Test anxiety, anxiety disorders, and school-related wellbeing: Manifestations of the same or different constructs?

David W. Putwain[a,*], Kristina Stockinger[b], Nathaniel P. von der Embse[c], Shannon M. Suldo[c], Martin Daumiller[b]

[a] *School of Education, Liverpool John Moores University, Liverpool, UK*
[b] *Department of Psychology, University of Augsburg, Augsburg, Germany*
[c] *University of South Florida, Tampa, USA*

1. Introduction

Although estimates differ based on the criterion and analytic approach used, high levels of test anxiety have been found in 10%–30% of secondary school students (ages 15–18 years) in the UK and US (Putwain, 2020; Putwain & Daly, 2014; von der Embse et al., 2014). Furthermore, meta-analyses (e.g., Hembree, 1988; von der Embse et al., 2018) and longitudinal designs that control for prior achievement (e.g., Putwain et al., 2015; Putwain et al., 2020) have indicated that higher levels of test anxiety are associated with lower achievement. Previous studies have shown that highly test anxious students also report higher scores on indicators of anxiety disorder

* Corresponding author.
E-mail address: d.w.putwain@ljmu.ac.uk (D.W. Putwain).

symptoms including generalized anxiety disorder (GAD) and panic disorder (PD; e.g., Weems et al., 2010). In addition, highly test anxious children and adolescents often meet diagnostic thresholds for anxiety disorders including social phobia (Herzer et al., 2014), now referred to as social anxiety disorder, and GAD (Beidel et al., 1994).

Test anxiety also correlates negatively with subjective wellbeing at school (Putwain et al., 2021). From the perspective of the Dual Factor Model of Mental Health (DFM; Suldo & Shaffer, 2008), wellbeing and the presence of psychopathology (i.e., internalizing and externalizing disorders) may be considered separate indicators of *complete* mental health. That is, someone may exhibit severe anxiety yet also demonstrate high wellbeing. Understanding how test anxiety, anxiety disorders, and wellbeing are related has important conceptual, theoretical, and practical implications. These include (a) identifying the antecedents and risk factors for individuals with high test anxiety, symptoms of anxiety disorders, and low wellbeing; and (b) designing and evaluating interventions to promote coping skills for those with high anxiety or low wellbeing. In the present study, we adopted a novel approach to evaluating these relationships in a sample of secondary school students through the use of network analysis and also through the use of a latent profile analysis (LPA) as a complementary analytic procedure. We begin by defining the key constructs used in the present study, including test anxiety, anxiety disorders, and school-related wellbeing.

1.1. Test anxiety

Test anxiety refers to an enduring individual difference in the tendency to appraise performance-evaluative situations as threatening (Spielberger & Vagg, 1995). In this respect, test anxiety is considered a situation-specific trait and highly test anxious persons will show elevated levels of state anxiety in evaluative, but not in non-evaluative, situations (Bertrams et al., 2010; Endler & Kocovski, 2001; Lotz & Sparfeldt, 2017; Segool et al., 2013). Test anxiety is widely considered to be multidimensional and as comprising theoretically distinct, yet empirically related, cognitive and affective-physiological components (Zeidner, 2007, 2014). In the present study, we adopted a higher-order model comprising two lower-order cognitive factors, namely worry and cognitive interference, and two lower-order affective-physiological factors, namely tension and physiological indicators of anxiety (Putwain et al., 2021). *Worry* refers to self-focused thoughts concerning failure and its consequences and *cognitive interference* refers to difficulty in memory and concentration. *Tension* refers to unpleasant feelings associated with anxiety, such as panic, and *physiological indicators* refers to the perception of autonomic arousal, such as a racing heart rate (see Table 2 for a full list of items corresponding to these components of test anxiety).

1.2. Anxiety disorders

The label “anxiety disorders” refers to a group of disorders characterized by a level of fear or anxiety that is excessive relative to the situation a person is in and that hinders one’s typical level of functioning (Anthony et al., 2008). In the most recent version of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5; American Psychiatric Association, 2013), six types of anxiety disorders were described, including (a) generalized anxiety disorder, (b) panic disorder, (c) specific phobia, (d) agoraphobia, (e) social anxiety disorder, and (f) separation anxiety disorder. Test anxiety is not considered as a discrete anxiety disorder in the DSM-5 or the 11th edition of the World Health Organization’s Classification of Diseases (2018). LeBeau et al. (2010) concluded in a review of recommendations for the DSM-5 that there was insufficient evidence to differentiate test anxiety from GAD and social phobia (subsequently referred to as social anxiety disorder in DSM-5) or to categorize test anxiety as a specific phobia different than any other type of anxiety disorder. Consequently, more research is required to unravel how test anxiety is related to, or differentiable from, anxiety disorders.

In the present study we focused on GAD and PD for three reasons. First, of the aforementioned anxiety disorders, indicators of test anxiety map most clearly onto GAD (worry) and PD (physiological indicators). GAD and PD are therefore highly relevant anxiety disorders to investigate alongside test anxiety. Second, similar to test anxiety, GAD and PD entail an environmental stimulus or referent, although PD can also occur without such a stimulus or referent. Third, to date no studies have examined test anxiety in relation to DSM-5 anxiety disorders. Thus, to have relevance to studies (described below) that considered test anxiety in relation to earlier iterations of the DSM, we focused on two anxiety disorders present in the DSM from 1980 onwards (Crocq, 2017; Nardi & Balon, 2020).

1.3. School-related wellbeing

Wellbeing is an omnibus term that can refer to objective indicators such as household income, access to resources, and health status (e.g., OECD, 2017), or subjective indicators such as perceived life satisfaction and a balance of positive over negative affect (e.g., Diener et al., 2003). In the present study, we align with the latter approach. Subjective wellbeing refers to global judgments about one’s life in general or to specific elements of one’s life such as school (Diener et al., 2018; Hascher, 2010). This is especially the case for children and adolescents (the focal sample of the present study) for whom school occupies a central place in their lives. Accordingly, we chose to focus specifically on subjective wellbeing at school (school-related wellbeing). School-related wellbeing is defined as the overall balance between negative and positive aspects of school life (Hascher, 2003, 2008). Numerous studies have highlighted the benefits of greater school-related wellbeing, including higher achievement (Bucker et al., 2018), fewer instances of poor behavior (Putwain et al., 2020), and greater academic perseverance (Renshaw et al., 2015). Notwithstanding the lack of consistency in the definition and measurement of wellbeing, the aforementioned studies broadly highlight the benefits of higher subjective and school-related wellbeing for beneficial outcomes at school.

1.4. Are anxiety disorders related to test anxiety?

Having defined the key constructs in our study (i.e., test anxiety, anxiety disorders, and school-related wellbeing) we next consider whether test anxiety could be related to anxiety disorders. Several studies have shown that some highly test anxious individuals meet criteria for anxiety disorders as determined through a diagnostic interview. Specific to the DSM-III (American Psychiatric Association, 1980), highly test anxious children in Grades 3–6 grade met criteria for social phobia (i.e., social anxiety disorder in DSM-5), overanxious disorder (i.e., GAD in DSM-5), specific phobia, and separation anxiety disorder, relative to low test anxious children (Beidel & Turner, 1988). In relation to the DSM-III-R (American Psychiatric Association, 1985), highly test anxious children (*M* age 10.3 years) met criteria for social phobia, overanxious disorder, and simple phobia (Beidel et al., 1994), and highly test anxious adolescents (Grades 9–10) met criteria for social phobia, simple phobia, and overanxious disorder (King et al., 1995). More recently, Herzer et al. (2014) reported that highly test anxious undergraduate students and adults taking vocational examinations (ages 20–33 years) met DSM-IV-TR (American Psychiatric Association, 2000) criteria for specific or social phobia.

Furthermore, highly test anxious adolescents (i.e., those reporting above a certain threshold on a continuous scale) have reported higher scores for indicators of anxiety disorders than their low test anxious counterparts (i.e., those reporting below a certain threshold on a continuous scale). In a sample of adolescents in Grades 9–10, King et al. (1995) showed that highly test anxious persons reported higher total scores ($ds = 0.90$–1.67) on the Revised Children's Manifest Anxiety Scale ([RCMAS] Reynolds & Richmond, 1978; measures physiological anxiety, worry, and social concerns). In a sample of children and adolescents in Grades 4, 7, and 10, Warren et al. (1996) indicated that highly test anxious children and adolescents reported higher physiological anxiety, worry, and social concerns based on RCMAS subscale scores ($ds = 0.72$ to 2.67). Using the Revised Children's Anxiety and Depression Scales (RCADS; Chorpita et al., 2005), Weems et al. (2010) found high scores on the generalized anxiety, specific phobia, separation anxiety, and PD subscales ($ds = 0.71$ to 0.95) in their sample of students in Grades 4–8.

The aforementioned studies have used different criteria on which to establish *high* test anxiety on a continuous scale. For example, Herzer et al. (2014) used test anxiety scores ≥66th *scale* percentile as a cut-off. This is an internal criterion-referenced approach and refers to the point at which participants move from reporting test anxiety from *often* to *always*. By comparison, King et al. (1995) used a norm-referenced approach (the ≥5% *distribution* of test anxiety scores) to establish high test anxiety.[1] Despite these differences, these findings provide convincing evidence of an overlap between higher test anxiety scores and anxiety disorders.

1.5. Test anxiety, anxiety disorders, and network analysis

There are two possible ways that test anxiety and anxiety disorders could be related. First, test anxiety and anxiety disorders can represent distinct types of anxiety, while still overlapping. This is analogous to the comorbidity typically found among the different categories of anxiety and mood disorders (e.g., Hankin et al., 2016). We refer to this as the *test anxiety as distinct but related* approach. Second, rather than being discrete constructs, test anxiety may be a manifestation, or an indicator, of one or more anxiety disorders (LeBeau et al., 2010). We refer to this as the *test anxiety as an indicator* approach. As the aforementioned studies indicate, test anxiety may be related to (using DSM-5 terminology) GAD, simple phobia, PD, social anxiety disorder, specific phobia, and separation anxiety disorder. Furthermore, test anxiety is not consistently related more strongly to any one specific category of anxiety disorder over any other.

Both approaches (i.e., test anxiety as distinct but related or as an indicator of anxiety disorders) assume a categorical diagnostic paradigm where different types of anxiety disorder can be established based on symptomology that reflects distinct antecedents, mechanisms, and risks (Berenbaum, 2013; Kendell & Jablensky, 2003). The ubiquitous comorbidity among anxiety and mood disorders, indicating shared pathology, has presented significant challenges to the validity of a categorical diagnostic approach (Caragher et al., 2015; Uher & Rutter, 2012) and calls into question the consequential validity of a unidimensional measurement approach. Furthermore, the categorical approach to diagnosis has been criticized for failing to account for variation between persons in the severity and duration of symptomology and response to treatment (Möller et al., 2014). The DSM-5 includes a dimensional component to allow for the assessment of symptom profiles but still assumes the presence of discrete anxiety disorders.

A relatively recent and novel alternative to the categorical diagnostic paradigm is Network Theory to Psychopathology (NT). NT is rooted in critiques of the traditional categorical diagnostic approach to mental disorders for failing to identify common etiological mechanisms for mental disorders. The position of NT is that such mechanisms are not found because they do not exist (Borsboom, 2017a; Fried et al., 2017). Instead, NT suggests that rather than the various symptoms of a mental disorder reflecting the effects of an underlying physiological and cognitive cause, the symptoms of mental disorders cause each other. In GAD, for instance, excessive worry could lead to irritability and impaired concentration. The same approach can be applied to trait anxiety in that disturbing thoughts can lead to feeling tense and feelings of failure can lead to self-depreciation (Heeren et al., 2018).

We are mindful that many colleagues in the fields of school and educational psychology may not be familiar with NT and next we introduce some of the key terms used by NT. In the parlance of NT, symptoms (i.e., indicators) are referred to as *nodes* and causal relations between nodes as *edges*. Networks of nodes that are densely and closely connected, but sparsely connected with others, are referred to as a *community*. Symptoms (i.e., indicators) of GAD would therefore be expected to form a community, PD symptoms or

[1] King et al. (1995) measured test anxiety using the Test Anxiety Scale for children (TASC; Sarason et al., 1958). The TASC uses dichotomous (*yes/no*) responses for 30 items to provide a score with a possible range of 0–30. King et al. (1995) reported $M = 11.15$ ($SD = 6.53$) TASC scores. A TASC score ≥ 5% ($z = 1.64$) was 21.9 ($M = z \times SD$).

indicators form another (adjacent) community, and likewise for other anxiety disorders. Nodes within a community will exert a greater mutual causal influence and thus activation within that community spreads more rapidly and freely than to nodes from adjacent communities.

Thus, activation of a GAD node would spread more readily to other GAD nodes than to PD nodes. Nodes that spread activation from one community (e.g., GAD) to another (e.g., PD) are referred to as *bridge nodes*. Conditions that activate, or deactivate, one or more nodes from outside the network is the *external field*. These can be internal (e.g., chronic pain) or external (e.g., environmental stressors) to the person. Comorbidity, from the perspective of NT, arises from mutual interactions between *bridge nodes* that spread network activation through different communities of symptoms.

To summarize, NT holds two central premises (Borsboom, 2017a; Fried et al., 2017). First, symptoms of anxiety disorders, and those of other mental disorders, exist in related networks. For instance, GAD would be represented as one network of symptoms, PD as another (related) network of symptoms, and so on. Second, symptoms exert a causal influence over other symptoms within a network. If one symptom becomes activated (e.g., a feeling of dread about something bad happening to oneself), it will result in other symptoms within the network also becoming activated (e.g., excessive worry about something bad happening to one's family members). Symptom networks operate as recursive feedback loops; once activated, symptoms keep others within the same network activated. These reciprocal links in the network are somewhat analogous to the way an echo chamber can reinforce and amplify sound. Rather than symptoms being manifestations of a latent disorder, from the perspective of NT, the network of activated symptoms represents what is commonly recognized as a mental disorder. For further introduction of NT, see Borsboom (2017b) and Cramer et al. (2010).

To illustrate the use and benefits of NT in more detail, we next consider two empirical examples of applying NT to the study of anxiety. First, to examine how the different elements of trait anxiety could influence one other, Heeren et al. (2018) performed a network analysis on responses to a well-established anxiety measure (i.e., State-Trait anxiety Inventory Y form [STAI-T]; Spielberger et al., 1983) in a community sample of adults (ages 18–74 years). Nodes (i.e., indicators of trait anxiety; participants' responses to individual STAI-T items) were represented as one single coherent community rather than as two or more related communities. However, within this network not all nodes were found to be equally influential. Nodes representing the presence of intrusive thoughts and not being able to forget about disappointments were central to the network in that (a) they showed a comparatively greater number of edges to other nodes within the network, (b) they showed stronger edges to other nodes within the network, and (c) when represented graphically, were placed at the center of the network rather than at the periphery. Traditional views of trait anxiety consider variance in STAI-T items as pointing to the presence of an underlying anxiety trait. However, this network analysis showed how trait anxiety can be alternately represented as a network of mutually interacting STAI-T nodes. Recourse to a latent underlying construct response for influencing STAI-T items is not necessarily required.

In a second example, Heeren et al. (2018) used NT with the Liebowitz Social Anxiety Scale (LSAS; Heeren et al., 2012; Liebowitz, 1987) and the Beck Depression Inventory (BDI-II; Beck et al., 1996), to examine comorbidity in a sample of 174 persons with a diagnosis of SAD. Two distinct communities emerged with one comprised of SAD nodes (i.e., responses to individual LSAS items) and one comprised of depression nodes (i.e., responses to individual BDI-II items). Specific nodes emerged as bridge nodes to link the two communities of SAD and depression nodes. For SAD, the bridge nodes were 'avoiding parties', 'participating in small groups', and 'fear of being observed working'. Activation of these SAD bridge nodes could result in activation of the depression community. For depression, the bridge nodes were 'suicidal ideation', 'loss of interest', and 'loss of pleasure'. Activation of these depression bridge nodes would result in activation of the SAD community. This network analysis showed how the co-occurrence of two related disorders can be a feature of bridge nodes in one network exerting a causal link on nodes in an associated network. A common cause or mechanism, the traditional view of comorbidity, is not necessarily required.

NT offers a promising theoretical and analytic approach with which to examine relations between indicators of anxiety disorders and test anxiety. Traditional factor-analytic approaches that treat latent constructs as the cause of covariance between observed indicators cannot identify how the different structural elements of a construct (i.e., indicators) can interact as a network or if specific indicators, or nodes, are influential within a network or bridge different networks.

No studies, to date, have utilized NT for this specific purpose. Furthermore, the aforementioned studies using NT to examine anxiety along with others (e.g., Heeren et al., 2020; Heeren & McNally, 2018) focused on adult samples. No studies, thus far, have used NT to examine anxiety in school-aged students. When indicators of test anxiety, GAD, and PD are conceptualized as nodes in an interacting network, it is possible to examine if they are represented as distinct or related communities, how nodes are connected, whether specific nodes emerge as more central to a community relative to others, and if there are any bridge nodes that link communities. Identification of influential nodes within a network may be useful for intervention to target as reducing activation in particularly influential nodes should help to more efficiently reduce activation across an entire network. In addition, the identification of bridge nodes may provide insight into transdiagnostic assessment of anxiety.

1.6. Dual factor model of mental health

The premise of the Dual Factor Model (DFM: Greenspoon & Saklofske, 2001; Suldo & Shaffer, 2008) is that low subjective wellbeing cannot be inferred solely from the presence of psychopathology (i.e., the presence or absence of internalizing or externalizing disorders), or vice versa. Psychopathology may substantially contribute to negative affect and low life satisfaction. However, as subjective wellbeing refers to an overall judgment of the positive and negative elements of one's life, there may be factors (e.g., the presence of supporting and trusting relationships and high self-esteem) that contribute to higher subjective wellbeing even in the presence of psychopathology. Accordingly, Suldo and Shaffer (2008) proposed a typology of mental health based on two dimensions, including (a) subjective wellbeing: low (≤30th percentile) vs. average/high (>30th percentile); and (b) psychopathology: low (<70th percentile) vs.

elevated (≥70th percentile).

In a sample of 349 students ages 10–16 years, Suldo and Shaffer (2008) found that 57% of the sample showed average/high subjective wellbeing and low levels of psychopathology and were described as having *complete mental health*, 13% showed low subjective wellbeing and low levels of psychopathology and were described as *vulnerable*, 17% showed low subjective wellbeing and elevated levels of psychopathology and were described as *troubled*, and 13% showed average/high subjective wellbeing and elevated levels of psychopathology and were described as *symptomatic but content*. As expected, the best academic, health, and social outcomes were observed in the complete mental health group. Notably, the symptomatic but content group showed fewer social problems with classmates, parents, and teachers, and reported better physical health than the troubled group, thereby supporting the proposition that positive elements of one's life can alleviate some of the negative aspects resulting from psychopathology (e.g., Suldo & Shaffer, 2008; also see Magalhães & Calheiros, 2017; Rose et al., 2017).

The two-dimensional typology has been confirmed in independent studies of samples of children and adolescents using the cut-score approach (Antaramian et al., 2010; Lyons et al., 2012; Smith et al., 2020; Suldo et al., 2016; Thayer et al., 2021; Xiong et al., 2017) and undergraduates (Antaramian, 2015; Eklund et al., 2011; Magalhães & Calheiros, 2017; Renshaw & Cohen, 2014) using a range of different measures of subjective wellbeing, indicators of psychopathology, and outcomes, albeit with different labels applied to the groups in some of the studies (Eklund et al., 2011; Renshaw & Cohen, 2014). Furthermore, the two-dimensional typology of mental health has also been confirmed in studies of children and adolescents using LPA (Rose et al., 2017; Thayer et al., 2021).

Despite the different instruments and analytic approaches used in these aforementioned studies to establish dimensions of subjective wellbeing and psychopathology, there appears to be a degree of consistency. Reassuringly, the largest group in samples of typical children, adolescents, and undergraduates was the group showing complete mental health (47%–78% of participants). The vulnerable (7%–26%), troubled (9%–21%), and symptomatic but content (4%–20%) groups showed smaller proportions of their respective samples.[2] However, not all studies using LPA have found the four groups predicted by the DFM. In a study of secondary school students in Grades 9–11, Moore et al. (2019) found groups of *complete mental health*, *symptomatic but content*, and *troubled students*, but no *vulnerable* group. A fourth profile of students was identified comprising of average-high wellbeing and low distress; this group was termed *moderately mentally healthy*. In a sample of primary school children ages 8–9 years, Petersen et al. (2020) identified *complete mental health*, *vulnerable*, and *two symptomatic but content* (one characterized by higher externalizing symptoms, and the other by higher internalizing symptoms) groups, but no *troubled*group.

Given the central role of tests and examinations as forms of educational assessment (e.g., Baird, 2018), the relatively high proportion of school-aged students identified as highly test anxious in UK and US samples (e.g., Putwain, 2020; Putwain & Daly, 2014; von der Embse et al., 2014), and the aforementioned links with anxiety disorders, test anxiety would seem to be highly relevant to the assessment of mental health of school-age populations. Although conceptualized as habitual, test anxiety is consistent with the core propositions of the DFM. Without intervention, anxiety and other internalizing disorders (i.e., indicators of psychopathology) tend to be long-lasting (e.g., Garber & Weersing, 2010), and subjective wellbeing should be influenced by stable personality traits and hence rather stable over time (e.g., Anglim et al., 2020).

No studies, thus far, have examined the DFM in relation to test anxiety. As anxiety disorders show high levels of comorbidity (e.g., Carragher et al., 2015; Uher & Rutter, 2012), and high levels of test anxiety co-occur with anxiety disorders (e.g., Herzer et al., 2014; Weems et al., 2010), we would not expect the DFM profiles to be differentiated by the type of anxiety. Rather, in keeping with the principles of NT and the activation of associated networks, the different forms of anxiety would co-occur. Studies have shown, however, that test anxiety is negatively correlated with subjective and school-related wellbeing in samples of adolescents (Hascher, 2007; Putwain, Loderer, et al., 2020) and undergraduates (Lin & McKeachie, 1971; Steinmayr et al., 2016).

However, the overall negative relation between test anxiety and subjective or school-related wellbeing may, from the perspective of the DFM, obscure possible subgroups comprised of high test anxiety and high subjective or school-related wellbeing (i.e., *symptomatic but content*, where positive elements of one's life alleviate the negatives resulting from high test anxiety) and low test anxiety and low subjective or school-related wellbeing (i.e., *vulnerable*, where despite the absence of test anxiety, other elements of one's life contribute to low wellbeing). This has important implications for practitioners involved in the assessment of mental health in school-aged populations regarding potentially missing the *vulnerable* and *symptomatic but content* groups who show significantly poorer educational, health, and social outcomes than the *complete mental health* groups (e.g., Antaramian et al., 2010; Lyons et al., 2012; Suldo et al., 2016).

The *vulnerable* and *symptomatic but content* groups may have different requirements for support from *troubled* groups and also respond positively to different and less intensive interventions (Doll et al., 2021; Rose et al., 2017). Irrespective of which perspective is adopted to conceptualize how test anxiety and anxiety disorders are related (i.e., test anxiety as distinct but related or indicator), the presence of high test anxiety would likely contribute to elevated psychopathology and be considered as an indicator of the psychopathology dimension of the aforementioned two-dimensional typology adopted by DFM.

1.7. Aim of the present study

The aim of the present study was to examine how test anxiety, two anxiety disorders (i.e., GAD and PD), and school-related wellbeing were related in a sample of secondary school students. The study was designed to offer insights into (a) the

[2] Excluding Magalhães and Calheiros (2017) who studied a non-typical sample (children ages 11–18 years in foster care).

conceptualization of mental health; (b) whether test anxiety is distinct from, or an indicator of, GAD, and PD; (c) whether psychopathology (i.e., test anxiety, GAD, and PD) is distinct from school-related wellbeing; and (d) whether specific symptoms of GAD and PD and indicators of test anxiety and school-related wellbeing are particularly influential within a network (i.e., to spread activation throughout test anxiety, school-related wellbeing, GAD, and PD) or to bridge communities. To address this aim, we used two complimentary analytic approaches, namely network analysis and latent profile analysis (LPA).

Network analysis is a variable-centered analytic approach used to empirically address questions posed by a NT approach. Nodes, edges, and communities were represented graphically and two numerical centrality metrics (i.e., one-step and two-step expected influence indices) were used to assess if one or more nodes occupied influential roles with networks (Fortunato, 2010; Newman, 2006). These terms associated with network analysis are explained below in the section entitled "Analytic Approach".

Using network analysis, we addressed two research questions. First, we examined whether test anxiety, GAD, PD, and school-related wellbeing are best represented as a combined network or as distinct communities. In DFM, indicators of elevated psychopathology and wellbeing are considered as distinct dimensions. Accordingly, in the network analysis we expected that school related being nodes would be represented as a distinct community of test anxiety, GAD, and PD nodes. In the absence of definitive theorizing or evidence, we left open the question of how test anxiety, GAD, and PD are related (i.e., test anxiety as distinct but related or indicator). Second, we examined how nodes were related and whether any bridge nodes emerged to link communities and whether there were any nodes particularly influential in the network (i.e., nodes that are closely and densely linked to many others). Although previous studies have shown that high test anxiety is linked to anxiety disorders, including GAD and PD (e.g., King et al., 1995; Weems et al., 2010), it is not clear whether this is a result from distinct communities with strong node connections or indicators of test anxiety and anxiety disorders cohering as a single network. In relation to the first research question we tested the following hypothesis:

Hypothesis 1. School-related wellbeing is distinct to test anxiety, GAD, and PD in communities of nodes.

LPA is a person-centered approach used to identify internally homogenous groups based on data characteristics (Berlin et al., 2013) and has become an increasingly popular approach to identifying profiles of mental health risk and strength in children and adolescents (Petersen et al., 2019). LPA offers distinct advantages over the cut-score approach typically used in DFM studies whereby the similarity between persons scoring on either side of a pre-determined threshold can contribute to spurious group membership and inflate group heterogeneity (Dowdy & Kamphaus, 2007).

Using LPA, we addressed a second research question: Do homogenous profiles emerge based on test anxiety, school-related wellbeing scores, GAD, and PD? There is substantial support for the two-dimensional typology of mental health proposed by Suldo and Shaffer (2008) based on dimensions of subjective wellbeing and psychopathology (e.g., Antaramian, 2015; Antaramian et al., 2010; Lyons et al., 2012; Suldo et al., 2016). Accordingly, we expected to find similar profiles based on low vs. average/high subjective wellbeing and based on low vs. elevated psychopathology to those found in existing studies. However, we were open to the possibility that LPA might identify additional categories that may be based on a more refined distinction of the dimensions than found in the cut-score approach used by the majority of DFM studies. Based on the DFM, we tested the following hypothesis:

Hypothesis 2. The existence of profiles will be found that represent sub-groups characterized as *complete mental health*, *vulnerable*, *troubled*, and *symptomatic but content*.

2. Method

2.1. Participants and procedure

Data from a convenience sample of 918 participants with a mean age of 15.77 years ($SD = 1.13$) were collected from one Welsh and seven English secondary schools. The sample consisted of 217 male students, 694 female students, and seven students who did not disclose their gender; two of the participating schools were girls' only schools, thereby accounting for the gender-biased sample. The ethnic heritage of the sample was comprised of students who reported Asian ($n = 29$), Black ($n = 48$), White ($n = 802$), dual heritage ($n = 21$), and Other ($n = 18$) backgrounds. A total of 145 students were eligible for free school meals, which was considered a proxy for low socio-economic status (SES).

Data were collected in a single wave using a web-based survey tool in October and November 2019, which is considered the latter half of the autumn term for English and Welsh schools. A liaison teacher in each school distributed the survey link to participants, explained key points about the ethics (i.e., anonymity, consent, and how to withdraw data retrospectively), and read instructions from a standardized script (instructions were also included in the survey). The survey link was distributed during a period of the school timetable used for registration and administration and so did not interfere with academic study. Participants could withdraw participation during data collection by closing the web browser in which case no data were saved. Furthermore, the survey tool prompted students to complete any missing responses and thus there were no missing data; furthermore, no participants subsequently requested their data to be retrospectively withdrawn. The project was approved by an institutional research ethics committee from the first author's institution and written consent provided by the head teacher at each school.

2.2. Instruments

The Multidimensional Test Anxiety Scale (MTAS; Putwain et al., 2021) was used to measure test anxiety. The MTAS contains four subscales comprised of four items each, including (a) Worry (e.g., "During a test/exam, I worry that I gave the wrong answers"), (b)

Cognitive Interference (e.g., "During tests/exams, I find it hard to concentrate"), (c) Tension (e.g., "Just before I take a test/exam, I feel panicky"), and (d) Physiological Indicators (e.g., "During a test/exam, I experience stomach discomfort"). Participants responded to each item on a 5-point scale (1 = *strongly disagree*, 3 = *neither*, and 5 = *strongly agree*). Putwain et al. (2021) and von der Embse et al. (2021) showed excellent internal consistency and construct validity for a higher-order model of MTAS data. In the present study, the internal consistency for the MTAS scale total was excellent (see Table 1).

The Revised Children's Anxiety and Depression Scale (RCADS; Chorpita et al., 2005) was used to measure symptoms of GAD and PD. The GAD subscale consists of six items (e.g., "I worry that something bad will happen to me") and the PD subscale consists of nine items (e.g., "I suddenly feel as if I can't breathe when there is no reason for this"). Participants responded to each item on a 4-point scale (0 = *never*, 1 = *sometimes*, 2 = *often*, and 3 = *always*). The RCADS is a widely used scale and previous studies have supported the unidimensional structure of the GAD and PD subscales and have shown strong internal consistency (e.g., Donnelly et al., 2018; Piqueras et al., 2017). In the present study, the internal reliability was also good (see Table 1).

The 6-item School-Related Wellbeing Scale (SWBS; Loderer et al., 2016) was used to measure subjective wellbeing in the school domain. Participants responded to items on a 5-point scale (1 = *strongly disagree*, 3 = *neither*, and 5 = *strongly agree*). The items complement existing measures of school satisfaction and reflect overall cognitive appraisals about schooling (e.g., "School is going well for me"), positive affect while at school (e.g., "I feel good at school") and attachment to school (e.g., "I like going to school"). Construct validity is supported through strong associations (r = 0.37–0.60) in the expected directions with positive and negative emotions in math class (Loderer et al., 2018). Good internal consistency and the unidimensionality of the SRWS have been demonstrated in previous studies (e.g., Loderer et al., 2018; Putwain, Loderer, et al., 2020). The internal consistency for the SWBS in the present study was excellent (see Table 1).

2.3. Analytic approach

2.3.1. Network analysis

Network analysis was conducted using 'network tools' package in R 4.0.3 (Jones, 2017). Network analysis has been frequently used to model the interrelation of symptoms of mental disorders in the clinical psychology literature (e.g., Beard et al., 2016; Cramer et al., 2010) and indicators of personality in the individual differences' literature (e.g., Costantini & Perugini, 2016; Heeren et al., 2018). With one notable exception, namely a study examining relations between achievement goals, intelligence beliefs, and effort beliefs (Garnett, 2020), network analysis has been limited to the study of social relationships in the classroom (e.g., Grunspan et al., 2014; Sweet, 2016) and has not been widely used in the school and educational psychology literatures.

To establish a visual representation of the network, a graphical Gaussian model was estimated using the Fruchterman-Reingold algorithm (Fruchterman & Reingold, 1991). The graph presents *nodes* as circles (indicators of test anxiety, school-related well-being, GAD, and PAD). To facilitate identification, we labelled nodes and used different colors to represent test anxiety (red), school-related wellbeing (blue), GAD (yellow), and PD (green). The connections between nodes are represented as *edges* and a thicker edge represents a stronger correlation between the two nodes. Positive relations are represented as blue edges and negative relations as red edges. Nodes that are more central and influential to the network can be identified through thicker edges, a greater number of edges, and a shorter distance through which edges pass through other nodes to connect nodes within a network.

Edge weights were estimated using 1000 non-parametric bootstrapped draws. The distance between nodes is represented by the shortest average shortest path length, which is the average number of paths to connect one node to another. For comparative purposes, the networks were estimated using semi-partial correlations between nodes (whereby small correlations may create network 'noise') and an approach that shrinks small semi-partial correlations between items to zero (regularized semi-partial correlations) using the Least Absolute Shrinkage and Selection Operator (LASSO; Friedman et al., 2008). In LASSO, the balance between (a) a model with greater number of, but potentially false-positive (i.e., spurious), edges and (b) a more parsimonious model with potentially true edges purged, is controlled by hyperparameter γ.

Hyperparameter values are typically set between 0 and 0.5. Higher thresholds will reject models based on smaller semi-partial correlations and result in a model with fewer edges overall and lower likelihood of these edges being spurious (Epskamp et al.,

Table 1
Descriptive statistics and bivariate correlations.

	1.	2.	3.	4.
1. Test Anxiety	–	−0.26	0.62	0.62
2. School-Related Wellbeing		–	−0.28	−0.33
3. GAD			–	0.80
4. PD				–
Theoretical Scale Range	16–80	7–35	0–18	0–27
Observed Scale Range	16–80	7–35	0–15	0–27
Mean	55.38	23.14	6.24	8.59
SD	12.22	5.12	3.83	6.85
McDonald's ω	0.75	0.90	0.91	0.93
Skewness	−0.53	−0.69	0.51	0.86
Kurtosis	0.20	0.43	−0.61	−0.11
ICC1(ρ_I)	0.01	0.08	0.01	<0.01

Note. All correlations statistically significant at $p < .001$.

2012; Epskamp et al., 2017). Following the approach used in existing studies (e.g., Beard et al., 2016; Bernstein et al., 2017; Heeren et al., 2018), a high threshold was set ($\gamma = 0.50$). The aim was for a conservative model with fewer, but more authentic, edges. Although networks estimated using regularized semi-partial correlations can appear sparse by comparison to those without, potentially false positive edges are removed. This approach is consistent with the aim of LPA to identify a parsimonious number of homogenous groups. To check the robustness of the LASSO model at $\gamma = 0.50$, we tested networks at several alternative hyperparameter values ($\gamma = 0.40$ to $\gamma = 0.65$).

The significance of a node to the overall network can be established quantitatively using centrality indices that establish the extent to which nodes are more central to the network relative to others (Opsahl et al., 2010). Commonly used centrality indices (i.e., betweenness, closeness, and degree) operate by summing edge weights. In networks that contain positive edges only, this is not problematic. In networks such as ours where it is expected that school-related wellbeing will be negatively related to test anxiety, GAD, and PD, the mixture of positive and negative edges will underestimate centrality (Robinaugh et al., 2016). Accordingly, we used Robinaugh et al.'s (2016) one-step (EI1) and two-step (EI2) *expected influence* indices.

EI1 is the summed weight of positive and negative edges of each node in the network. Thus, nodes within a network showing stronger, and a greater number of, edges will result in a higher EI1 index. However, this approach does not account for the influence of neighboring nodes in the network. If a particular test anxiety node (TA1) is connected with only one other test anxiety node (TA2), it may not appear to be highly central using the EI1 metric. However, if test anxiety node TA2 is connected to all other nodes in the network, then TA1 could be influential by virtue of its connection with TA2. To account for the influence of neighboring nodes with shared edges, the EI2 index includes the sum of EI1 values of all remaining nodes weighted be the strength of their respective edges.

2.3.2. Latent profile analysis

Second, we conducted an LPA for test anxiety (see von der Embse et al., 2014), GAD, PD, and school-related wellbeing in M*plus* version 8.3 (Muthén & Muthén, 2017) using maximum likelihood estimation. We compared solutions containing between two and ten profiles (an upper limit beyond which there should be no more clusters that are theoretically and empirically meaningful to differentiate between). The DFM predicts profiles where there would be correspondingly higher (or lower) scores on dimensions of psychopathology and wellbeing (e.g., complete mental health) and other profiles where higher scores on one dimensioned are coupled with lower scores on the other (e.g., troubled). Accordingly, we assumed partial local independence (see Masyn, 2013) and covariances between test anxiety, GAD, PD, and school-related wellbeing were allowed to differ across profiles. As the DFM makes no such prediction for the variances of test anxiety, GAD, PD, and school-related wellbeing across profiles, they were constrained to be equal (the M*plus* default option).

Choice of profile solutions was guided by the Akaike Information Criterion (AIC; Akaike, 1987), sample-size adjusted Bayesian Information Criterion (aBIC; Sclove, 1987), Lo-Mendell-Rubin adjusted likelihood ratio test (LMR; Lo et al., 2001), and the Vuong-Lo-Mendell Rubin Likelihood Ratio Test (VLMR). The AIC and aBIC values were used to compare the different solutions with progressively greater numbers of solutions; lower relative AIC and aBIC values indicate a better model fit (Hix-Small et al., 2004). The LMR and VLMR test whether the model with k number of profiles provides a significantly better fit than a model with k-1 profiles (Beyers & Seiffge-Krenke, 2007). The entropy value of the chosen profile solution was used to gauge the quality of classification accuracy, where values closer to 1 represent a more accurate latent classification (Celeux & Soromenho, 1996). When using four indicators, the minimum requirement of 18 participants per class required to achieve a target power of 0.90 when using LPA (see Dziak et al., 2014) was easily met.

3. Results

3.1. Descriptive statistics and bivariate correlations

Descriptive statistics and bivariate correlations are reported in Table 1. Skewness and kurotsis (within ± 1) did not indicate problems with the normal distribution of scores. Test anxiety correlated negatively with school-related wellbeing ($r = -0.26$) and positively with GAD ($r = 0.62$) and PD ($r = 0.62$). School-related wellbeing correlated negatively with GAD ($r = -0.28$) and PD ($r = -0.33$). GAD and PD were positively intercorrelated ($r = 0.80$). With the exception of school-related wellbeing ($\rho_I = 0.08$), the proportion of variance between schools was negligible. The internal consistency estimates (McDonald's ωs) were estimated in M*plus* 8.3 using maximum likelihood estimation with 1000 bootstrapped draws. School-related wellbeing, GAD, and PD were all treated as unidimensional one-factor models. Test anxiety was modeled as a higher-order factor model with worry, cognitive interference, tension, and physiological indicators as lower-order factors; hence, hierarchical ω_H was estimated. The internal consistency of all scales was good (ωs ≥ 0.75). Descriptive statistics for individual items used in the network analysis that follows are presented in the Supplementary Materials.

3.2. Network analysis

3.2.1. Graphical networks

Graphical networks are shown in Fig. 1 (semi-partial correlations between nodes) and Fig. 2 (regularized semi-partial correlations between nodes that limit potentially spurious associations). There are five salient features to highlight from Fig. 2 (to facilitate interpretation, items are also listed in Table 2). First, the question of whether nodes were clustered as a single community, or grouped into distinct communities, can be answered by inspecting the following: (a) the positioning of nodes relative to others, (b) the number of edges between nodes, and (c) the size of the edges between nodes. As illustrated in Fig. 2, nodes did not form one single coherent community. Rather, nodes were clustered as four relatively distinct communities. That is, nodes for the four different communities representing test anxiety, school-related wellbeing, GAD, and PD tended to be located more closely to one another, show a greater number of edges to other nodes within their community (relative to nodes in an adjacent community), and show stronger edges to other nodes within their community (relative to nodes in an adjacent community).

Wellbeing was the most clearly distinct community by virtue of fewer and weaker edges to adjacent communities. There was a greater number of edges between test anxiety, GAD, and PD. The positioning of the test anxiety nodes further indicates that nodes for physiological indicators (particularly MTAS4 and MTAS12) were positioned closer to PD (particularly RCADS2 and RCADS3) than to GAD or to school-related wellbeing. Furthermore, the test anxiety nodes for cognitive interference were positioned closer to school-related wellbeing and one cognitive interference node in particular (MTAS14) showed the strongest edge to a wellbeing node (WELL1).

Second, nodes within the test anxiety community were positioned most closely to other nodes and showed thicker edges to other nodes in the corresponding dimensions of (a) cognitive interference (MTAS2, MTAS6, and MTAS10), (b) worry (MTAS1, MTAS5, and MTAS9), (c) tension (MTAS7, MTAS11, and MTAS15), and (d), physiological indicators (MTAS4, MTAS8, MTAS12 and MTAS16). Nodes appeared like clusters (i.e., more closely positioned and within stronger edges) nested within a larger test anxiety community. This is not surprising given that the test anxiety measure used in the present study were comprised of four components. The positioning of test anxiety nodes also indicated that those for worry and tension were located closely and adjacent to one another. Physiological indicators nodes were located adjacent to tension, which is consistent with both being affective-physiological dimensions of test anxiety. Cognitive indicators items were located adjacent to worry which is consistent with both being cognitive dimensions of test anxiety. In the two-dimensional space of the graphical network, cognitive inference nodes (especially MTAS 2, MTAS6, and MTAS10) were positioned slightly separated from the remaining test anxiety nodes, although are linked via edges.

Third, in relation to associations between nodes of different communities, the link between test anxiety and school-related wellbeing was primarily through the negative association with cognitive interference (WELL1: school is going well with MTAS14: problems concentrating during tests). However, MTAS14 may not function as a strong bridge node to school-related wellbeing given the position slightly apart from, and lack of strong edges to, other test anxiety nodes. The link between school-related wellbeing and PD was primarily through the negative association between two pairs of nodes (WELL5: like going to school with RCADS13: heart beats fast for no reason; WELL2: feel good at school with RCADS14: feeling unnecessarily scared). Strong links between test anxiety and PD were shown through three pairs of positive associations with physiological indicators nodes (RCADS2: funny feeling in stomach with MTAS12: stomach discomfort during tests; RCADS3: heart beats fast with MTAS8: heart races during tests; RCADS7: feel shaky and MTAS4: hand trembles during tests). The strongest link between test anxiety and GAD was shown through a positive association with one worry node (RCADS1: worry about things with MTAS1: worry about test failure). RCADS1 and RCADS2 were positioned slightly separate from the GAD and PD communities, respectively, but showed strong edges to other nodes within their networks and hence may still function as bridge nodes.

Fourth, the identification of potential bridge nodes through the positioning of nodes and their edges indicated that three physiological indicator nodes (MTAS4: hand trembles during tests; MTAS8: heart races during tests; and MTAS12: stomach discomfort during tests) bridge test anxiety to panic. One worry node (MTAS1: worry about test failure) was the primary bridge to GAD. One cognitive interference item (MTAS14: concentration problems during tests) was the principal bridge from test anxiety to school-related

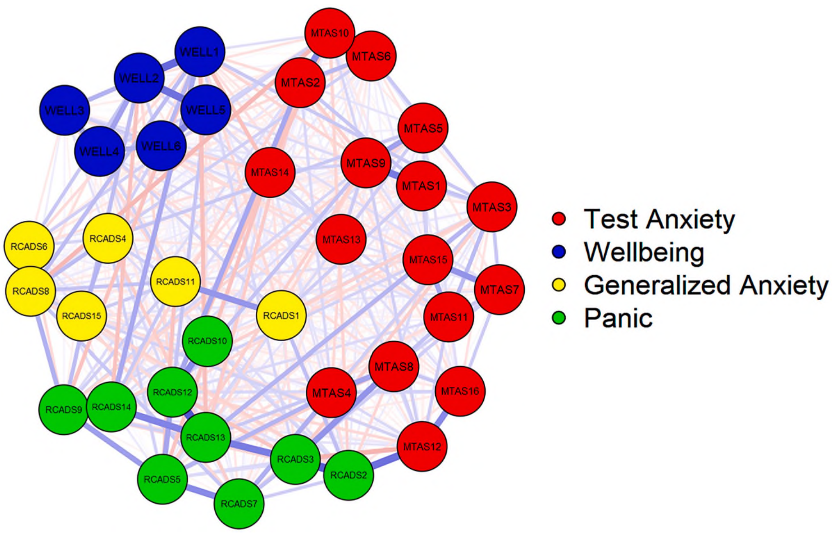

Fig. 1. Graphical network based on the semi-partial correlations between nodes.
Note. Blue edges represent positive, and red edges negative, semi-partial correlations. Test anxiety indicators are labelled as MTAS1 to MTAS16 and school-related wellbeing as WELL1 to WELL6. GAD indicators are labelled as RCADS1, 4, 6, 8, 11, and 15. PD indicators are labelled as RCADS2, 3, 5, 7, 9, 10, 12, 13, and 14.

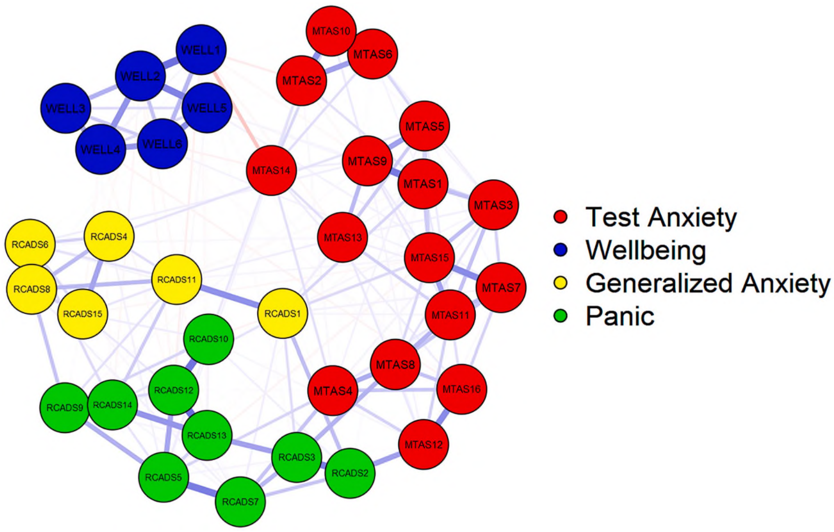

Fig. 2. Graphical network based on regularized semi-partial correlations between nodes.
Note. Blue edges represent positive, and red edges negative, regularized semi-partial correlations. Test anxiety indicators are labelled as MTAS1 to MTAS16 and school-related wellbeing as WELL1 to WELL6. GAD indicators are labelled as RCADS1, 4, 6, 8, 11, and 15. PD indicators are labelled as RCADS2, 3, 5, 7, 9, 10, 12, 13, and 14.

wellbeing. Fifth, the node occupying the most centrally located position in the two-dimensional network was RCADS1 (worry about things).

We re-tested the networks with the gamma hyperparameter set at a number of different values ($\gamma = 0.40$, 0.45, 0.55, and 0.60). As expected, when the hyperparameter values were set to be more lenient (i.e., $\gamma = 0.40$ and 0.45), a greater number of small edges were represented in the network. When hyperparameter values were set to be more strict (i.e., $\gamma = 0.60$ and 0.65), there were fewer larger edges. Critically, however, there were no substantive differences in the positioning of nodes at the different hyperparameter values. Accordingly, the hyperparameter $\gamma = 0.50$ provided an authentic representation of the network while providing an optimal balance between a model including a greater number of small edges that will be of little substantive relevance and a model that rejected larger edges that represent meaningful links in the network.

3.2.2. Centrality statistics

Expected influence metrics are plotted in Fig. 3. As shown in previous studies (e.g., Heeren et al., 2018; Robinaugh et al., 2016), the analyses of expected influence aligned with the observations from the graphical network indicated that negligible differences existed between the two steps of expected influence. For school-related wellbeing, the highest levels of EI1 and EI2 were found for WELL2 (feel good at school), corresponding with the central position in the wellbeing community and strong edges to other school-related wellbeing nodes in the graphical network. WELL1 (school is going well) portrayed especially low levels. Overall, relatively high EI1 and EI2 levels were observed for GAD and PD nodes, with exceptions being low levels of RCADS4 (worry about things happening to family), RCADS10 (becoming dizzy or fainting), and RCADS15 (thinking about death). Finally, for test anxiety, similarly high EI1 and EI2 levels were observed with generally little variation. However, low levels were observed for MTAS2 (forgetting previously known material). MTAS11 (feeling panic during a test) and RCADS8 (worry something bad will happen) were the most influential nodes to the work as identified through EI1 and EI2 indices.

Expected influence metrics for bridges are plotted in Fig. 4. Corresponding to the central position in the graphical network, the strongest bridge node was RCADS1 (worry about things). RCADS2 (funny feeling in stomach) and RCADS3 (heart beats fast) also showed particularly high levels of EI1 and EI2, which reflects their close positioning and strong edges to test anxiety physiological indicator nodes. For test anxiety, particularly strong levels were observed for MTAS4 (trembling hands), MTAS8 (racing heart), and MTAS12 (stomach discomfort), paired with low levels for MTAS14 (difficulty concentrating). It is notable that MTAS14 also showed low network influence EI1 and EI2 metrics (see Fig. 3) and was positioned slightly apart from other test anxiety nodes in the graphical network. For school-related wellbeing, the strongest bridge node was WELL5 (like going to school). Overall however, school-related wellbeing showed relatively low bridge EI1 and EI2 metrics. The especially low levels portrayed by WELL1 (school is going well) corresponds with the strongest link to test anxiety being with a node (MTAS14) that was not located closely to, or showed strong links with, other test anxiety nodes.

In summary, the network analysis showed that test anxiety, school-related wellbeing, GAD, and PD were largely separate but related constructs. The strongest overlap was observed between the physiological indicator nodes of test anxiety and PD nodes. Accordingly, the strongest bridge from PD to test anxiety was through the test anxiety physiological indicators nodes. The strongest bridge from GAD to test anxiety was through the test anxiety worry nodes. The strongest bridge from school-related wellbeing to test anxiety was through the test anxiety cognitive interference nodes. The nodes with the greatest influence (i.e., the largest and strongest

Table 2
Items included in the network analysis and the associated codes used in Figs. 1 and 2.

Code	Item
WELL1	School is going well for me.
WELL2	I feel good at school.
WELL3	School allows me to fulfil my needs.
WELL4	I feel comfortable at school.
WELL5	I like going to school.
WELL6	All in all, I am content with my day-to-day school experiences.
RCADS1	I worry about things. (GAD)
RCADS2	When I have a problem I get a funny feeling in my stomach. (PD)
RCADS3	When I have a problem, my heart beats really fast. (PD)
RCADS4	I worry that something awful will happen to someone in my family. (GAD)
RCADS5	I suddenly start to tremble or shake when there is no reason for this. (PD)
RCADS6	I worry that bad things will happen to me. (GAD)
RCADS7	When I have a problem, I feel shaky. (PD)
RCADS8	I worry that something bad will happen to me. (GAD)
RCADS9	All of a sudden I feel scared for no reason at all. (PD)
RCADS10	I suddenly become dizzy or faint when there is no reason for this. (PD)
RCADS11	I worry about what is going to happen. (GAD)
RCADS12	I suddenly feel as if I can't breathe when there is no reason for this. (PD)
RCADS13	My heart suddenly starts to beat too quickly for no reason. (PD)
RCADS14	I worry that I will suddenly get a scared feeling when there is nothing to be afraid of. (PD)
RCADS15	I think about death. (GAD)
MTAS1	Before a test/exam, I am worried I will fail. (W)
MTAS2	I forget previously known material before taking a test/exam. (CI)
MTAS3	Even when I have prepared for a test/exam I feel nervous about it. (T)
MTAS4	Before I take a test/exam my hand trembles. (PI)
MTAS5	During tests/exams, I worry about the consequences of failing. (W)
MTAS6	I forget facts I have learnt during tests/exams. (CI)
MTAS7	I feel tense before taking a test/exam. (T)
MTAS8	My heart races when I take a test/exam. (PI)
MTAS9	After a test/exam, I am worried I have failed. (W)
MTAS10	During tests/exams, I forget things that I have learnt. (CI)
MTAS11	Just before I take a test/exam, I feel panicky. (T)
MTAS12	During a test/exam I experience stomach discomfort. (PI)
MTAS13	During a test/exam, I worry that I gave the wrong answers. (W)
MTAS14	During tests/exams, I find it hard to concentrate. (CI)
MTAS15	Before a test/exam, I feel nervous. (T)
MTAS16	During a test/exam, my muscles are tight. (PI)

Note. W = worry, CI = cognitive interference, T = tension, PI = physiological indicators, GAD = generalized anxiety disorder, and PD = panic disorder.

links to other nodes) throughout the network were "feeling panic during a test" (a test anxiety tension node) and "worry something bad will happen" (a GAD node).

3.2.3. *Latent profile analysis*

Model fit indices for latent profile solutions (indicator covariances freely estimated and variances constrained across profiles) are reported in Table 3. As the number of profiles increased, model fit improved as indicated through the lower AIC and aBIC values, whereas classification accuracy was reduced as indicated by the decreasing entropy values. However, there was a leveling out of the AIC and aBIC values from the 5-profile solution onwards, somewhat analogous to the elbow of a scree plot. The LMR and VLMR tests showed there was no statistically significant advantage for the 5-profile over the 4-profile solution, whereas the advantage for the 4-profile over the 3-profile solution was statistically significant ($p = .002$). The classification probabilities for latent class membership (Table 4) were all >0.8 for the 4-profile solution, indicating a relatively high precision and reliability of classification (Rost, 2006). Furthermore, estimated mean values for test anxiety, GAD, PD, and school-related wellbeing (Table 5) showed the four profiles were empirically differentiable. Accordingly, we accepted the 4-profile solution as the final solution. Latent mean z-standardized scores for the 4-profile solution are shown in Fig. 5.

Profile 1 contained 21.5% of participants ($n = 196$) and consisted of moderate to high anxiety (test anxiety, GAD, and PD) and moderate to low school-related wellbeing. We labelled this group *moderate risk*. Profile 2 was the largest group and contained 38.9% of participants ($n = 354$) and consisted of low anxiety (test anxiety, GAD, and PD) and moderate school-related wellbeing. We labelled this group *low risk* and note that it is parallel to a complete mental health status. Profile 3 was the smallest group and contained 7.9% of participants ($n = 72$) and consisted of high anxiety (test anxiety, GAD, and PD) and low school-related wellbeing. We labelled this group *high risk*, parallel to a troubled status. Profile 4 contained 31.7% of participants ($n = 289$) and consisted of slightly above average test anxiety and school-related wellbeing and slightly below average PD. We labelled this group *coping* and note that it is most similar to a symptomatic (mild test anxiety) but content status.

We also examined whether the demographic characteristics of participants differed across latent profiles for age, ethnic heritage,

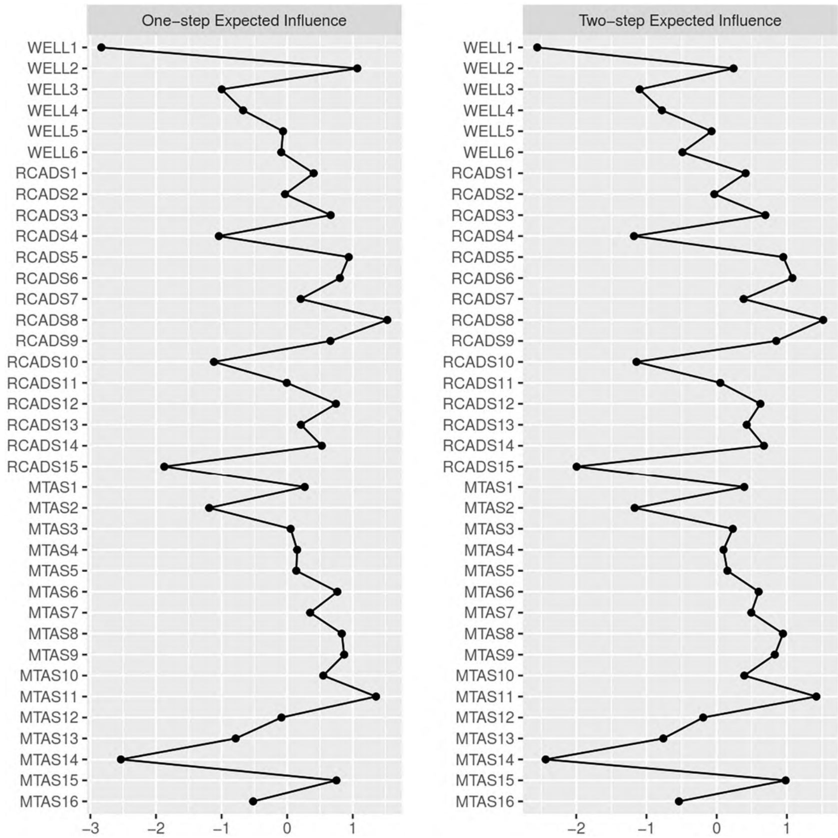

Fig. 3. Plot denoting the one-step and two-step expected influence metrics for the graphical LASSO network.
Note. Test anxiety indicators are labelled as MTAS1 to MTAS16 and school-related wellbeing as WELL1 to WELL6. GAD indicators are labelled as RCADS1, 4, 6, 8, 11, and 15. PD indicators are labelled as RCADS2, 3, 5, 7, 9, 10, 12, 13, and 14.

and SES. As two of the schools from which participants were recruited were single-sex girls' schools, gender was not included. A small but statistically significant difference emerged for SES, $F(3, 2254) = 5.993$, $p = .001$, $\eta_p^2 = 0.019$. Post-hoc tests with a Bonferroni correction showed a smaller proportion of participants from low SES households in the *low risk profile* as compared with the *moderate risk* ($p = .005$), *high risk* ($p = .01$), and *coping profiles* ($p = .04$). There were no differences across the profiles for age or ethnic heritage ($ps > 0.05$).

4. Discussion

The aim of the present study was to examine how test anxiety, GAD, PD, and school-related wellbeing are related in order to inform the assessment of mental health in secondary school populations. We addressed research questions using two complimentary analytic approaches, namely network analysis and LPA. Network analysis is a novel approach to investigating psychopathology (e.g., Heeren et al., 2018), personality traits (e.g., Heeren et al., 2018), and social relationships (e.g., Sweet, 2016). Specifically, network analysis provides insight into the relations between test anxiety, GAD, PD, and school-related wellbeing by establishing whether indicators (i.e., responses to self-report items) or, in the parlance of NT, *nodes*, form part of one single network or are organized into distinct communities.

Network analysis shares some features with other variable-centric approaches (e.g., factor analysis) but has the added advantage of establishing which nodes are influential within a network through the number and strength of direct or indirect links to other nodes (centrality) and whether certain nodes are responsible for linking communities (bridge nodes). Insights from network analysis have important implications for practice by identifying which indicators would be beneficial for intervention to target. LPA, in turn, is a more established analytical technique used to identify homogenous groups of individuals based on data characteristics and has been used to identify different patterns of mental health risk and strength in children (Petersen et al., 2019) and in DFM studies (e.g., Moore et al., 2019; Rose et al., 2017; Thayer et al., 2021). Studies have yet to examine the DFM in relation to test anxiety, however.

We initially proposed two potential relationships among the variables of interest, including that (a) test anxiety and GAD/PD were distinct but related constructs and (b) test anxiety was an indicator of GAD and/or PD (see LeBeau et al., 2010). The network analysis indicated that test anxiety, GAD, and PD formed relatively distinct but internally coherent communities (based on their respective nodes). GAD and PD nodes, within their respective communities, were organized more closely together and showed thicker edges to

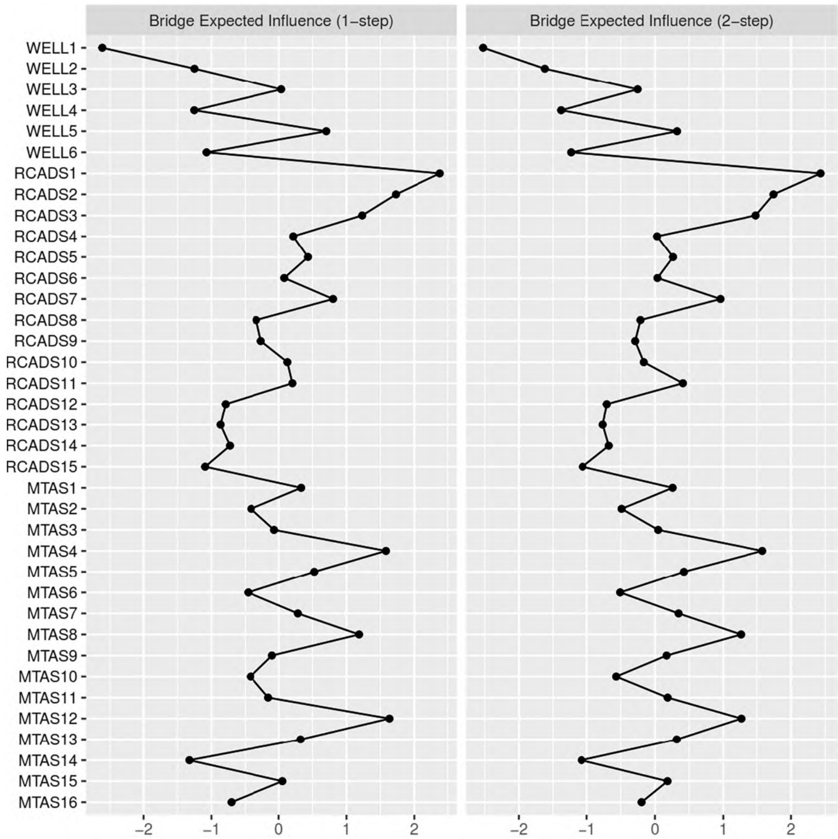

Fig. 4. Plot denoting the bridge one-step and the bridge two-step expected influence metrics for the graphical LASSO network.
Note. Test anxiety indicators are labelled as MTAS1 to MTAS16 and school-related wellbeing as WELL1 to WELL6. GAD indicators are labelled as RCADS1, 4, 6, 8, 11, and 15. PD indicators are labelled as RCADS2, 3, 5, 7, 9, 10, 12, 13, and 14.

Table 3
Model fit indices for profile solutions.

k Profiles	AIC	aBIC	LMR (*p*)	VLMR (*p*)	Entropy
2	9129.48	9150.78	1198.57 (<0.001)	−5168.61 (<0.001)	0.881
3	8756.43	8785.93	372.13 (0.002)	−4551.74 (0.001)	0.833
4	8554.84	8592.53	205.56 (0.002)	−4360.22 (0.002)	0.836
5	8460.66	8506.54	101.21 (0.06)	−4254.42 (0.06)	0.812
6	8401.44	8560.32	67.25 (0.07)	−4202.30 (0.07)	0.811
7	8377.42	8439.69	73.54 (0.69)	−4188.55 (0.56)	0.799
8	8370.99	8441.45	17.83 (0.32)	−4151.66 (0.32)	0.829
9	8350.61	8429.27	16.88 (0.18)	−4135.99 (0.18)	0.835
10	8318.04	8404.89	32.43 (0.33)	−4122.71 (0.32)	0.808

Table 4
Classification probabilities for the most likely latent class membership (column) by latent class (row).

Latent class	1	2	3	4
1.	**0.911**	<0.001	0.032	0.057
2.	<0.001	**0.935**	<0.001	0.065
3.	0.077	<0.001	**0.923**	<0.001
4.	0.044	0.094	<0.001	**0.862**

Note. The average posterior probability of a person being assigned to a particular class is presented on the diagonal in bold.

other nodes within the same constructs (indicative of stronger relations) than for nodes associated with adjacent communities. The four factors that comprised test anxiety, namely worry, cognitive interference, tension, and physiological indicators, formed ‘mini-communities’ within the overarching community of test anxiety nodes. This mirrors the factor structure of test anxiety but also meant

Table 5
Model estimated means, standard errors, and counts for 4-profile solution.

	Latent profile			
	Low risk	Moderate risk	High risk	Coping
Test Anxiety	−0.81 (0.09)	0.67 (0.06)	1.21 (0.07)	0.22 (0.06)
School-Related Wellbeing	0.30 (0.06)	−0.36 (0.10)	−0.79 (0.16)	0.08 (0.06)
GAD	−0.89 (0.05)	0.91 (0.06)	1.84 (0.12)	0.01 (0.11)
PD	−0.86 (0.03)	0.97 (0.11)	2.16 (0.10)	−0.15 (0.09)
n	354 (38.9%)	196 (21.5%)	72 (7.9%)	289 (31.7%)

Note. Standard errors are in parentheses. For test anxiety, school-related wellbeing, GAD, and PD, all mean levels of the four profiles were statistically significantly different from each other, as indicated by a multivariate analysis of variance with Bonferroni post-hoc tests: Wilks $\Lambda = 0.073$, *multivariate* $F(12, 2392) = 337.85$, $p < .001$, $\eta_p^2 = 0.583$; all multiple comparisons $p \leq .027$.

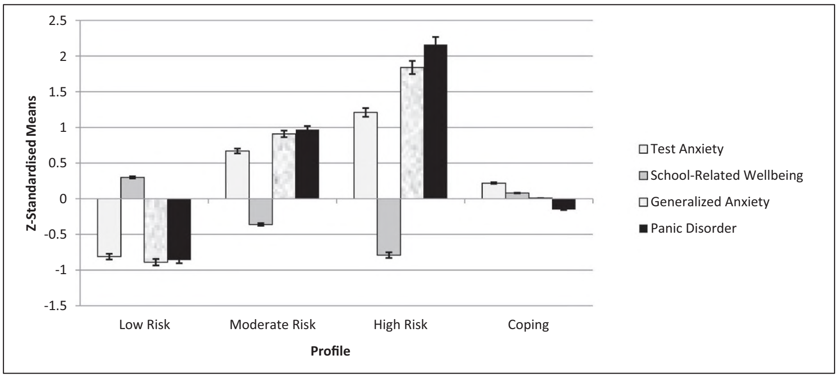

Fig. 5. Mean standardized scores for test anxiety, GAD, PD, and school-related wellbeing for the 4-profile solution.
Note. Error bars are 95% CIs.

that test anxiety nodes, although forming a coherent community, were more dispersed in comparison to the GAD, PD, and school-related wellbeing communities. Physiological indicators nodes were positioned more closely to PD nodes, cognitive interference adjacent to school-related wellbeing nodes, and worry/tension nodes centrally in the test anxiety node community. This pattern of findings offered greater support for the first of the two possibilities that we offered, which was that test anxiety is distinct but related to, rather than an indicator of, GAD and PD.

Not only were physiological indicators nodes located more closely to PD nodes, but three physiological indicator nodes were also identified as likely bridges to PD. It is notable that the three test anxiety bridge nodes shared common referents with three PD nodes (i.e., *stomach discomfort*, *elevated heart rate*, and *shakes/trembles*). The common referents for the aforementioned test anxiety physiological indicators nodes likely contribute to their positioning closer to PD than to GAD or school-relating wellbeing and identification as a bridge to PD. The critical point of difference was that the test anxiety indicators were situation-specific to tests or exams, whereas the PD indicators were not situation-specific as they could occur in other situations as well as in tests or exams. From the perspective of network theory, activation of test anxiety physiological indicator nodes (i.e., *stomach discomfort*, *elevated heart rate*, and *shakes/trembles*) in a performance-evaluative situation specifically will activate similar types of physiological reactions associated with PD in other situations more generally.

Activation of the autonomic nervous system causing distress is a defining characteristic of both test anxiety (see Roos et al., 2021; Spielberger et al., 1978) and PD (Nardi & Balon, 2020). It is difficult to foresee how either test anxiety or PD could be accurately measured via self-report without including items referencing distressing physiological arousal. Accordingly, we view the substantive issue from the perspective of NT and contend that different forms of anxiety with similar elements are likely linked by mutual causality and not an artifact of item wording.

NT presumes that nodes are related through reciprocal causation (Borsboom, 2017a; Fried et al., 2017), although many network analysis studies (e.g., Beard et al., 2016; Heeren et al., 2018), like ours, have used cross-sectional designs. If the constructs included in the present study *are* reciprocally related, the shared commonality between test anxiety and PD is based on a sensitivity, or tendency, to respond to stress situations (e.g., performance-evaluative situations) with more intense and unpleasant physiological arousal. In performance-evaluative situations, therefore, activation of test anxiety nodes could trigger PD nodes and test anxiety could become a risk factor for developing PD. Conversely, persons with PD who may have a specific environmental trigger other than performance-evaluative situations (referred to in DSM-5 as expected panic attacks), or which may be unexpected (i.e., no specific environmental trigger), may also activate test anxiety nodes and become manifest in performance-evaluative situations. That is, PD becomes a risk factor for elevated test anxiety.

Two nodes were identified as being of particular influence throughout the entire network of related communities. These were *feeling panic during a test* and *anticipation of negative outcomes*. Furthermore, one GAD node (i.e., *the tendency to worry*) was the most influential bridge to link up associations between test anxiety, school-related wellbeing, PD, and GAD. These findings, showing how specific nodes bridge test anxiety, GAD, and PD, are consistent with the extant literature suggesting that elevated anxiety and anxiety disorders are generally characterized by a tendency to appraise situations as being of high threat and respond with worry, rumination about deleterious outcomes, and the emotional adjunct, panic (e.g., Papageorgiou & Wells, 2009; Wells & Mathews, 1996). Accordingly, functional mechanisms that underlie high anxiety as proposed in the Self-Regulatory Executive Function Model (e.g., ineffective planning, metacognitive beliefs that exacerbate anxiety, and maladaptive person-situation interactions) may be common to different (and perhaps all) anxiety disorders (Matthews & Wells, 2004) as well as high test anxiety (Zeidner & Matthews, 2005).

No specific school-related wellbeing node emerged as a strong bridge to test anxiety, GAD, or PD. The strongest edge (notably less strong than those bridging test anxiety with GAD and PD) was with a cognitive interference node that itself was less strongly linked with, and positioned close to, other test anxiety nodes. Accordingly, that node did not show strong bridge EI1 and EI2 metrics. Given the negative correlations shown between school-related wellbeing and test anxiety, GAD, and PD ($rs = -0.26$ to -0.33; see Table 1), it may appear counter-intuitive that more negative edges were not shown between school-related wellbeing nodes and test anxiety, GAD, and PD nodes.

However, from the perspective of the DFM this finding may not be so surprising. The DFM (Suldo & Shaffer, 2008) predicts some profiles (e.g., complete mental health) characterized by higher school-related being in conjunction with lower indicators of psychopathology (e.g., test anxiety, GAD, PD). Other DFM profiles (e.g., symptomatic but content) are characterized by higher school-related being in tandem with higher indicators of psychopathology. The overall small negative correlations between school-related wellbeing and test anxiety, GAD, and PD may be concealing subgroups where the negative correlations are stronger (i.e., the low risk profile identified in the LPA) and weaker (i.e., the coping profile identified in the LPA). No school-related wellbeing nodes, therefore, emerged with strong negative edges to, or bridges with, test anxiety, GAD, and PD.

Of central importance to the theory is that subjective wellbeing is a distinct construct from that of psychopathology (Antaramian et al., 2010; Greenspoon & Saklofske, 2001; Suldo et al., 2016). The present study was the first to examine this proposition with test anxiety as a potential indicator of elevated psychopathology and also to do so by using network analysis. The network analysis clearly showed school-related wellbeing was distinct from test anxiety, GAD, and PD, thereby offering strong support for Hypothesis 1. The LPA showed three profiles that map onto DFM. The 'low risk' profile closely resembled the 'complete mental health' profile and was, reassuringly, the largest profile in terms of the number of students comprising this profile. The 'high risk' profile closely resembled the 'troubled' profile and was, reassuringly, the smallest profile. The 'coping' profile resembled the 'symptomatic but content' profile.

The finding that fewer students from lower SES backgrounds were found in the 'low risk' profile provides further evidence for the differentiation of profiles and is consistent with findings from earlier studies (e.g., Suldo et al., 2016; Suldo & Shaffer, 2008). There is a long-standing body of evidence showing how the difficult life circumstances associated with low SES can contribute to poor mental health and also how poor mental health can adversely influence employment and earning potential (e.g., Collishaw, 2015; Reiss, 2013).

We did not find evidence of a 'vulnerable' profile comprised of low wellbeing in the absence of test anxiety, GAD, and PD. As we did not include a measure of externalizing disorders or symptoms, we preferred to present our profiles as analogous, rather than commensurate, to DFM profiles based on measures that did include externalizing symptoms (hence the different terms used). In finding three of the four profiles predicted by DFM, results indicated substantial, if not equivocal, support for Hypothesis 2. Instead, we found a group exhibiting 'moderate risk.' As a less extreme version of the 'troubled' profile, the 'moderate risk' group does not necessarily run counter to DFM. It is a more fine-grained, yet statistically significant, differentiation of a sub-group running on the continuum of high wellbeing and absence of psychopathology to low wellbeing and presence of psychopathology. This subgroup shares the diminished wellness apparent in a 'vulnerable' mental health status, but in combination with mildly to moderately elevated test anxiety, GAD, and PD, similar to a group Keyes (2006) referred to as 'languishing' on the basis of wellbeing indicators. This 'moderate risk' group would have likely been missed when using a cut-score approach and grouped together with 'high risk' and therefore highlights the value of using LPA to identify homogenous groups of moderate and high risk.

As expected, the different types of anxiety measured in the present study tended to co-occur together in all four profiles. That is, test anxiety, GAD, and PD were all lower in the 'low risk' profile, all higher in the 'high' risk profile, and so on. This is not surprising given the strong correlations between test anxiety, GAD, and PD ($rs = 0.62$–0.80; see Table 1), the high level of comorbidity typically found between different forms of anxiety (Carragher et al., 2015; Uher & Rutter, 2012), and the co-occurrence shown between high test anxiety and anxiety disorders (Herzer et al., 2014; Weems et al., 2010). Furthermore, the DFM does not differentiate between profiles on varying contributions of distinct internalizing problems (i.e., different types of anxiety) as contributors to elevated psychopathology. The critical point for analytic approaches such as LPA that seek to categorize persons into relatively homogenous groups are the levels of anxiety rather than the specific type of anxiety. For the DFM, test anxiety can sit alongside GAD and PD as a contributor to elevated psychopathology.

Two studies using LPA (i.e., Rose et al., 2017; Thayer et al., 2021; see first wave of data collection) found similar groups (i.e., 'complete mental health', 'symptomatic but content', 'troubled', and 'vulnerable') as those using cut-score approaches. Moore et al. (2019) found a 'moderately mentally healthy' profile comprised of high-average well-being and low distress (i.e., internalizing and externalizing problems) alongside the 'complete mental health', 'symptomatic but content', and 'troubled' profiles. Furthermore, in the second round of data collection, Thayer et al. (2021) found only 'complete mental health' and 'vulnerable' profiles. Thus, our study is not alone in failing to find all four theoretically predicted DFM profiles and in identifying an additional profile.

The lack of full empirical support for the four theoretically-based DFM profiles does not, in our view, challenge the basic premise of the DFM that wellbeing and indicators of the presence of psychopathology are broadly independent dimensions (e.g., Doll et al., 2021;

Suldo & Shaffer, 2008). A potential drawback of using data-driven approaches, such as LPA, is the identification of sample-idiosyncratic profiles that may not be consistently found in other samples (Bauer & Curran, 2004). This may be the cause for our 'moderate risk' profile and further studies will be required to ascertain its replicability. Furthermore, it is likely that identification of profiles with a greater or lesser match to those theoretically predicted by the DFM will be influenced by the specific measures chosen as indicators of wellbeing and psychopathology. Some measures may be more or less sensitive to life circumstances that contribute to either of the DFM dimensions (e.g., wellbeing measures with a greater vs. lesser emphasis on life satisfaction). In addition, the combination of some measures may be more suited to the identification of some profiles than others (e.g., a troubled profile harder to identify using measures of wellbeing that emphasize self-regulation).

The existing LPA studies (Moore et al., 2019; Rose et al., 2017; Thayer et al., 2021) all included measures that represented both internalizing and externalizing disorders in the assessment of psychopathology and global measures of subjective wellbeing. In contrast, our study only included markers of internalizing disorders (i.e., indicators of test anxiety and symptoms of GAD and PD) and school-related subjective wellbeing. The identification of the 'moderate risk' may be partly an artifact of not including externalizing symptoms. Female participants (children, adolescents, and undergraduates) have been found to report higher test anxiety (e.g., Putwain, 2007; Putwain & Daly, 2014) and are at higher risk for developing anxiety disorders (Baxter et al., 2013; Vizard et al., 2018) than males. Male participants (children, adolescents, and undergraduates) are more likely to develop externalizing disorders (e.g., Boyd et al., 2015; Mandalia et al., 2018). The overall level of test anxiety, GAD, and PD may be higher in this sample than a more gender balanced equivalent and contributed to the identification of a 'moderate risk' group.

Furthermore, the measure of subjective wellbeing used in the present study focusing specifically on the school context differed to those used in extant DFM studies that typically measured subjective wellbeing more broadly and in context-unspecific ways (i.e., global life satisfaction and frequency of positive and negative affect throughout days-weeks [vs. solely when at school]; Suldo et al., 2016). When used in tandem with test anxiety as a marker of psychopathology, we have a measure of wellbeing and psychopathology inextricably linked to the school context. Our study is the first to address mental health profiles that arise from considerations of school-related subjective wellbeing and internalizing symptoms.

Nonetheless, the implication is that assessment of mental health in school-age populations that relies exclusively on cut-scores may not adequately differentiate groups of students with specific needs for support or intervention. Those in the 'high risk' profile would likely respond more favorably to indicated treatments. These are retroactive, and sometimes more intensive, interventions focused on treating more deleterious and/or prevalent symptoms or, in the traditional diagnostic-categorical approach to mental disorders, those who have received a diagnosis of GAD or PD. In contrast, those in the 'moderate risk' profile would likely respond more favorably to selective treatments. These are proactive, and sometimes less intensive, interventions focused on those with early stage symptoms but who have yet to receive a diagnosis of GAD or PD (see Mrazek & Haggerty, 1994; Stockings et al., 2016).

4.1. Limitations and suggestions for future research

Despite the novel approach that we utilized in the present study to examine how test anxiety, GAD, PD, and school-related wellbeing were related, there are four principal limitations to highlight. First, as we noted above, the sample was weighted more heavily in terms of female participants by virtue of two girls' only schools participating in the study. It is possible, therefore, that relations between test anxiety, GAD, PD, and school-related wellbeing were represented more strongly than they would have been with a more gender-balanced sample. Furthermore, the make-up (i.e., identification of a moderate risk group and the absence of a 'vulnerable' group) and size of the profiles identified in the LPA may have been influenced by the large number of female participants. Future studies should aim for a more gender-balanced sample and investigate potential gender differences in networks and profiles.

Second, we only included two anxiety disorders (i.e., GAD and PD) in the present study. Although these are two of the most commonly occurring anxiety disorders in children and adolescents, it would be beneficial to also examine how test anxiety and school-related wellbeing are related to other anxiety disorders. In addition to nonsocial aspects (e.g., fear of failure leading to thwarted personal aspirations), test anxiety contains features (e.g., fear of negative evaluation by others) that may overlap with the performance element of social anxiety (Bogels et al., 2010). Establishing how test anxiety networks and profiles relate to social anxiety disorder in particular would be an important next step. Given the high level of comorbidity between anxiety and depression (Hankin et al., 2016), it would also be beneficial to broaden the question as how test anxiety and school-related wellbeing are related to emotion disorders more generally (i.e., including both anxiety and depression).

Third, school-related wellbeing was represented as a distinct community to that of test anxiety, GAD, and PD. Furthermore, the strongest edge was to a test anxiety node that was not located close to, or showed strong edges with, other test anxiety nodes. This finding is not a limitation in itself, but it is possible that the relations shown are an artifact of the measurement variance specifically associated with the measure of school-related wellbeing used (SWBS). It would be prudent for future studies to use an additional measure of school-related wellbeing alongside the SWBS, such as the Student Subjective Wellbeing Questionnaire (Renshaw et al., 2015) or the Subjective Well-Being in School Questionnaire (Hascher, 2008). This would allow multiple versions of the network analysis to be performed using random draws of items from the pool created from the measures chosen and whether the present findings were wholly or partly related to the specific measure of wellbeing used.

Fourth, as noted above, we used a cross-sectional design. This is sufficient for network analysis and LPA but leaves open questions of directionality when assessing relations between test anxiety, anxiety disorders, and school-related wellbeing. Future research could consider longitudinal designs that permit the direction of relations to be established.

There are three specific implications for theory and practice. First, network analysis showed that test anxiety was distinct from, but related to, GAD and PD. Although test anxiety is not a manifestation of GAD and PD, these findings imply that test anxiety is a risk factor for developing GAD and PD, and vice versa. Practitioners who are involved with the assessment of test anxiety in school age-populations should be alert to the possibility that the test anxiety reported by students may not remain restricted to tests and examinations, but can generalize to other areas of anxiety, including those of GAD and PD. Similarly, students with GAD and PD are also likely to experience high test anxiety in performance-evaluative situations. We are mindful, however, that in DSM-5, test anxiety is not considered as a distinct anxiety disorder. In order to access examination accommodations, or reasonable adjustments to examination arrangements (e.g., extended time allotted to the examinee), evidence for a 'medical' condition may be required. In the case of high test anxiety, a DSM-5 diagnosis may be a necessary proxy until such time that test anxiety is included as an anxiety disorder (or subtype of a disorder) or the diagnostic-categorical approach is replaced with an alternative.

Our findings also speak to transdiagnostic perspectives on the conceptualization classification of, and intervention with, anxiety disorders and emotion disorders more generally (e.g., Clark, 2009; Norton & Paulus, 2017). Transdiagnostic models propose that the various anxiety disorders differentiated in categorical-diagnostic systems, such as the DSM, do not represent discrete conditions with distinct etiologies (Barlow et al., 2004; Norton, 2006). Rather, forms of anxiety differ by their triggering stimuli and the cognitive and behavioral coping strategies used by persons to control that anxiety. Therefore, NT shares overlapping features with transdiagnostic models, notably that comorbidity between anxiety disorders calls into question the very notion of differentiated anxiety disorders. There are specific characteristics of test anxiety, namely performance-evaluative triggers and dysfunctional forms of avoidance such as procrastination and a strategic withdrawal of academic effort, that are not captured in other forms of anxiety. These specific features indicate the importance of considering test anxiety alongside those other, more established, anxiety disorders, especially in populations for whom testing occupies a ubiquitous presence (e.g., school and university students).

Second, our focus in network analysis was on the *activation*of nodes spreading from test anxiety to GAD, PD, school-related wellbeing, and vice versa. The reverse, however, is also true. From the perspective of NT *deactivation*of nodes, especially influential nodes such as those identified in our analysis (i.e., worry, panic, and rumination) will prevent the maintenance of network activation occurring through recursive loops and gradually dampen activation to reduce anxiety (e.g., Fried et al., 2017; Heeren et al., 2018). Thus, interventions designed for GAD and PD could also benefit students with high test anxiety (and vice versa) to the extent to which interventions target bridge nodes. An additional aim of the transdiagnostic perspective is to identify common mechanisms across different types of anxiety that are responsive to common treatment (e.g., transdiagnostic cognitive behavioral therapy; Paulus et al., 2015). The unique and specific contribution of network analysis is to assist this process through the identification of nodes that are highly influential within a community and that bridge communities. The nodes identified in the present study as being influential, or a bridge, would be highly relevant for transdiagnostic treatments to focus on. Notably, they are similar to transdiagnostic mechanisms identified previously as being core to different forms of anxiety: the presence of intrusive, worrisome thoughts, and a difficulty in disengaging from threat triggers (Clark & Rhyno, 2005). Evidence of transdiagnostic benefit has been shown in a 6-session intervention for text anxiety in adolescents that not only reduced test anxiety, but also GAD and PD (Putwain & von der Embse, 2021).

Third, network analysis and LPA showed that school-related wellbeing can be clearly differentiated from test anxiety, GAD, and PD. Thus, consistent with the central proposition of the DFM (Suldo & Shaffer, 2008), higher school-related wellbeing cannot be simply inferred from the absence of higher test anxiety, GAD, and PD symptoms. For colleagues involved in the assessment and promotion of student wellbeing, it needs to be considered as distinct from indicators of poor mental health (i.e., the presence of internalizing symptoms), not merely an adjunct or epiphenomenon emerging from the absence of psychopathology. DFM profiles may also provide assistance in providing data on which to guide tiered interventions to mental health support and specifically to differentiate those requiring more from less intensive forms of intervention intended to increase subjective well-being, decrease psychopathology, or both (Doll et al., 2021). Persons with a 'high risk' profile may benefit from more intensive, or 'indicated' intervention, whereas those with a moderate risk profile may benefit from less intensive, or 'selective', intervention (also see Stockings et al., 2016).

5. Conclusion

The network analysis showed that test anxiety was distinct from, rather than a manifestation of, GAD and PD. The relations between test anxiety, GAD, and PD could be treated as analogous to comorbidity, and the network analysis identified bridge nodes from the test anxiety to GAD and PD that may account for the links. In support of DFM (Suldo & Shaffer, 2008), the network analysis identified school-related wellbeing to be distinct from test anxiety, GAD, and PD. Furthermore, three profiles were identified using LPA that mapped onto existing DFM categories. We found a fourth profile that, although not directly contradicting DFM, highlighted the value of using LPA to identify more subtly distinct homogenous sub-groups than may be found using a cut-score approach. Broadly, our findings found strong, if not equivocal, support for the DFM even when wellbeing is focused on positive affect and satisfaction specifically in the school setting. The implications are that (a) test anxiety may be a risk factor for the development of GAD and PD (and vice versa), (b) intervention for test anxiety will likely reduce GAD and PD symptoms (and vice versa); and (c) school-related wellbeing needs to be assessed and promoted as distinct from the mere absence of internalizing symptoms (e.g., test anxiety, GAD, and PD).

Funding

This project was funded by British Academy Award to the first author (SG170738).

References

Akaike, H. (1987). Factor analysis and AIC. *Psychometrika, 52*, 317–332. https://doi.org/10.1007/BF02294359.

American Psychiatric Association. (1980). *Diagnostic and statistical manual of mental disorders* (3rd ed.). American Psychiatric Association.

American Psychiatric Association. (1985). *Diagnostic and statistical manual of mental disorders* (3rd edition revised). American Psychiatric Association.

American Psychiatric Association. (2000). *Diagnostic and statistical manual of mental disorders* (4th Edition Text Revised). American Psychiatric Association.

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.). American Psychiatric Publishing. https://doi.org/10.1176/appi.books.9780890425596.

Anglim, J., Horwood, S., Smillie, L. D., Marrero, R. J., & Wood, J. K. (2020). Predicting psychological and subjective well-being from personality: A meta-analysis. *Psychological Bulletin, 146*, 279–323. https://doi.org/10.1037/bul0000226.

Antaramian, S. (2015). Assessing psychological symptoms and well-being: Applications of a dual-factor mental health model to understand college student performance. *Journal of Psychoeducational Assessment, 33*, 419–449. https://doi.org/10.1177/0734282914557727.

Antaramian, S. P., Huebner, E. S., Hills, K. J., & Valois, R. F. (2010). A dual-factor model of mental health: Toward a more comprehensive understanding of youth functioning. *American Journal of Orthopsychiatry, 80*, 462–472. https://doi.org/10.1111/j.1939-0025.2010.01049.x.

Anthony, M. M., Federici, A., & Stein, M. B. (2008). Overview and introduction to anxiety disorders. In M. M. Antony, & M. B. Stein (Eds.), *Oxford handbook of anxiety and related disorders* (pp. 3–15). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780195307030.013.0001.

Baird, J.-A. (2018). *On different paradigms of educational assessment: Implications for the relationships with learning and teaching.* British Psychological Society.

Barlow, D. H., Allen, L. B., & Choate, M. L. (2004). Toward a unified treatment for emotional disorders. *Behavior Therapy, 35*, 205–230. https://doi.org/10.1016/S0005-7894(04)80036-4.

Bauer, D. J., & Curran, P. J. (2004). The integration of continuous and discrete latent variable models: Potential problems and promising opportunities. *Psychological Methods, 9*, 3–29. https://doi.org/10.1037/1082-989X.9.1.3.

Baxter, A., Scott, J. M., Vos, T., & Whiteford, H. (2013). Global prevalence of anxiety disorders: A systematic review and meta-regression. *Psychological Medicine, 43*, 897–910. https://doi.org/10.1017/S003329171200147X.

Beard, C., Millner, A. J., Forgeard, M. J. C., Fried, E. I., Hsu, K. J., Treadway, M., … Björgvinsson, T. (2016). Network analysis of depression and anxiety symptom relations in a psychiatric sample. *Psychological Medicine, 46*, 3359–3369. https://doi.org/10.1017/S0033291716002300.

Beck, A. T., Steer, R. A., & Brown, G. (1996). *Beck depression inventory–II.* The Psychological Corporation. https://doi.org/10.1037/t00742-000.

Beidel, D. C., Turner, M. W., & Trager, K. N. (1994). Test anxiety and childhood anxiety disorders in African-American and white school children. *Journal of Anxiety Disorders, 8*, 169–179. https://doi.org/10.1016/0887-6185(94)90014-0.

Beidel, D. C., & Turner, S. M. (1988). Comorbidity of test anxiety and other anxiety disorders in children. *Journal of Abnormal Child Psychology, 16*, 275–287. https://doi.org/10.1007/BF00913800.

Berenbaum, H. (2013). Classification and psychopathology research. *Journal of Abnormal Psychology, 122*, 894–901. https://doi.org/10.1037/a0033096.

Berlin, K. S., Williams, N. A., & Parra, G. R. (2013). An introduction to latent variable mixture modeling (part 1): Overview and cross-sectional latent class and latent profile analyses. *Journal of Pediatric Psychology, 39*, 174–187. https://doi.org/10.1093/jpepsy/jst084.

Bernstein, E. E., Heeren, A., & McNally, R. J. (2017). Unpacking rumination and executive control: A network perspective. *Clinical Psychological Science, 5*, 816–826. https://doi.org/10.1177/2167702617702717.

Bertrams, A., Englert, C., & Dickhäuser, O. (2010). Self-control strength in the relation between trait test anxiety and state anxiety. *Journal of Research in Personality, 44*, 738–741. https://doi.org/10.1016/j.jrp.2010.09.005.

Beyers, W., & Seiffge-Krenke, I. (2007). Are friends and romantic partners the "best medicine?" how the quality of other close relations mediates the impact of changing family relationships on adjustment. *International Journal of Behavioral Development, 31*, 559–568. https://doi.org/10.1177/0165025407080583.

Bögels, S. M., Alden, L., Beidel, D. C., Clark, L. A., Pine, D. S., & Stein, M. B. (2010). Social anxiety disorder: Questions and answers for the DSM-V. *Depression and Anxiety, 27*, 168–189. https://doi.org/10.1002/da.20670.

Borsboom, D. (2017a). A network theory of mental disorders. *World Psychiatry, 16*, 5–13. https://doi.org/10.1002/wps.20375.

Borsboom, D. (2017b). Mental disorders, network models, and dynamical systems. In K. S. Kendler, & J. Parnas (Eds.), *Philosophical issues in psychiatry IV: Psychiatric nosology* (pp. 80–97). Oxford University Press.

Boyd, A., Van de Velde, S., Vilagut, G., de Graaf, R., O'Neill, S., Florescu, S., … Kovess-Mafesty, V. (2015). Gender differences in mental disorders and suicidality in Europe: Results from a large cross-sectional population-based study. *Journal of Affective Disorders, 173*, 245–254. https://doi.org/10.1016/j.jad.2014.11.002.

Bucker, S., Nuraydin, S., Simonsmeier, B. A., Schneider, M., & Luhmann, M. (2018). Subjective well-being and academic achievement: A meta-analysis. *Journal of Research in Personality, 74*, 83–94. https://doi.org/10.1016/j.jrp.2018.02.007.

Carragher, N., Krueger, R. F., Eaton, N. R., & Slade, T. (2015). Disorders without borders: Current and future directions in the meta-structure of mental disorders. *Social Psychiatry and Psychiatric Epidemiology, 50*, 339–350. https://doi.org/10.1007/s00127-014-1004-z.

Celeux, G., & Soromenho, G. (1996). An entropy criterion for assessing the number of clusters in a mixture model. *Journal of Classification, 13*(2), 195–212. https://doi.org/10.1007/BF01246098.

Chorpita, B. F., Moffitt, C., & Gray, J. (2005). Psychometric properties of the Revised Child Anxiety and Depression Scale in a clinical sample. *Behaviour Research and Therapy, 43*, 309–322. https://doi.org/10.1016/j.brat.2004.02.004.

Clark, D. A. (2009). Cognitive behavioral therapy for anxiety and depression: Possibilities and limitations of a transdiagnostic perspective. *Cognitive Behaviour Therapy, 38*(Suppl. 1), 29–34. https://doi.org/10.1080/16506070902980745.

Clark, D. A., & Rhyno, S. (2005). Unwanted intrusive thoughts in nonclinical individuals: Implications for clinical disorders. In D. A. Clark (Ed.), *Intrusive thoughts in clinical disorders: Theory, research, and treatment* (pp. 1–29). Guilford Press.

Collishaw, S. (2015). Annual research review: Secular trends in child and adolescent mental health. *Journal of Child Psychology and Psychiatry, 56*, 370–393. https://doi.org/10.1111/jcpp.12372.

Costantini, G., & Perugini, M. (2016). The network of conscientiousness. *Journal of Research in Personality, 65*, 68–88. https://doi.org/10.1016/j.jrp.2016.10.003.

Cramer, A. O. J., Waldorp, L. J., van der Maas, H. L. J., & Borsboom, D. (2010). Comorbidity: A network perspective. *Behavioral and Brain Sciences, 33*, 137–193. https://doi.org/10.1017/S0140525X09991567.

Crocq, M.-A. (2017). The history of generalized anxiety disorder as a diagnostic category. *Dialogues in Clinical Neuroscience, 19*, 107–116. https://doi.org/10.31887/DCNS.2017.19.2/macrocq.

Diener, E., Oishi, S., & Lucas, R. E. (2003). Personality, culture, and subjective well-being: Emotional and cognitive evaluations of life. *Annual Review of Psychology, 54*, 403–425. https://doi.org/10.1146/annurev.psych.54.101601.145056.

Diener, E., Oishi, S., & Tay, L. (2018). Advances in subjective well-being research. *Nature Human Behaviour, 2*, 253–260. https://doi.org/10.1038/s41562-018-0307-6.

Doll, B., Dart, E. H., Arora, P. G., & Collins, T. A. (2021). Framing school mental health services within a dual-factor model of mental health. In P. J. Lazarus, S. M. Suldo, & B. Doll (Eds.), *Fostering the emotional well-being of our youth: A school-based approach* (pp. 40–60). Oxford University Press. https://doi.org/10.1093/med-psych/9780190918873.003.0003.

Donnelly, A., Fizgerald, A., Shevlin, M., & Dooley, B. (2018). Investigating the psychometric properties of the Revised Child Anxiety and Depression Scale (RCADS) in a non-clinical sample of Irish adolescents. *Journal of Mental Health, 15*, 1–12. https://doi.org/10.1080/09638237.2018.1437604.
Dowdy, E., & Kamphaus, R. W. (2007). A comparison of classification methods for use in predicting school-based outcomes. *The California School Psychologist, 12*, 121–132. https://doi.org/10.1007/BF03340936.
Dziak, J. J., Lanza, S. T., & Tan, X. (2014). Effect size, statistical power, and sample size requirements for the bootstrap likelihood ratio test in latent class analysis. *Structural Equation Modeling, 21*, 1–19. https://doi.org/10.1080/10705511.2014.919819.
Eklund, K., Dowdy, E., Jones, C., & Furlong, M. (2011). Applicability of the dual-factor model of mental health for college students. *Journal of College Student Psychotherapy, 25*, 79–92. https://doi.org/10.1080/87568225.2011.532677.
von der Embse, N. P., Jester, D., Roy, D., & Post, J. (2018). Test anxiety effects, predictors, and correlates: A 30-year meta-analytic review. *Journal of Affective Disorders, 227*, 483–493. https://doi.org/10.1016/j.jad.2017.11.048.
von der Embse, N. P., Mata, A., Segool, N., & Scott, E. C. (2014). Latent profile analysis of test anxiety: A pilot study. *Journal of Psychoeducational Assessment, 32*, 165–172. https://doi.org/10.1177/0734282913504541.
von der Embse, N. P., Putwain, D. W., & Francis, G. (2021). Interpretation and use of the Multidimensional Test Anxiety Scale (MTAS). *School Psychology, 36*(2), 86–96. https://doi.org/10.1037/spq0000427.
Endler, N. S., & Kocovski, N. L. (2001). State and trait anxiety revisited. *Journal of Anxiety Disorders, 15*, 231–245. https://doi.org/10.1016/S0887-6185(01)00060-3.
Epskamp, S., Cramer, A. O. J., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). Qgraph: Network visualizations of relationships in psychometric data. *Journal of Statistical Software, 48*. https://doi.org/10.18637/jss.v048.i04. Article no. 1018.
Epskamp, S., Rhemtulla, M. T., & Borsboom, D. (2017). Generalized network psychometrics: Combining network and latent variable models. *Psychometrika, 82*, 904–927. https://doi.org/10.1007/s11336-017-9557-x.
Fortunato, S. (2010). Community detection in graphs. *Physics Reports, 486*, 75–174. https://doi.org/10.1016/j.physrep.2009.11.002.
Fried, E. I., van Borkulo, C. D., Cramer, A. O. J., Boschloo, L., Schoevers, R. A., & Borsboom, D. (2017). Mental disorders as networks of problems: A review of recent insights. *Social Psychiatry and Psychiatric Epidemiology, 52*, 1–10. https://doi.org/10.1007/s00127-016-1319-z.
Friedman, J., Hastie, T., & Tibshirani, R. (2008). Sparse inverse covariance estimation with the graphical lasso. *Biostatistics, 9*, 432–441. https://doi.org/10.1093/biostatistics/kxm045.
Fruchterman, T. M., & Reingold, E. M. (1991). Graph drawing by force-directed placement. *Software: Practice and Experience, 21*, 1129–1164. https://doi.org/10.1002/spe.4380211102.
Garber, J., & Weersing, V. R. (2010). Comorbidity of anxiety and depression in youth: Implications for treatment and prevention. *Clinical Psychology, 17*, 293–306. https://doi.org/10.1111/j.1468-2850.2010.01221.
Garnett, N. J. (2020). *Enabling teachers to promote incremental theories of intelligence in young children: An intervention and an instrument* [Unpublished doctoral thesis]. Keele University.
Greenspoon, P. J., & Saklofske, D. H. (2001). Toward an integration of subjective well-being and psychopathology. *Social Indicators Research, 54*, 81–108. https://doi.org/10.1023/A:1007219227883.
Grunspan, D. Z., Wiggins, B. L., & Goodreau, S. M. (2014). Understanding classrooms through social network analysis: A primer for social network analysis in education research. *CBE Life Sciences Education, 13*, 167–178. https://doi.org/10.1187/cbe.13-08-0162.
Hankin, B. L., Snyder, H. R., Gulley, L. D., Schweizer, T. H., Bijttebier, P., Nelis, S., Toh, G., & Vasey, M. W. (2016). Understanding comorbidity among internalizing problems: Integrating latent structural models of psychopathology and risk mechanisms. *Development and Psychopathology, 28*, 987–1012. https://doi.org/10.1017/s0954579416000663.
Hascher, T. (2003). Well-being in school: Why students need social support. In P. Mayring, & C. von Rhöneck (Eds.), *Learning emotion – The influence of affective factors on classroom learning* (pp. 127–142). Lang.
Hascher, T. (2007). Exploring student's wellbeing by taking a variety of looks into the classroom. *Hellenic Journal of Psychology, 4*, 331–349.
Hascher, T. (2008). Quantitative and qualitative research approaches to assess student well-being. *International Journal of Educational Research, 47*, 84–96. https://doi.org/10.1016/j.ijer.2007.11.016.
Hascher, T. (2010). Wellbeing. In P. Peterson, E. Baker, & B. McGaw (Eds.), *International encyclopedia of education* (pp. 732–738). Elsevier. https://doi.org/10.1016/B978-0-08-044894-7.00633-3.
Heeren, A., Bernstein, E. E., & McNally, R. J. (2018). Deconstructing trait anxiety: A network perspective. *Anxiety, Stress, and Coping, 31*, 262–276. https://doi.org/10.1080/10615806.2018.1439263.
Heeren, A., Bernstein, E. E., & McNally, R. J. (2020). Bridging maladaptive social self-beliefs and social anxiety: A network perspective. *Journal of Anxiety Disorders, 74*. https://doi.org/10.1016/j.janxdis.2020.102267. Article no. 102267.
Heeren, A., Jones, P. J., & McNally, R. J. (2018). Mapping network connectivity among symptoms of social anxiety and comorbid depression in people with social anxiety disorder. *Journal of Affective Disorders, 228*, 75–82. http://www.psy.auth.gr/el/conference/programme10.1016/j.jad.2017.12.003.
Heeren, A., Maurage, P., Rossignol, M., Vanhaelen, M., Peschard, V., Eeckhout, C., & Philippot, P. (2012). Self-report version of the Liebowitz Social Anxiety Scale: Psychometric properties of the French version. *Canadian Journal of Behavioural Science, 44*(2), 99–107. https://doi.org/10.1037/a0026249.
Heeren, A., & McNally, R. J. (2018). Social anxiety disorder as a densely interconnected network of fear and avoidance for social situations. *Cognitive Therapy and Research, 42*, 103–113. https://doi.org/10.1007/s10608-017-9876-3.
Hembree, R. (1988). Correlates, causes, effects and treatment of test anxiety. *Review of Educational Research, 58*, 47–77. https://doi.org/10.3102/00346543058001047.
Herzer, F., Wendt, J., & Hamm, A. O. (2014). Discriminating clinical from nonclinical manifestations of test anxiety: A validation study. *Behavior Therapy, 45*, 222–231. https://doi.org/10.1016/j.beth.2013.11.001.
Hix-Small, H., Duncan, T. E., Duncan, S. C., & Okut, H. (2004). A multivariate associative finite growth mixture modeling approach examining adolescent alcohol and marijuana use. *Journal of Psychopathology and Behavioral Assessment, 26*, 255–270. https://doi.org/10.1023/B:JOBA.0000045341.56296.fa.
Jones, P. J. (2017). Networktools: Tools for identifying important nodes in networks. R Package Version 1.1.0 https://CRAN.R-project.org/package=networktools.
Kendell, R., & Jablensky, A. (2003). Distinguishing between the validity and utility of psychiatric diagnoses. *American Journal of Psychiatry, 160*, 4–12. https://doi.org/10.1176/appi.ajp.160.1.4.
Keyes, C. (2006). Mental health in adolescence: Is America's youth flourishing? *American Journal of Orthopsychiatry, 76*, 395–402. https://doi.org/10.1037/0002-9432.76.3.395.
King, N. J., Mietz, A., Tinney, L., & Ollendick, T. H. (1995). Psychopathology and cognition in adolescents experiencing severe test anxiety. *Journal of Clinical Child Psychology, 24*, 49–54. https://doi.org/10.1207/s15374424jccp2401_6.
LeBeau, R. T., Glenn, D., Liao, B., Wittchen, H., Beesdo-Baum, K., Ollendick, T., & Craske, M. G. (2010). Specific phobia: A preliminary review of DSM-IV specific phobia and preliminary recommendations for DSM-V. *Depression and Anxiety, 27*, 148–167. https://doi.org/10.1002/da.20655.
Liebowitz, M. R. (1987). Social phobia. *Modern Problems in Pharmacopsychiatry, 22*, 141–173. https://doi.org/10.1159/000414022.
Lin, Y.-G., & McKeachie, W. J. (1971). Sex similarity in personality correlates of test anxiety. *Psychological Reports, 29*, 515–520. https://doi.org/10.2466/pr0.1971.29.2.515.
Lo, Y., Mendell, N., & Rubin, D. (2001). Testing the number of components in a normal mixture. *Biometrika, 88*, 767–778. https://doi.org/10.1093/biomet/88.3.767.
Loderer, K., Murayama, K., Putwain, D. W., Pekrun, R., Tanaka, A., Vogl, E., & Loeffler-Gutmann, A. (2018). Does students' well-being at school measure up across cultures? Validating the school-related well-being scale (SWBS) with German, English, and Japanese students. International Conference on Motivation, Aarhus, Denmark (15–17 August 2018) https://conferences.au.dk/icm-2018/.
Loderer, K., Vogl, E., & Pekrun, R. (2016). Students' well-being at school revisited: Development and initial validation of a unidimensional self-report scale [Conference Session]. International Conference on Motivation, Thessaloniki, Greece (24–27 August 2016) http://www.psy.auth.gr/el/conference/programme.

Lotz, C., & Sparfeldt, J. R. (2017). Does test anxiety increase as the exam draws near? – Students' state test anxiety recorded over the course of one semester. *Personality and Individual Differences, 104*, 397–400. https://doi.org/10.1016/j.paid.2016.08.032.

Lyons, M. D., Huebner, E. S., Hills, K. J., & Shinkareva, S. V. (2012). The dual-factor model of mental health: Further study of the determinants of group differences. *Canadian Journal of School Psychology, 27*, 183–196. https://doi.org/10.1177/0829573512443669.

Magalhães, E., & Calheiros, M. M. (2017). A dual- factor model of mental health and social support: Evidence with adolescents in residential care. *Children and Youth Services Review, 79*, 442–449. https://doi.org/10.1016/j.childyouth.2017.06.041.

Mandalia, D., Sadler, K., Vizard, T., Ford, T., Goodman, A., Goodman, R., & McManus, S. (2018). *Mental health of children and young people in England, 2017: Behavioural disorders*. NHS Digital: Health and Social Care Information Centre.

Masyn, K. E. (2013). Latent class analysis and finite mixture modeling. In T. D. Little (Ed.), *The Oxford handbook of quantitative methods: Vol. 2. Statistical analysis* (pp. 551–611). Oxford University Press.

Matthews, G., & Wells, A. (2004). Rumination, depression and metacognition: The S-REF model. In C. Papageorgiou, & A. Wells (Eds.), *Depressive rumination: Nature, theory and treatment* (pp. 125–151). Wiley.

Möller, E. L., Majdandžić, M., Craske, M. G., & Bögels, S. M. (2014). Dimensional assessment of anxiety disorders in parents and children for DSM-5. *International Journal of Methods in Psychiatric Research, 23*, 331–344. https://doi.org/10.1002/mpr.1450.

Moore, S. A., Dowdy, E., Nylund-Gibson, K., & Furlong, M. J. (2019). A latent transition analysis of the longitudinal stability of dual-factor mental health in adolescence. *Journal of School Psychology, 73*, 56–73. https://doi.org/10.1016/j.jsp.2019.03.003.

Mrazek, P. J., & Haggerty, R. J. (1994). *Reducing risks for mental disorders: Frontiers for preventive intervention research*. The National Academies Press.

Muthén, L. K., & Muthén, B. O. (2017). *Mplus user's guide* (8th ed.). Muthén & Muthén.

Nardi, A. E., & Balon, R. (2020). The 40th anniversary of panic disorder: From *DSM-III* to the future. *Journal of Clinical Psychopharmacology, 40*, 105–108. https://doi.org/10.1097/JCP.0000000000001185.

Newman, M. E. J. (2006). Modularity and community structure in networks. *Proceedings of the National Academy of Sciences of the United States of America, 103*, 8577–8582. https://doi.org/10.1073/pnas.0601602103.

Norton, P. J. (2006). Toward a clinically-oriented model of anxiety disorders. *Cognitive Behaviour Therapy, 35*, 88–105. https://doi.org/10.1080/16506070500441561.

Norton, P. J., & Paulus, D. J. (2017). Transdiagnostic models of anxiety disorder: Theoretical and empirical underpinnings. *Clinical Psychology Review, 56*, 122–137. https://doi.org/10.1016/j.cpr.2017.03.004.

OECD. (2017). *PISA 2015 results (volume III). Students' well-being*. OECD Publishing. https://doi.org/10.1787/9789264273856-en. Retrieved April 24, 2017 from.

Opsahl, T., Agneessens, F., & Skvoretz, J. (2010). Node centrality in weighted networks: Generalizing degree and shortest paths. *Social Networks, 32*, 245–251. https://doi.org/10.1016/j.socnet.2010.03.006.

Papageorgiou, C., & Wells, A. (2009). A prospective test of the clinical metacognitive model of rumination and depression. *International Journal of Cognitive Therapy, 2*, 123–131. https://doi.org/10.1521/ijct.2009.2.2.123.

Paulus, D. J., Talkovsky, A. M., Heggeness, L. F., & Norton, P. J. (2015). Beyond negative affectivity: A hierarchical model of global and transdiagnostic vulnerabilities for emotional disorders. *Cognitive Behaviour Therapy, 44*, 389–405. https://doi.org/10.1080/16506073.2015.1017529.

Petersen, K, J, Humphrey, N, & Qualter, P (2020). Latent class analysis of mental health in middle childhood: Evidence for the dual-factor model. *School Mental Health, 12*, 786–800. https://doi.org/10.1007/s12310-020-09384-9.

Petersen, K. J., Qualter, P., & Humphrey, N. (2019). The application of latent class analysis for investigating population child mental health: A systematic review. *Frontiers in Psychology, 10*, 1214. https://doi.org/10.3389/fpsyg.2019.01214.

Piqueras, J. A., Martín-Vivar, M., Sandin, B., San Luis, C., & Pineada, D. (2017). The revised child anxiety and depression scale: A systematic review and reliability generalization meta-analysis. *Journal of Affective Disorders, 218*, 153–169. https://doi.org/10.1016/j.jad.2017.04.022.

Putwain, David, W (2007). Test Anxiety in UK schoolchildren: prevalence and demographic patterns. *British Journal of Educational Psychology, 77*(3), 579–593. https://doi.org/10.1348/000709906X161704.

Putwain, D. W. (2020). *Examination pressures on children and young people: Are they taken seriously enough?* The British Academy.

Putwain, D. W., Chamberlain, S., Daly, T., & Saddredini, S. (2015). Academically buoyant students are less anxious about and perform better in high-stakes examinations. *British Journal of Educational Psychology, 85*, 247–263. https://doi.org/10.1111/bjep.12068.

Putwain, D. W., & Daly, A. L. (2014). Test anxiety prevalence and gender differences in a sample of English secondary school students. *Educational Studies, 40*, 554–570. https://doi.org/10.1080/03055698.2014.953914.

Putwain, D. W., Loderer, K., Gallard, D., & Beaumont, J. (2020). School-related wellbeing promotes adaptability, achievement and behavioural conduct: A longitudinal examination. *British Journal of Educational Psychology, 90*, 92–108. https://doi.org/10.1111/bjep.122669.

Putwain, D. W., & von der Embse, N. P. (2021). Cognitive-behavioural intervention for test anxiety in adolescent students: Do benefits extend to school-related wellbeing and clinical anxiety. *Anxiety, Stress, and Coping, 34*, 22–36. https://doi.org/10.1080/10615806.2020.1800656.

Putwain, D. W., von der Embse, N. P., Rainbird, E. C., & West, G. (2021). The development and validation of a new multidimensional test anxiety scale (MTAS). *European Journal of Psychological Assessment, 37*(3), 236–246. https://doi.org/10.1027/1015-5759/a000604.

Putwain, D. W., Wood, P., & Pekrun, R. (2020). Achievement emotions and academic achievement: Reciprocal relations and the moderating influence of academic buoyancy. *Journal of Educational Psychology*. https://doi.org/10.1037/edu0000637. Advance online publication.

Reiss, F. (2013). Socioeconomic inequalities and mental health problems in children and adolescents: A systematic review. *Social Science & Medicine, 90*, 24–31. https://doi.org/10.1016/j.socscimed.2013.04.026.

Renshaw, T. L., & Cohen, A. S. (2014). Life satisfaction as a distinguishing indicator of college student functioning: Further validation of the two-continua model of mental health. *Social Indicators Research, 117*, 319–334. https://doi.org/10.1007/s11205–013-0342.

Renshaw, T. L., Long, A. C. J., & Cook, C. R. (2015). Assessing adolescents' positive psychological functioning at school: Development and validation of the student subjective wellbeing questionnaire. *School Psychology Quarterly, 30*, 534–552. https://doi.org/10.1037/spq0000088.

Reynolds, C. R., & Richmond, B. O. (1978). What I think and feel: A revised measure of children's manifest anxiety. *Journal of Abnormal Child Psychology, 6*(27), 271–280. https://doi.org/10.1007/BF00919131.

Robinaugh, D. J., Millner, A. J., & McNally, R. J. (2016). Identifying highly influential nodes in the complicated grief network. *Journal of Abnormal Psychology, 125*, 747–757. https://doi.org/10.1037/abn0000181.

Roos, A.-L., Goetz, T., Voracek, M., Krannish, M., Bieg, M., Jarrell, A., & Pekrun, R. (2021). Test anxiety and physiological arousal: A systematic review and meta-analysis. *Educational Psychology Review, 33*, 579–618. https://doi.org/10.1007/s10648-020-09543-z.

Rose, T., Lindsey, M. A., Xiao, Y., Finigan-Carr, N. M., & Joe, S. (2017). Mental health and educational experiences among Black youth: A latent class analysis. *Journal of Youth and Adolescence, 46*, 2321–2340. https://doi.org/10.1007/s10964-017-0723-3.

Rost, J. (2006). Latent-class-analyse [latent-class-analysis]. In F. Petermann, & M. Eid (Eds.), *Handbuch der psychologischen diagnostik [Handbook of psychological diagnostics]* (pp. 275–287). Hogrefe.

Sarason, S. B., Davidson, K., Lighthall, F., & Waite, R. (1958). A test anxiety scale for children. *Child Development, 29*(1), 105–113. https://doi.org/10.2307/1126274.

Sclove, L. (1987). Application of model-selection criteria to some problems in multivariate analysis. *Psychometrika, 52*, 333–343. https://doi.org/10.1007/BF02294360.

Segool, N., Carlson, J., Goforth, A., von der Embse, N., & Barterian, J. (2013). Heightened test anxiety among young children: Elementary school students' anxious responses to high-stakes testing. *Psychology in the Schools, 50*, 489–499. https://doi.org/10.1002/pits.21689.

Smith, N. D. W., Suldo, S. M., Hearon, B. V., & Ferron, J. M. (2020). An application of the dual factor model of mental health in elementary school students: Examining academic engagement and social outcomes. *Journal of Positive School Psychology, 4*, 49–68. https://www.journalppw.com/index.php/JPPW/article/view/186.

Spielberger, C. D., Gonzalez, H. P., Taylor, C. J., Algaze, B., & Anton, W. D. (1978). Examination stress and test anxiety. In C. D. Spielberger, & I. G. Sarason (Eds.), *Vol. 5. Stress and anxiety* (pp. 167–191). Hemisphere/Wiley.

Spielberger, C. D., Gorsuch, R. L., Vagg, P. R., & Jacobs, G. A. (1983). *Manual for the state-trait anxiety inventory (form Y) ("Self-Evaluation Questionnaire")*. Consulting Psychologists Press.

Spielberger, C. D., & Vagg, R. P. (1995). Test anxiety: A transactional process model. In C. D. Spielberger, & P. R. Vagg (Eds.), *Test anxiety: Theory, assessment and treatment* (pp. 3–14). Taylor & Francis.

Steinmayr, R., Crede, J., McElvany, N., & Wirthwein, L. (2016). Subjective well-being, test anxiety, academic achievement: Testing for reciprocal effects. *Frontiers in Psychology, 6*. https://doi.org/10.3389/fpsyg.2015.01994. Article no. 1994.

Stockings, E. A., Degenhardt, L., Dobbins, T., Lee, Y. Y., Erskine, H. E., Whiteford, H. A., & Patton, G. (2016). Preventing depression and anxiety in young people: A review of the joint efficacy of universal, selective and indicated prevention. *Psychological Medicine, 46*, 11–26. https://doi.org/10.1017/S0033291715001725.

Suldo, S. M., & Shaffer, E. J. (2008). Looking beyond psychopathology: The dual-factor model of mental health in youth. *School Psychology Review, 37*, 52–68. https://doi.org/10.1080/02796015.2008.12087908.

Suldo, S. M., Thalji-Raitano, A., Kiefer, S. M., & Ferron, J. M. (2016). Conceptualizing high school students' mental health through a dual-factor model. *School Psychology Review, 45*, 434–457. https://doi.org/10.17105/SPR45-4.434-457.

Sweet, T. M. (2016). Social network methods for the educational and psychological sciences. *Educational Psychologist, 51*, 381–394. https://doi.org/10.1080/00461520.2016.1208093.

Thayer, A. J., Weeks, M. R., & Cook, C. R. (2021). Dual factor mental health model: Validation through mixture modeling and cut scores. *Psychology in the Schools, 58*(2), 286–306. https://doi.org/10.1002/pits.22447.

Uher, R., & Rutter, M. (2012). Basing psychiatric classification on scientific foundation: Problems and prospects. *International Review of Psychiatry, 24*, 591–605. https://doi.org/10.3109/09540261.2012.721346.

Vizard, T., Pearce, N., Davis, J., Sadler, K., Ford, T., Goodman, A., Goodman, R., & McManus, S. (2018). *Mental health of children and young people in England, 2017: Emotional disorders*. NHS Digital: Health and Social Care Information Centre.

Warren, M. K., Ollendick, T. H., & King, N. J. (1996). Test anxiety in girls and boys: A clinical-developmental analysis. *Behaviour Change, 13*, 157–170. https://doi.org/10.1017/S0813483900004939.

Weems, C. F., Scott, B. G., Taylor, L. K., Cannon, M. F., Romano, D. M., Perry, A. M., & Triplett, V. (2010). Test anxiety prevention and intervention programs in schools: Program development and rationale. *School Mental Health, 2*, 62–71. https://doi.org/10.1007/s12310-010-9032-7.

Wells, A., & Mathews, G. (1996). Modelling cognition in emotional disorder: The S-REF model. *Behaviour Research and Therapy, 32*, 867–870. https://doi.org/10.1016/S0005-7967(96)00050-2.

World Health Organization. (2018). *International classification of diseases for mortality and morbidity statistics* (11th ed.). World Health Organization. Retrieved December 11, 2020, from https://icd.who.int/browse11/l-m/en.

Xiong, J., Qin, Y., Gao, M., & Hai, M. (2017). Longitudinal study of a dual-factor model of mental health in Chinese youth. *School Psychology International, 38*, 287–303. https://doi.org/10.1177/0143034317689970.

Zeidner, M. (2007). Test anxiety in educational contexts: Concepts, findings and future directions. In P. A. Schutz, & R. Pekrun (Eds.), *Emotion in education* (pp. 165–184). Elsevier.

Zeidner, M. (2014). Anxiety in education. In R. Pekrun, & L. Linnenbrink-Garcia (Eds.), *International handbook of emotions in education* (pp. 265–288). Routledge.

Zeidner, M., & Matthews, G. (2005). Evaluation anxiety. In A. J. Elliot, & C. S. Dweck (Eds.), *Handbook of competence and motivation* (pp. 141–163). Guilford Press.