factors for STBs are not all interrelated, and appear to influence STBs and each other through specific paths.

Moreover, risk for STBs may be compounded when more than one risk factor occurs, potentially contributing to self-reinforcing feedback systems of risk. For example, pairwise associations were observed between STBs, parental monitoring, school protective factors, family conflict, and low-level substance use. Low parental monitoring can increase a youth's risk for early initiation of substance use (Dever et al., 2012) and poorer school performance and engagement (Lowe & Dotterer, 2013). This could in turn contribute to higher family conflict, which may then reinforce ongoing school and substance use concerns (Timmons & Margolin, 2015). After a youth experiences significant family and school difficulties, they are at elevated risk for poor academic and behavioral outcomes (including STBs), and evidence-based interventions may be less accessible and effective (Lloyd et al., 2019). Thus, activation of one or more of these risk factors may increase the other risk factors, exacerbating and potentially perpetuating overall risk for STBs (Borsboom, 2017; Dablander et al., 2020). However, because these variables were all related, results also suggest that intervening on one of these risk factors may have protective effects on the other nodes.

Hence, in addition to direct predictive effects, interrelations *between* risk and protective factors may impact the development and course STBs. When multiple pathways of risk for STBs become activated, STBs could potentially become more severe and persistent (Delgadillo et al., 2023). Many of these effects may be obscured in traditional predictive models that do not account for shared variance and pairwise relations between all variables. Thus, the present study supports the use of longitudinal network analyses to provide information about complex systems of risk and protection for STBs (de Beurs, 2017). Future applications of network analysis could yield additional insight into how the nuanced interplay between risk and protective factors can influence STBs (e.g., in specific at-risk populations or during time periods of elevated risk).

Results also have important implications for intervention. Several of the risk and protective factors identified in presented models are malleable, and could be amenable to prevention and early intervention initiatives (McGorry & Mei, 2018). To date, relatively few suicide-focused interventions have been specifically tailored to late childhood and early adolescence (Robinson et al., 2018). Psychosocial interventions specifically designed for early adolescents may benefit from prioritizing increased school support and engagement, as well as improving family support, engagement, and communication. Results also suggest internalizing is a more central risk factor for STBs than other mental health symptom dimensions in this age range. Given its high centrality in the network models, intervening on internalizing symptoms might also have subsequent protective effects on other, indirect risk factors for STBs. Interventions that provide age-appropriate psychoeducation about mental health (including anxious and depressive symptoms), teach skills to promote socioemotional functioning, and reduce stigma could be valuable (Wasserman et al., 2021).

Universal school-based interventions have shown promise for protecting against mental health concerns broadly (e.g., Catalano et al., 2021). Early research suggests universally implemented programs can effectively integrate curricula focused on STBs specifically (Calear et al., 2016; Schilling et al., 2016; Wasserman et al., 2015). Continued development and evaluation of such school-based programs is recommended. It is also important to improve the accessibility of targeted interventions for early adolescents experiencing STBs, internalizing symptoms, and other psychosocial stressors. For example, evidence-based psychotherapies (e.g., cognitive behavioral and third-wave therapies) and psychiatric medication have been effective in reducing STBs (Mann et al., 2021; Wasserman et al., 2021). However, many families do not have consistent access to these services, and access can be especially challenging for youth in underserved communities (Lloyd et al., 2019; McGorry & Mei, 2018). Interventions that prevent or delay the initiation of recreational substance use may also have protective effects against STBs (Stockings et al., 2016).

Limitations and Future Directions

Results from the present study should be considered in the context of some limitations. First, the currently available ABCD data only includes three complete waves of data, each separated by approximately 12-months. This timeframe allowed for the examination of effects across multiple years of a critical developmental period. However, given the likelihood that the causal timescales between STBs and risk and protective factors is shorter than one year, an intensive longitudinal design (e.g., daily diary or ecological momentary assessment) would better capture real-time relations between variables (Harmer et al., 2021). An intensive longitudinal design could also better identify specific periods of elevated risk when timely interventions may be most needed (e.g., Bryan et al., 2022). Models were estimated using fixed effects, in which parameters were assumed to be the same across participants; having more timepoints of data would also allow for estimation of random effects, which could be used to examine person-specific differences in network structures. Additionally, having data spanning from early adolescence into early adulthood would provide more information about the developmental course of early-onset STBs. Replication of the study results after additional waves of ABCD data are released will therefore be important.

The second limitation pertains to the study measures. Although the ABCD study battery allowed for examination of a wide range of potential predictors of STBs, the annual measurement battery provided sparse detail about the specific timing, severity, and frequency of many variables of interest. For example, most measures assessed past-year or past-six-month experiences. Moreover, not all relevant risk and protective factors for STBs were assessed in the network models. Due to statistical assumptions of panel GVAR models, all variables examined in the networks were measured at all three timepoints. Some relevant variables were not included due to not presently having available data at all timepoints (e.g., impulsivity and emotion dysregulation). Also, static risk factors that can influence long-term risk for suicide but do not change over time and/or were not repeatedly measured were not considered (e.g., family history of suicide). As data collection continues, the rich ABCD battery will include more measures at enough timepoints (three or more) to examine longitudinal effects. It will be valuable to replicate and extend results from the present study after additional, relevant data become available. For example, ongoing measurement of youth peer experiences began in Year 2, at the age when peer experiences become increasingly salient for youth.

Third, analyses relied on self-report and parent-report data. As noted above, interrater agreement was generally low and data were often not consistently available from both youth- and parent-report measures. Youth and their parents/caregivers may have under- or over-reported youth's experiences. Use of multimodal measures, such as biological and behavioral data, could increase confidence in study results (Cha et al., 2018).

Fourth, defining STBs as ever having any reported form of suicidality may have obscured differences in risk and protective pathways for different levels of STB severity and frequency. Although STBs of any type are clinically concerning in early adolescence, suicidal ideation does not always progress to a suicidal behaviors (Klonsky et al., 2016). Further, different factors may contribute to chronic versus infrequent experiences of STBs. The rarity of active suicidal ideation and attempt in the present sample disallowed for separate examination of different STBs in complex network models. Future applications of network analyses that evaluate potential differences in types of STBs and their progression over time could help to identify individuals with greatest risk for death by suicide and/or functional impairment (Bloch-Elkouby et al., 2020; Klonsky et al., 2017; Nock et al., 2009).

Fifth, relations between STB risk and protective factors may also vary across STB age at onset, sex, gender, and other social identities (Cha et al., 2018; Klonsky et al., 2017; Wiglesworth et al., 2022). Future investigations of these constructs as potential clinical moderators of risk for STBs may help to identify individuals with elevated vulnerability to persistent and severe suicidality. In particular, minoritized identity status, and the intersectionality of multiple minoritized identities, has been associated with increased STBs (e.g., VanBronkhorst et al., 2021). The small subsamples of youth with minoritized identities precluded multi-group comparisons of social identities in the network models. However, it is noteworthy that the subsample of participants who endorsed STBs had higher rates of youth from lower income families, and nearly threefold higher rates of youth who self-identified as sexual and gender minorities than the full sample (Table 2). The ABCD battery includes measures of discrimination and identity development (Gonzalez et al., 2021; Zucker et al., 2018). Future work could examine how minoritized identity status and experiences of minority stress and social safety influence the development and longitudinal course of STBs in this sample (e.g., Diamond & Alley, 2022).

Sixth, despite the use of a school-based population level sampling design to reduce selection bias, the ABCD sample includes overrepresentation of dominant social identities. Some groups of youth with elevated risk for STBs compared to the general population, such as youth involved in foster care, Child Protective Services, and the juvenile justice system (Teplin et al., 2015), are less likely to participate in population-based research studies than those from more privileged backgrounds (Feldstein Ewing et al., 2018; Sharma et al., 2021). Thus, results of the present study may not generalize to all youth who experience early onset STBs in the United States. Replication of study results in more diverse and underserved populations of youth is warranted (Cha et al., 2018).

Conclusions

Despite the aforementioned limitations, the present study provides valuable information about potential risk and protective pathways for STBs in early adolescents. There is a critical need for research focusing on STBs during this developmental stage. Rates of youth STBs are rising and early adolescence is an age range when STBs often onset, yet early adolescents have received relatively little attention in STB literature compared to older age groups (Ayer et al., 2020; de Sousa et al., 2017; Nock et al., 2013). This study represents a novel extension of the network approach to psychopathology to increase understanding of early onset STBs. Results identified malleable risk and protective factors that could be targeted in early intervention initiatives to protect against negative mental health outcomes (Cha et al., 2018; Copeland et al., 2017). Results emphasize that family and school experiences are salient social risk factors for STBs in this age group. Additionally, internalizing problems appear to be a more important risk factor than other mental health symptoms in this age range, and internalizing could possibly be a causal pathway through which stressful life events and other mental health symptoms contribute to STBs. Low-level substance use was also associated with elevated risk for STBs. Results also suggest the potential for self-reinforcing feedback systems of risk, in which the activation of multiple risk factors might compound and perpetuate risk for STBs. Thus, age-specific early interventions may benefit from focusing on increased social support in family and school domains, identifying and intervening on internalizing symptoms, and preventing early onset substance use. The present study supports the continued application of network approaches to elucidate complex pathways of risk and protection for STBs.

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APPENDIX

Child Behavior Checklist Scoring

Anxious/depressive = cbcl_q14_p + cbcl_q29_p + cbcl_q30_p + cbcl_q31_p + cbcl_q32_p + cbcl_q33_p + cbcl_q35_p + cbcl_q45_p + cbcl_q50_p + cbcl_q52_p + cbcl_q71_p + cbcl_q112_p

Withdrawn/depressed = cbcl_q05_p + cbcl_q42_p + cbcl_q65_p + cbcl_q69_p + cbcl_q75_p + cbcl_q102_p + cbcl_q103_p + cbcl_q111_p

Somatic = cbcl_q49_p + cbcl_q51_p + cbcl_q54_p + cbcl_q56a_p + cbcl_q56b_p + cbcl_q56c_p + cbcl_q56d_p + cbcl_q56e_p + cbcl_q56f_p + cbcl_q56g_p

Social = cbcl_q11_p + cbcl_q12_p + cbcl_q25_p + cbcl_q27_p + cbcl_q34_p + cbcl_q36_p + cbcl_q38_p + cbcl_q48_p + cbcl_q62_p + cbcl_q64_p + cbcl_q79_p

Thought = cbcl_q09_p + cbcl_q40_p + cbcl_q46_p + cbcl_q58_p + cbcl_q59_p + cbcl_q60_p + cbcl_q66_p + cbcl_q70_p + cbcl_q83_p + cbcl_q84_p + cbcl_q85_p

Attention = cbcl_q01_p + cbcl_q04_p + cbcl_q08_p + cbcl_q10_p + cbcl_q13_p + cbcl_q17_p + cbcl_q41_p + cbcl_q61_p + cbcl_q78_p + cbcl_q80_p

Rule Breaking = cbcl_q26_p + cbcl_q28_p + cbcl_q39_p + cbcl_q43_p + cbcl_q63_p + cbcl_q67_p + cbcl_q72_p + cbcl_q73_p + cbcl_q81_p + cbcl_q82_p + cbcl_q90_p + cbcl_q96_p + cbcl_q101_p + cbcl_q106_p

Aggressive = cbcl_q03_p + cbcl_q16_p + cbcl_q19_p + cbcl_q20_p + cbcl_q21_p + cbcl_q22_p + cbcl_q23_p + cbcl_q37_p + cbcl_q57_p + cbcl_q68_p + cbcl_q86_p + cbcl_q87_p + cbcl_q88_p + cbcl_q89_p + cbcl_q94_p + cbcl_q95_p + cbcl_q97_p + cbcl_q104_p

Supplemental Table S1

Linear regression coefficients of each study variable regressed on youth age

Variable	Full sample (N = 9,854) B (SE)	STB Subsample (n = 1,699) B (SE)
1. Suicidality	0.008 (0.006)	0.001 (0.001)
2. Internalizing	0.005 (0.006)	0.003 (0.001)
3. Social problems	-0.062 (0.006) **	-0.003(0.001)
4. Thought problems	-0.044 (0.006) **	-0.001 (0.001)
5. Attention problems	-0.031 (0.006) **	0.001 (0.001)
6. Externalizing	-0.037 (0.006) **	-0.002 (0.001)
7. Sleep problems	-0.007 (0.006)	0.001 (0.001)
8. Family conflict	-0.033 (0.006) **	-0.001 (0.001)
9. Parental monitoring	-0.104 (0.006) **	-0.007 (0.001) **
10. Neighborhood safety	-0.007 (0.006)	0.002 (0.001)
11. School protective factors	-0.074 (0.006) **	-0.007 (0.001) **
12. Stressful life events	-0.005 (0.006)	0.001 (0.001)
13. Material hardship	-0.036 (0.006) **	-0.003 (0.001) *
14. Low-level substance use	-0.077 (0.006) **	-0.005 (0.001) **

Note: Resulting residuals for each variable were saved and modeled as nodes in panel GVAR Models 1-2. Linear modeling was used despite non-normal variables to be consistent with parametric estimation in the panel GVAR models; model selection and bootstrapping procedures increase confidence that non-normality did not bias results (Epskamp, 2020). * $p < 0.01$, ** $p < 0.001$.

Supplemental Table S2

Demographic characteristics and STB endorsement across study timepoints for the original ABCD sample (N = 11,876)

	Baseline (*N* = 11,876) Mean (*SD*) or *n* (%)	Year 1 (*N* = 11,225) Mean (*SD*) or *n* (%)	Year 2 (*N* = 10,414) Mean (*SD*) or *n* (%)
Age (in years)	9.91 (0.62)	10.92 (0.64)	12.00 (0.66)
n unknown	0	0	0
Race			
AIAN/NHPI	78 (0.7%)	72 (0.7%)	66 (0.6%)
Asian	275 (2.3%)	261 (2.4%)	236 (2.3%)
Black	1,869 (16%)	1,672 (15%)	1,494 (15%)
Mixed	1,434 (12%)	1,347 (12%)	1,256 (12%)
Other	525 (4.5%)	476 (4.3%)	444 (4.3%)
White	7,524 (64%)	7,244 (65%)	6,773 (66%)
n unknown	171	153	145
Annual household income [1]			
< 50K	3,223 (30%)	–	–
≥ 50 & < 100K	3,071 (28%)	–	–
≥ 100K	4,564 (42%)	–	–
n unknown	1,018	–	–
Highest education of parent [1]			
< HS Diploma	593 (5.0%)	–	–
HS Diploma or GED	1,132 (9.5%)	–	–
Some College	3,079 (26%)	–	–
Bachelor	3,015 (25%)	–	–
Post Graduate Degree	4,043 (34%)	–	–
n unknown	14	–	–
Sex assigned at birth			
Female	5,680 (48%)	5,353 (48%)	4,962 (48%)
Male	6,196 (52%)	5,872 (52%)	5,452 (52%)
n unknown	0	0	0
"Are you gay or bisexual?"			
Yes	39 (0.3%)	136 (1.2%)	427 (4.2%)
Maybe	112 (0.9%)	257 (2.3%)	385 (3.8%)
No	8,701 (73%)	9,765 (87%)	9,107 (89%)
I do not understand this question	3,005 (25%)	1,022 (9.1%)	332 (3.2%)
n unknown	19	45	163
"Are you transgender?"			
Yes	12 (0.1%)	16 (0.1%)	42 (0.4%)
Maybe	46 (0.4%)	82 (0.7%)	64 (0.6%)
No	7,112 (60%)	9,040 (81%)	9,637 (93%)
I do not understand this question	4,691 (40%)	2,060 (18%)	590 (5.7%)
n unknown	15	27	81
Endorsed STBs since last measurement occasion			
Never	10,763 (91%)	10,190 (92%)	9,517 (92%)
Ever	1,040 (8.8%)	910 (8.2%)	796 (7.7%)
n unknown	73	125	101

Note: Values represent sample characteristics for the original ABCD sample, before randomly dropping sibling participants from the same household. [1] Annual household income and parental level of education were only measured at baseline. Gender and sexual identities were self-reported by youth. All other demographics items were assessed by parent/caregiver report. STBs = suicidal thoughts and behaviors, *SD* = standard deviation, AIAN/NHPI = American Indian/Alaska Native or Native Hawaiian and other Pacific Islander, HS = high school.

Supplemental Table S3

Estimated directed partial correlations for the temporal network in the full sample using non-detrended data (Supplemental Model 1, N = 9,854)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Suicidality	0.079	–	–	–	–	–	–	–	–	–	–	–	–	–
2. Internalizing	–	0.109	–	–	-0.016	-0.019	–	–	–	–	–	–	–	–
3. Social problems	–	–	0.104	0.038	0.025	0.029	0.014	–	–	–	–	–	–	–
4. Thought problems	–	–	–	0.096	0.010	0.014	–	–	–	–	–	–	-0.034	–
5. Attention problems	–	–	–	–	0.140	–	–	–	–	–	–	–	0.028	–
6. Externalizing	–	–	0.034	–	–	0.116	–	–	–	–	–	–	–	–
7. Sleep problems	–	0.026	0.023	0.032	0.031	–	0.185	–	–	–	–	–	–	–
8. Family conflict	–	0.010	–	–	–	0.018	–	0.136	0.004	–	–	–	–	–
9. Parental monitoring	–	–	–	–	–	–	–	0.007	0.198	–	–	–	–	–
10. Neighborhood safety	–	–	–	–	–	–	–	–	–	0.113	–	–	–	–
11. School protective factors	–	–	-0.028	–	-0.026	–	–	-0.025	-0.056	–	0.192	–	–	–
12. Stressful life events	–	–	–	–	–	–	–	–	–	–	–	-0.057	–	–
13. Material hardship	–	–	–	-0.033	–	–	–	–	–	–	–	0.062	0.136	–
14. Low-level substance use	–	–	0.008	–	–	–	–	–	–	–	0.077	–	0.025	0.147

Note: Data were not detrended for the linear effects of age. Values represent lagged and autoregressive (i.e., across timepoints) directed partial correlations at the within-person level. Values on the diagonal are autocorrelations. See Supplemental Figure S1A for graphical representation of the temporal network structure in the full sample.

Supplemental Table S4

Estimated undirected partial correlations for the contemporaneous network in the full sample using non-detrended data (Supplemental Model 1, N = 9,854)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Suicidality	NA													
2. Internalizing	0.051	NA												
3. Social problems	–	0.255	NA											
4. Thought problems	–	0.185	0.124	NA										
5. Attention problems	–	0.091	0.151	0.163	NA									
6. Externalizing	–	0.184	0.264	0.182	0.282	NA								
7. Sleep problems	–	0.137	0.031	0.053	0.074	0.041	NA							
8. Family conflict	0.072	–	–	–	–	0.029	–	NA						
9. Parental monitoring	0.030	–	–	–	–	0.028	–	0.097	NA					
10. Neighborhood safety	–	–	–	–	–	–	–	–	–	NA				
11. School protective factors	-0.044	-0.033	–	0.032	-0.047	–	–	-0.116	-0.201	–	NA			
12. Stressful life events	–	0.084	–	–	–	–	0.041	–	–	–	–	NA		
13. Material hardship	–	0.053	–	–	0.037	–	–	–	–	–	–	0.060	NA	
14. Low-level substance use	0.037	–	–	–	–	–	–	0.035	0.062	–	–	–	–	NA

Note: Data were not detrended for the linear effects of age. Values represent contemporaneous (i.e., same measurement occasion) undirected partial correlations at the within-person level after controlling for temporal effects. See Supplemental Figure S1B for graphical representation of the contemporaneous network structure in the full sample.

Supplemental Table S5

Estimated undirected partial correlations for the between-subjects network in the full sample using non-detrended data (Supplemental Model 1, N = 9,854)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Suicidality	NA													
2. Internalizing	0.130	NA												
3. Social problems	–	0.424	NA											
4. Thought problems	–	0.226	0.161	NA										
5. Attention problems	0.022	-0.152	0.256	0.386	NA									
6. Externalizing	–	–	0.299	0.115	0.264	NA								
7. Sleep problems	–	0.339	-0.084	0.100	0.143	0.109	NA							
8. Family conflict	–	-0.069	–	–	-0.095	0.252	–	NA						
9. Parental monitoring	0.230	–	–	–	0.187	-0.142	–	0.379	NA					
10. Neighborhood safety	–	–	–	-0.023	–	–	0.050	–	0.049	NA				
11. School protective factors	–	-0.025	–	–	–	–	–	-0.128	-0.510	–	NA			
12. Stressful life events	–	0.121	–	–	–	0.135	0.072	–	–	0.050	–	NA		
13. Material hardship	–	-0.083	0.149	–	-0.088	–	0.113	–	0.102	0.320	–	0.287	NA	
14. Low-level substance use	0.200	–	0.006	–	–	–	–	–	-0.272	–	-0.433	–	-0.116	NA

Note: Data were not detrended for the linear effects of age. Values represent undirected partial correlations at the between-person level (i.e., associations between overall variable means) after controlling for other variables in the model. See Supplemental Figure S1C for graphical representation of the between-person network structure in the full sample.

Supplemental Table S6

Estimated directed partial correlations for the temporal network in the STB subsample using non-detrended data (Supplemental Model 2, n = 1,699)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Suicidality	–	–	–	–	–	–	–	–	–	–	–	–	–	–
2. Internalizing	–	0.235	0.121	0.101	–	0.086	0.080	–	–	–	–	0.116	0.061	–
3. Social problems	0.032	0.115	0.188	0.112	0.163	0.151	–	–	–	–	–	–	–	0.021
4. Thought problems	–	0.066	–	0.107	–	0.054	0.146	–	–	–	–	–	–	–
5. Attention problems	–	–	0.177	0.089	0.285	0.141	–	–	–	–	–	–	–	–
6. Externalizing	–	–	–	–	–	–	-0.058	–	–	–	–	–	–	–
7. Sleep problems	–	0.038	–	0.119	–	–	0.232	–	–	–	–	–	–	–
8. Family conflict	–	–	–	–	–	–	–	0.161	–	–	–	–	–	–
9. Parental monitoring	–	–	–	–	–	–	–	–	0.151	–	–	–	–	–
10. Neighborhood safety	–	–	–	–	–	–	–	–	–	–	–	0.093	–	–
11. School protective factors	–	–	–	–	–	–	–	–	–	–	0.194	–	–	–
12. Stressful life events	–	–	–	–	–	–	–	–	–	–	–	-0.150	–	–
13. Material hardship	–	–	–	–	–	–	–	–	–	–	–	–	0.161	–
14. Low-level substance use	–	–	0.016	–	–	–	–	–	–	–	–	–	–	–

Note: Data were not detrended for the linear effects of age. Values represent lagged and autoregressive (i.e., across timepoints) directed partial correlations at the within-person level. Values on the diagonal are autocorrelations. The *psychonetrics* package does not currently provide standard errors for partial directed correlations (Epskamp, 2022). See Supplemental Figure S3A for graphical representation of the temporal network structure in the STB subsample.

Supplemental Table S7

Estimated undirected partial correlations for the contemporaneous network in the STB subsample using non-detrended data (Supplemental Model 2, n = 1,699)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Suicidality	NA													
2. Internalizing	0.088	NA												
3. Social problems	–	0.325	NA											
4. Thought problems	–	0.239	0.075	NA										
5. Attention problems	–	–	0.249	0.172	NA									
6. Externalizing	–	0.187	0.280	0.219	0.275	NA								
7. Sleep problems	–	0.173	–	0.164	0.061	–	NA							
8. Family conflict	0.123	–	–	–	–	–	–	NA						
9. Parental monitoring	0.094	–	–	–	–	0.056	–	0.100	NA					
10. Neighborhood safety	–	–	–	–	–	–	–	–	–	NA				
11. School protective factors	-0.095	-0.059	–	–	–	–	–	-0.169	-0.149	–	NA			
12. Stressful life events	–	0.120	–	–	–	–	0.067	–	–	–	–	NA		
13. Material hardship	–	0.065	–	–	0.055	–	–	–	–	–	–	0.070	NA	
14. Low-level substance use	0.092	–	–	–	–	–	–	–	0.082	–	–	–	–	NA

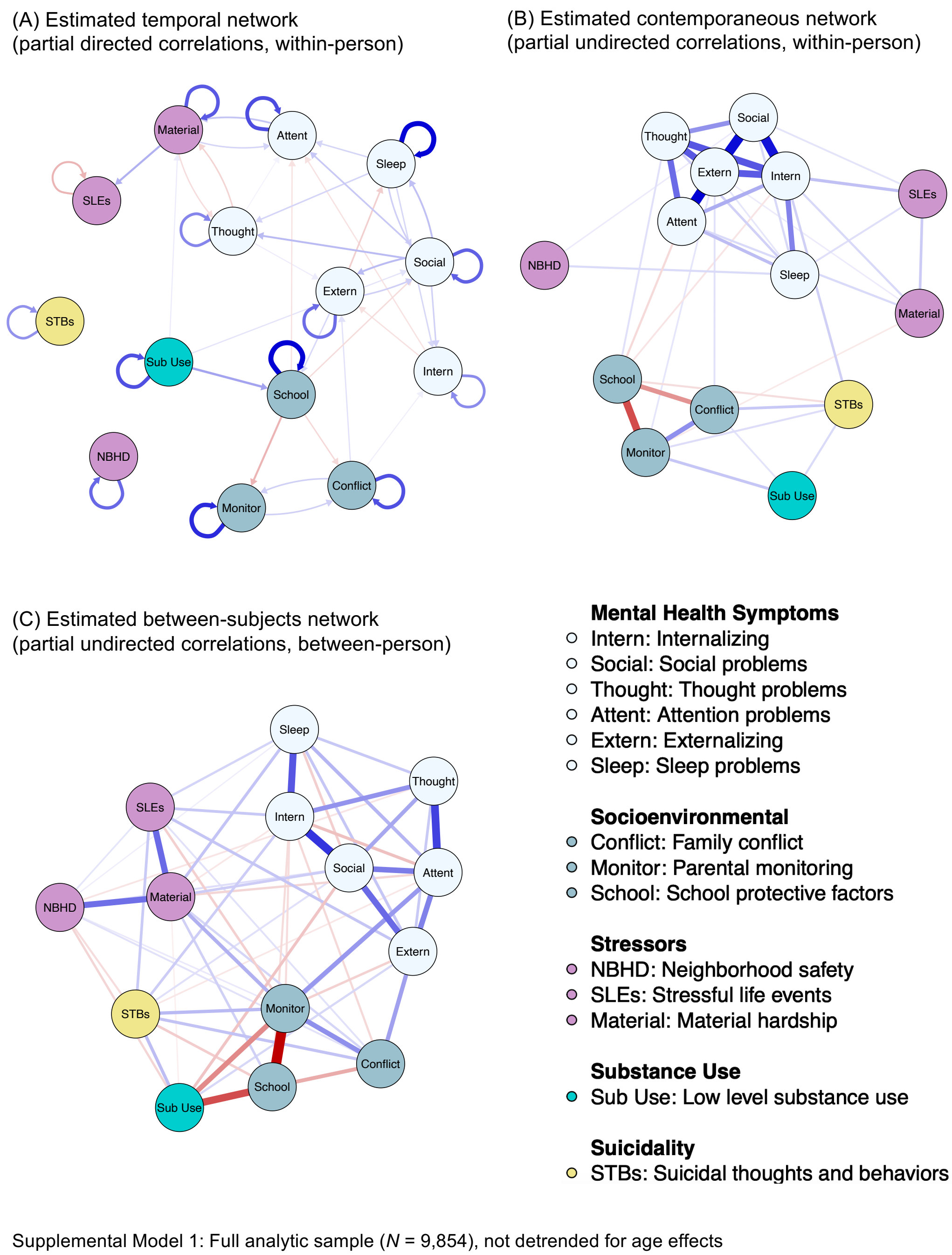
Note: Data were not detrended for the linear effects of age. Values represent contemporaneous (i.e., same measurement occasion) undirected partial correlations at the within-person level after controlling for temporal effects. Standard errors are provided in parentheses. See Supplemental Figure S3B for graphical representation of the contemporaneous network structure in the STB subsample.

Supplemental Table S8

Estimated undirected partial correlations for the between-subjects network in the STB subsample using non-detrended data (Supplemental Model 2, n = 1,699)

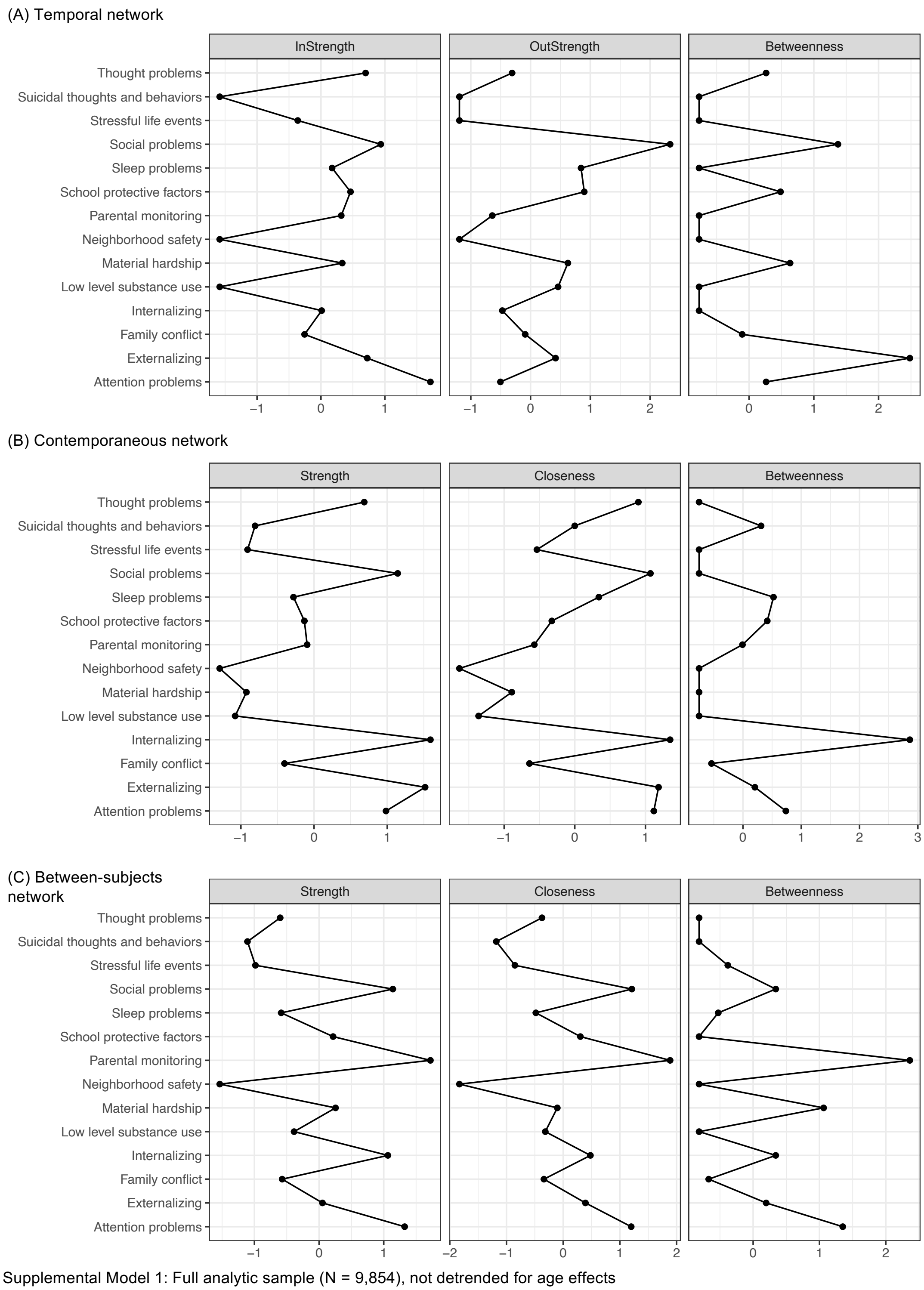
Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Suicidality	NA													
2. Internalizing	–	NA												
3. Social problems	–	–	NA											
4. Thought problems	–	–	–	NA										
5. Attention problems	–	–	–	0.476	NA									
6. Externalizing	–	–	0.280	0.201	0.161	NA								
7. Sleep problems	–	0.382	0.218	–	0.247	0.144	NA							
8. Family conflict	–	–	0.167	–	–	0.144	–	NA						
9. Parental monitoring	–	–	–	–	0.181	-0.121	–	0.331	NA					
10. Neighborhood safety	–	–	0.193	–	–	–	–	0.075	–	NA				
11. School protective factors	–	–	–	–	–	–	–	–	-0.544	–	NA			
12. Stressful life events	–	0.166	0.156	–	–	0.089	–	–	–	–	–	NA		
13. Material hardship	0.547	–	–	–	–	–	0.112	–	–	0.254	–	0.273	NA	
14. Low-level substance use	–	–	–	–	–	–	–	–	–	–	–	–	–	NA

Note: Data were not detrended for the linear effects of age. Values represent undirected partial correlations at the between-person level (i.e., associations between overall variable means) after controlling for other variables in the model. Standard errors are provided in parentheses. See Supplemental Figure S3C for graphical representation of the between-person network structure in the STB subsample.

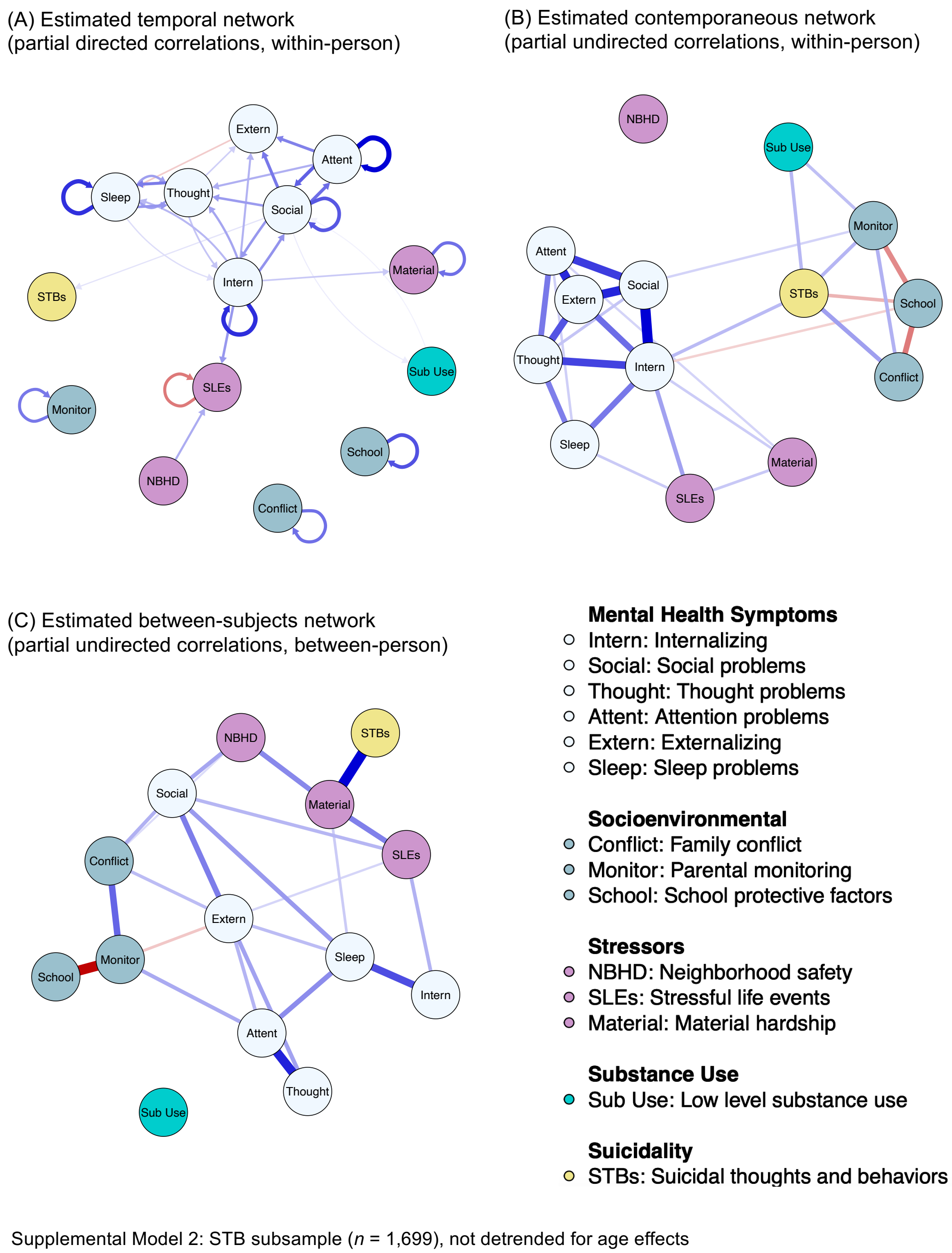


Supplemental Figure S1: *Pruned network structures for the panel GVAR model in the full sample using non-detrended data (N = 9,854)*

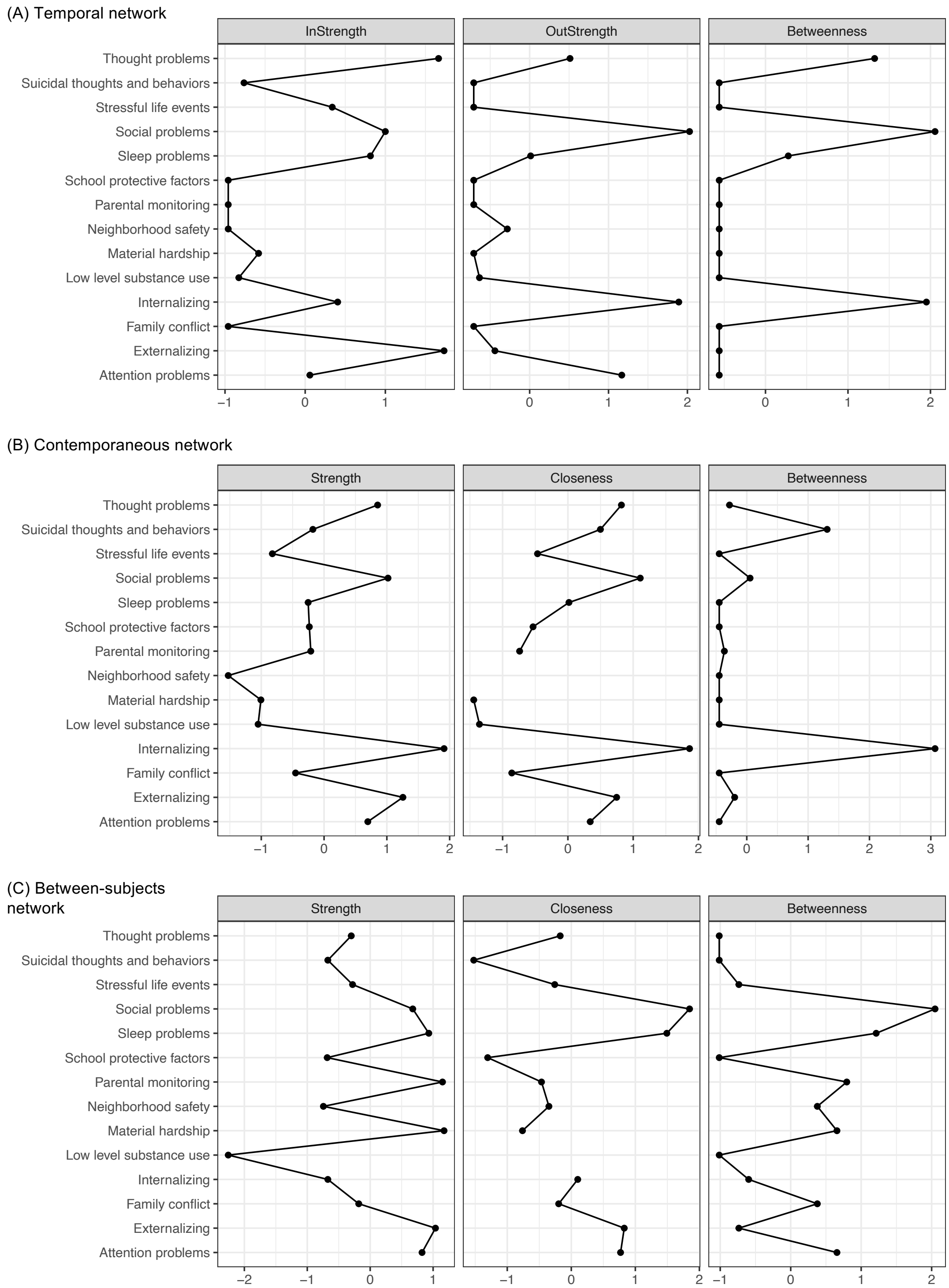
Note: Edge color represents effect direction (blue = positive, red = negative), while edge thickness represents effect strength (darker, thicker edges denote larger effects). Corresponding numeric results are presented in Supplemental Tables S3-5.



Supplemental Figure S2: *Node centrality metrics for the panel GVAR model in the full sample using non-detrended data (N = 9,854)*
Note: Centrality is shown in the metric of *z*-scores.



Supplemental Figure S3: *Pruned network structures for the panel GVAR model in the STB subsample using non-detrended data (n = 1,699)*
Note: Edge color represents effect direction (blue = positive, red = negative), while edge thickness represents effect strength (darker, thicker edges denote larger effects). Corresponding numeric results are presented in Supplemental Tables S6-8.



Supplemental Model 2: STB subsample (n = 1,699), not detrended for age effects

Supplemental Figure S4: *Node centrality metrics for the panel GVAR model in the STB subsample using non-detrended data (n = 1,699)*
Note: Centrality is shown in the metric of *z*-scores.