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Mapping Adolescent Wellbeing: Developmental Network Shifts from Early to Middle Adolescence in 24 Countries

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Abstract

This study applied psychometric network analysis to examine the structure of adolescent wellbeing across 49 indicators of subjective and psychological wellbeing in a large international sample (N = 6,445; ages 11-18) from 38 schools across 24 countries. We estimated networks separately for early (11-14) and middle (15-18) adolescents to assess developmental change. The overall network was moderately dense and highly stable. Overall life satisfaction, satisfaction with student life, and optimism about the future emerged as central nodes. While the global network structure was similar across age groups, older adolescents showed increased centrality for negative affect ("bad"), relaxed mood, and future optimism, and decreased centrality for current life evaluation. These findings underscore the integrated and developmentally shifting nature of adolescent wellbeing, and offer practical insights for monitoring, intervention, and policy. Results highlight the value of developmentally sensitive strategies that support both present experience and future-oriented resilience across diverse youth populations.

Keywords: Adolescent wellbeing; Psychometric network analysis; Developmental change; Cross-culture; future-orientation

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Introduction

There is growing interest in promoting the wellbeing of children and adolescents—both within educational settings and more broadly (Marquez et al., 2024; OECD, 2021; Taylor et al., 2022). This increased attention is driven by several factors. First, a number of countries have reported declining trends in adolescent wellbeing over the past 15 to 20 years, with younger cohorts consistently reporting lower levels of wellbeing over time (Marquez et al., 2024). Second, adolescence represents a critical developmental window during which wellbeing tends to decline, with decreases often beginning around age 11 (Casas & Gonzalez-Carrasco, 2019). Mental health difficulties also frequently emerge during this period, with the average onset age around 14.5 years (Solmi et al., 2022). Third, higher adolescent wellbeing has been robustly linked to a wide range of positive life outcomes, including academic achievement, physical and mental health, social relationships, and labour market success (De Neve & Oswald, 2012; Geijsen & Bartels, 2024; Goodman et al., 2015). Importantly, researchers have argued there is no trade-off between academic and wellbeing outcomes, strengthening the potential for prioritising student wellbeing in schools (Ambrosetti et al., 2022; Bortes et al., 2021; Cárdenas et al., 2022; Clarke, 2020; Duncan et al., 2021; Putwain et al., 2020; Zhou & McLellan, 2021).

Any effort to promote wellbeing must begin with a clear conceptualisation of what is meant by the term. Wellbeing has traditionally been understood through two main theoretical perspectives. Subjective wellbeing (SWB), or hedonic wellbeing, emphasizes feeling good and includes both affective (positive and negative emotions) and cognitive (life satisfaction) components (Diener et al., 2002). In contrast, psychological wellbeing (PWB), or eudaimonic wellbeing, focuses on functioning well and is typically defined by constructs such as

autonomy, purpose in life, environmental mastery, optimism, personal growth, self-acceptance, and positive relationships (Ryff et al., 2021). A third approach, common in health sciences, conceptualizes mental wellbeing in terms of the absence of mental health difficulties, sometimes using the terms wellbeing and mental health interchangeably (Campbell et al., 2021; Fuhrmann et al., 2022; Orben & Przybylski, 2019; Stewart-Brown et al., 2009;). To support clarity throughout this paper, we adopt a definition of wellbeing that integrates both subjective (hedonic) and psychological (eudaimonic) dimensions.

Efforts to promote wellbeing also require clarity in how wellbeing is measured. Traditional measurement approaches have relied on latent variable models, such as factor analysis and structural equation modelling (Diener et al., 1999; Ryff & Keyes, 1995), which posit that wellbeing indicators reflect an underlying construct. From this perspective, SWB is a latent factor that accounts for variance in life satisfaction and affect, while PWB is seen as a latent dimension explaining constructs such as self-acceptance, autonomy, and purpose. However, recent work has proposed network analysis as a promising alternative (Borsboom, 2017; Bringmann et al., 2019; Epskamp et al., 2018). The network approach conceptualizes psychological phenomena as systems of mutually interacting components, where constructs like PWB are understood to emerge from dynamic interactions among their indicators. For example, self-acceptance may reinforce positive relationships, which in turn could foster life purpose - collectively giving rise to psychological wellbeing as an emergent property.

Despite its growing popularity, the application of network analysis in child and adolescent populations remains limited, especially in international samples that span both early and middle adolescence. The following sections outline the importance of this approach, review the current literature using network analysis to study adolescent wellbeing, and describe how the present study addresses key research gaps.

Why network analysis is important

Foundational wellbeing frameworks were originally developed in adult populations (e.g., Diener et al., 1985; Ryff, 1989). Despite substantial progress in adapting and validating these constructs for children and adolescents in the past two decades (Casas, 2011; Casas & Gonzalez-Carrasco, 2021, 2022; Savahl et al., 2021, 2023), relatively few studies have applied network analysis. This method offers unique opportunities to understand and promote wellbeing in adolescence.

In particular, network analysis offers several important advantages for researchers and practitioners seeking to understand and measure wellbeing in more nuanced and context-sensitive ways. This approach enables researchers to explore the structure of wellbeing by examining how specific elements such as life satisfaction, positive affect, or purpose are directly connected, offering a more nuanced, systems-level understanding of wellbeing. Network analysis also allows for the identification of redundant items, revealing overlapping or low-uniqueness indicators that may inflate or obscure measurement precision (Christensen et al., 2020). This has important implications for refining wellbeing assessments to be both more efficient and psychometrically robust.

Beyond measurement, the network approach has powerful applications for practice. A key advantage is its ability to identify central nodes - wellbeing components that are highly connected and therefore may play a disproportionately influential role within the network (Bringmann et al., 2019; Epskamp et al., 2018). Targeting such components in interventions could produce cascading effects across the broader system. Unlike latent models, which imply acting on an unobservable construct, network models suggest that intervening on specific indicators, such as boosting self-acceptance or fostering life purpose, may lead to meaningful change in other wellbeing domains. This is particularly relevant in school-based settings as understanding the specific interrelations among indicators can help move the field beyond generic interventions and toward more targeted, evidence-based strategies.

Finally, network analysis provides tools to examine population and developmental differences, allowing researchers to compare wellbeing structures across age groups, genders, or cultural contexts (Dalege et al., 2017; Hevey, 2018). This is especially valuable in adolescence which is a period marked by rapid developmental change and emerging wellbeing challenges. Network models are also well-suited to capture dynamic processes, particularly when applied longitudinally, by showing how changes in one domain (e.g., optimism) may propagate through others (Robinaugh et al., 2020). Additionally, their data-driven visualisation offers an intuitive map of these complex relationships, facilitating hypothesis generation and communication with practitioners. Because these models are not bound to predefined latent structures, they provide an open framework for uncovering alternative pathways and mechanisms (Marsman et al., 2017), making them especially valuable for theory development, intervention design, and policy translation.

Network analysis and adolescent wellbeing

The use of network analysis in the adolescent wellbeing literature has grown in recent years. Most studies have focused on risk and protective factors for wellbeing (Wang et al., 2024) and related constructs such as internalizing difficulties (Black et al., 2023), as well as in the interconnections between wellbeing and other psychological constructs such as character strengths, and mental health symptoms of depression and anxiety (Blasco-Belled, 2023; Campbell & Osborn, 2021; Putwain et al., 2021; Tejada-Gallardo et al., 2022; Wasil et al., 2021).

Only a small number of studies have used network analysis to examine adolescent wellbeing as it is traditionally conceptualised, that is, in terms of SWB and/or PWB wellbeing. For example, in a study of 4,282 Chinese high school students (mean age = 16.32), Wang et al. (2023) applied network analysis to items from one scale - the General Well-Being Schedule scale. While this instrument primarily assesses SWB (mostly negative

affect), it also includes elements of PWB (e.g., vitality, purpose). Their findings showed that the item “Have you been anxious, worried, or upset?” was the most central node, suggesting it may be a strategic target for interventions.

Another study by Vieta-Piferrer et al. (2024) involved 888 Spanish adolescents (ages 12–16), and examined the longitudinal associations between cyberbullying victimisation and SWB using psychometric network analysis. Participants completed measures of overall and domain-specific life satisfaction as well as positive and negative affect at two time points. Despite including a contextual risk factor (cyberbullying), the study provided valuable insights into the internal structure of SWB. Overall life satisfaction emerged as a central node across life domains, and the affect item “happy” showed the highest centrality at both time points. Using the same sample, Blasco-Belled et al. (2024) explored the interactions between SWB and PWB over time. Their findings showed that positive affect, particularly feeling happy and satisfied, acted as key connectors between the two domains, while negative affect (e.g., worry) was inversely linked to PWB longitudinally. These results point to specific components that may drive change across wellbeing domains. However, neither study examined differences across age groups or used cross-cultural sample, limiting the ability to draw conclusions about developmental variation and cross-cultural generalisability.

To our knowledge, only one study to date has used network analysis to examine adolescent wellbeing across multiple national contexts. In a cross-sectional study of adolescents in India (ages 12-18, N = 310), Israel (12-18, N = 306), and the United Kingdom (12-25, N = 1,666), Shukla et al. (2022) employed the Short Warwick-Edinburgh Mental Well-Being Scale (SWEMWBS) to assess wellbeing during the COVID-19 pandemic. This scale primarily reflects PWB, with emphasis on functioning, agency, and connectedness. Network analysis revealed cultural variation in central wellbeing components: “feeling useful” was most central in India, while “dealing with problems well” was central in both

Israel and the UK. However, the study did not examine differences by age group and was limited to only one measure capturing several PWB aspects. These findings align with adult research suggesting that core wellbeing components vary across sociocultural contexts (Höltge et al., 2022) and highlight the need for more comparative studies involving adolescents.

The current study

Despite a growing body of literature applying network analysis to adolescent wellbeing, two main gaps remain. First, few studies have examined the interconnections between SWB and PWB indicators. And second, evidence is lacking on whether the structure of wellbeing networks differs across age (e.g., early vs. middle adolescence). This question is particularly salient, given that adolescence is marked by rapid and multidimensional changes in cognitive, emotional, and social functioning.

To address these gaps, the present study applies network analysis to examine adolescent wellbeing in a large, cross-national sample of students aged 11 to 18 with consideration of a comprehensive set of measures of SWB and PWB. Specifically, we address the following research questions:

1. How do different SWB and PWB components interact in adolescence?
2. How does this network structure vary across the crucial developmental periods of early and middle adolescence (ages 11-14 and 15-18, respectively)?

By exploring these questions, this study contributes to the understanding of how wellbeing is structured during adolescence, and identifies potential targets for policy and intervention that are sensitive to developmental and cultural variation.

Method

Sample

Data collection was conducted in May 2024 via an online questionnaire hosted on Qualtrics. Schools were invited to participate based on their affiliation with the International Baccalaureate (IB) school system, as many had previously expressed interest in the IB's another school project. This provided an opportunity to reach out to IB schools across diverse global regions. All hypotheses, sampling plans, and analytic strategies were pre-registered prior to data analysis at the Open Science Framework (Zhou, 2024). The study received ethical approval from the University of Oxford's Central University Research Ethics Committee (CUREC; Ethics Approval Reference: R90787/RE001). A passive parental consent (opt-out) procedure was used, and adolescents provided active assent at the beginning of the questionnaire, with the option to withdraw at any time. Students completed the questionnaire during school lesson time. The final sample consisted of 6,445 students aged between 11 and 18 years, drawn from 38 schools across 24 countries (51.9% aged 11-14 and 48.1% aged 15-18).

The original English questionnaire was translated into French and Spanish with the support of two native-speaking collaborators. Translation quality was ensured through group discussions involving a subject expert (a postdoctoral-level native speaker), a professional translator (a native speaker), and a researcher for each language. Together, they compared and refined the final versions. Where official translations of the questionnaire were available, these were also reviewed and compared to the team's versions to enhance consistency and validity. Back-translation was then conducted using ChatGPT-4 to assess semantic accuracy and consistency across language versions. The final translations were confirmed once the back-translations aligned closely with the original English questionnaire

Measures

Participants completed a battery of self-report measures capturing multiple dimensions of SWB and PWB.

Overall life evaluation was assessed using three single-item measures rated on scales from 0 to 10: overall life satisfaction, current life evaluation, and future life evaluation. The latter two were adapted from the Cantril Ladder (Cantril, 1965), a widely used tool in global wellbeing research that asks respondents to rate their life on a "ladder" from the worst to the best possible life.

Domain-specific life satisfaction was measured with 14 items, also using 0 to 10 scales, covering satisfaction across a range of life domains including relationships (e.g., family, friends, teachers), environment (e.g., home area, safety), self-perception (e.g., appearance, health, future expectations), and daily life (e.g., learning at school, time use). These items were adapted from previous large-scale international studies of child and adolescent wellbeing (e.g., Casas et al., 2012).

The Satisfaction with Life Scale (SWLS) (Diener et al., 1985) consists of 5 items rated on 7-point Likert scales ranging from Strongly disagree to Strongly agree. It captures global cognitive evaluations of life, such as "I'm satisfied with my life."

Affective wellbeing was assessed using 12 items from the Scale of Positive and Negative Experience (SPANE) (Diener et al., 2010). This includes 6 items for positive affect (e.g., joyful, contented) and 6 items for negative affect (e.g., sad, afraid), each rated on 5-point scales from 'Very rarely or never' to 'Very often or always', referring to the past four weeks.

Psychological wellbeing was measured using two validated instruments. The Flourishing Scale (Diener et al., 2010) includes 8 items assessing aspects such as life purpose, competence, virtue, and social contribution, using 7-point Likert scales from Strongly disagree to Strongly agree. The Short Warwick-Edinburgh Mental Well-Being Scale (SWEMWBS; Stewart-Brown et al., 2009; Tennant et al., 2007) includes 7 items measuring positive psychological functioning (e.g., optimism, problem-solving, feeling connected),

rated on 5-point scales from ‘None of the time’ to ‘All of the time’, referring to the past two weeks.

We followed Sawyer et al.’s (2018) broader definition of adolescence (ages 10–24) and further categorized our sample into early and middle adolescence to facilitate comparability with recent research and to reflect extended developmental transitions. However, we acknowledge ongoing debate about the boundaries of adolescence and recognize that such categorizations may not fully capture developmental or contextual variation.

Network Analysis Procedures

This study followed established reporting standards for psychological network analysis and relevant methodological guidelines (Burger et al., 2022; Epskamp et al., 2018). Network analysis was conducted in R (version 4.4.2) in March, 2025.

The following process has been meticulously replicated across the entire sample as well as in the various age groups. These subgroups include a. those within the age range of 11 to 14 (referred to as early adolescence), and b. those within the age range of 15 to 18 (referred to as middle adolescence).

Preliminary Analysis: Assessing Topological Overlap and Multicollinearity

To ensure the validity of the network structure, we first assessed potential topological overlap, which can result from excessive conceptual similarity between items and inflate node strength estimates. We conducted Unique Variable Analysis (UVA) using the EGAnet package (version 2.1.0) in R (version 4.4.2), applying a stringent cut-off of 0.3 to retain only variables with distinct contributions (Hair et al., 2019). In addition, we evaluated multicollinearity by calculating Variance Inflation Factors (VIFs) for each variable, ensuring

that all values remained below the commonly accepted threshold of 5, thereby minimizing redundancy and enhancing the interpretability of the network (James et al., 2013).

Network Estimation

To ensure that the network analysis captured only unique associations between variables while accounting for potential confounds, we controlled for both categorical (school, language used, countries and gender) and numerical variables (age) prior to computing partial correlations. This approach mitigates potential biases due to uneven group sizes across countries or language groups. The network structure was estimated using the qgraph (version 1.9.8) and bootnet (version 1.6) packages (Epskamp et al., 2018). Pairwise associations between items, conditioned on all other items, were computed using the cor_auto function in qgraph. To derive a clear psychometric network model, we applied the graphical Least Absolute Shrinkage and Selection Operator (gLASSO) with the Extended Bayesian Information Criterion (EBIC) set at $\gamma = 0.5$, and a minimal lambda ratio of 0.1 (Epskamp et al., 2018). This approach selects the most robust edges while minimizing false positives. Network visualization were conducted using spring algorithm of qgraph R package, and the node colour were added through the Inkscape app for a clearer visual presentation . We also report network density, edge weights and standardized centrality indices, mainly node strength.

Network Accuracy and Stability

The network accuracy and stability were assessed using the bootnet R package (version 1.6). To assess the accuracy of edge weights, we performed nonparametric bootstrapping with 10,000 resamples, which involves repeatedly estimating the network on resampled datasets and computing the variability of edge weights (Efron, 1979). We also plot

the bootstrapped confidence intervals (CIs) for estimated edge parameters. A wide bootstrapped CIs indicating a less accuracy to interpret the strength of an edge (Epskamp et al., 2018).To evaluate the stability of node strength and edge weights, we conducted a case-dropping bootstrap procedure with 10,000 resamples, using a network based on a Spearman correlation matrix. We report correlation stability (CS) coefficients, which indicate maximum drop proportions to retain correlation of 0.7 in at least 95% of the samples between the full sample's estimates and those from the bootstrapped samples. In this case, stability indices should exceed 0.25, and preferably 0.5 (Epskamp et al., 2018).

Finally, to compare the differences in edge weights or centrality, bootstrapped difference tests (with 95% CIs) were carried out using non-parametric bootstrap results (Epskamp et al., 2018). We also plotted centrality (strength) to assess whether the strengths were significantly different from each other.

Network Comparison test

Network Comparison Test (NCT) was conducted to examine differences in the psychological networks of early (ages 11-14) and late (ages 15-18) adolescence. Using the NCT() function from the EGAnet package in R, we tested for differences in overall network structure, global connectivity strength, and specific edge relationships between psychological variables. The analysis included 5,000 permutations to ensure stable statistical inference. We tested for significant differences in network structure (M-statistic, p-value) and global strength (S-statistic, p-value). Additionally, we identified specific psychological connections that differed significantly across age groups and examined shifts in centrality measures (i.e., strength, betweenness, and closeness) to determine if any psychological factors became more or less influential in late adolescence. To control for multiple comparisons, we applied False

Discovery Rate (FDR) correction. Visualization of the results was conducted to illustrate significant edge and centrality differences between the two networks.

Results

Preliminary analysis

The final sample consisted of 6,445 students aged between 11 and 18 years, drawn from 38 schools across 24 countries. Prior to analysis, the Interquartile Range (IQR) method was used to identify potential outliers. While all participants fell within the lower bound, a small number exceeded the upper bound. These cases were retained, as further inspection indicated no data quality issues, and their elevated values were likely attributable to contextual factors (e.g., temporary internet delays during submission). Assessment of multicollinearity showed that all Variance Inflation Factors (VIFs) were well below the conventional threshold of 5 (range: 1.2-3.0, see Appendix 1), indicating low redundancy and supporting the robustness of the network estimation. The dataset contained no missing data. The sample was balanced across age groups, with 51.9% aged 11-14 (early adolescence) and 48.1% aged 15-18 (middle adolescence), although this proportion varied substantially across countries, as shown in Appendix 2, which presents more details about the sample. In terms of gender, 45.2% identified as boys, 51.7% as girls, and 3.1% as another gender identity. Survey language distribution was as follows: 82.2% completed the survey in English, 11.7% in French, and 6.2% in Spanish.

Network structure and centrality

The estimated whole-sample network exhibited a mean edge weight of 0.0173 (SD = 0.0456) and a density of 0.4804, reflecting a moderately interconnected structure.

Centrality was evaluated using strength, closeness, and betweenness, with strength forming the basis for our rankings. ‘Overall Satisfaction’, ‘LS3’ (“satisfied with my life”),

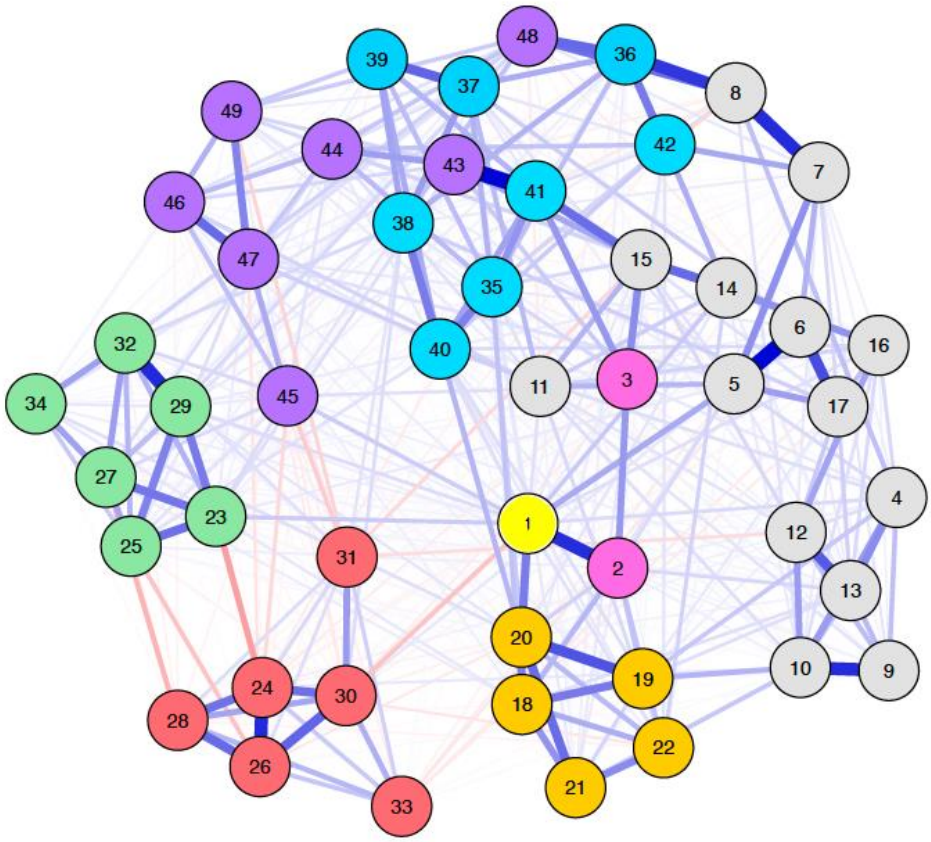
and 'Your Life as a Student' emerged as the most central nodes across all three metrics, which followed by 'Optimism about the Future'.

In particular, in terms of strength centrality, Overall Satisfaction had the highest value (2.58), followed by LS3 ("I'm satisfied with my life") at 1.95 and Your Life as a Student at 1.65. The measures with the lowest strength centrality were Afraid (-1.50), Contented (-2.26), and Angry (-2.27). For betweenness centrality, Overall Satisfaction again led with a value of 4.99, with LS3 ("I'm satisfied with my life") at 2.01 and Sad at 1.82. The lowest betweenness values were found for LS5 ("change almost nothing"), The Area Where You Live, and Angry. Closeness centrality was highest for Overall Satisfaction (2.77), followed by LS3 (1.86) and Cantril Ladder (Now) (1.80). WEMWBS-4 ("deal with problems well"), The Area Where You Live, and Unpleasant had the lowest closeness scores.

The strongest positive edges in the network were Your Life as a Student – Things You Have Learned at School (0.36), WEMWBS-1 ("optimistic about the future") – FS7 ("optimistic about my future") (0.36), Joyful – Happy (0.30), Bad –Negative (0.30), and Other Peers in Your Class – Your Friends (0.30). The strongest negative associations were observed between Negative – Positive (-0.117) and Unpleasant – Pleasant (-0.091).

Metrics of network structure and centrality measures obtained for the early and middle group can be found in Appendix 3.

Figure 1. The estimated whole-sample network.

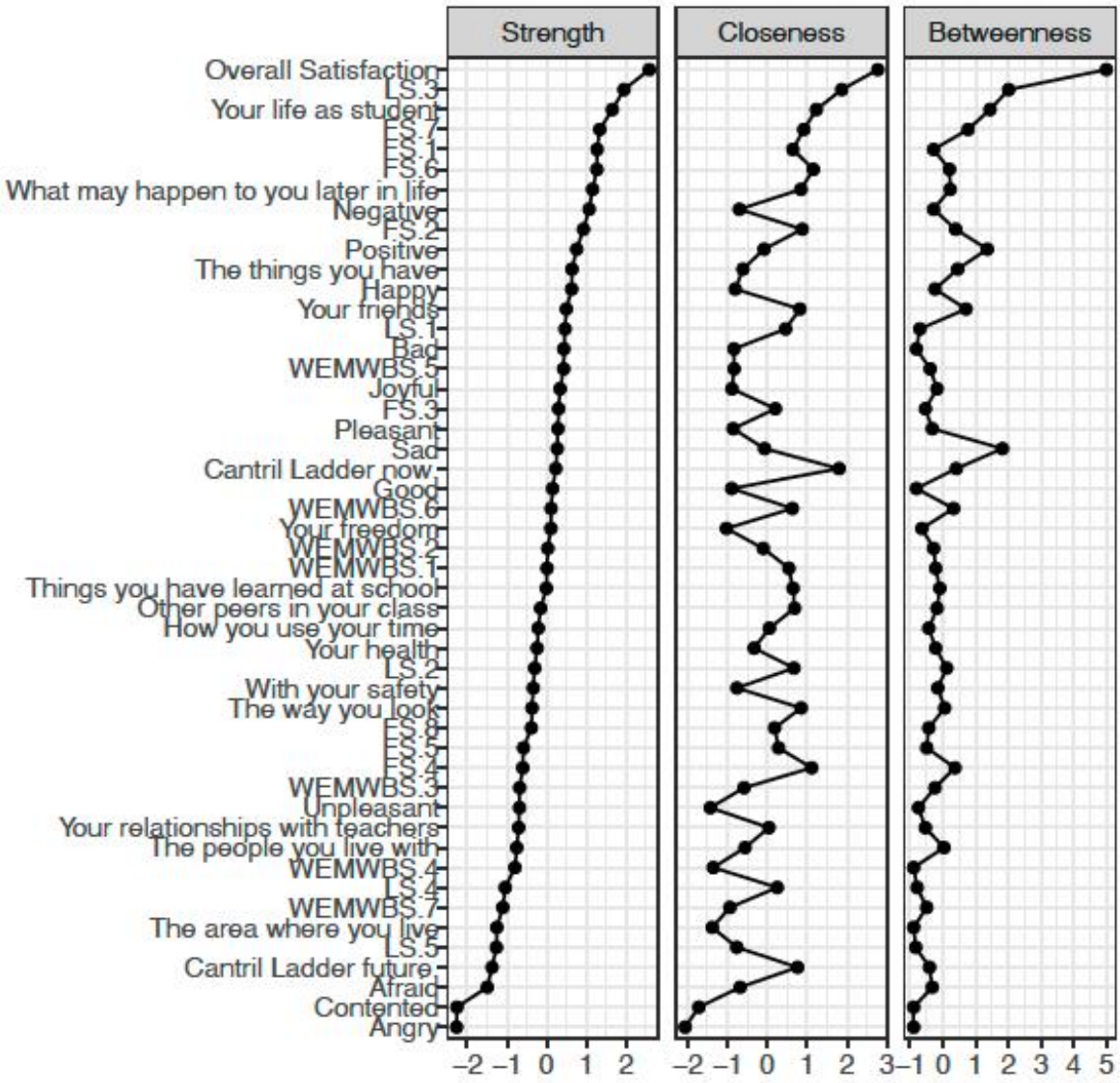


Note.

1.Overall satisfaction
2.Cantril Ladder (now)
3.Cantril Ladder (future)
4.The people you live with
5.Your life as student
6.Things you have learned at school
7.Other peers in your class
8.Your friends
9.The area where you live
10.The things you have
11.How you use your time
12.With your safety
13.Your freedom
14.The way you look
15.What may happen to you later in life
16.Your health
17.Your relationships with teachers
18.LS1-close to my ideal
19.LS2-conditions are excellent
20.LS3-I'm satisfied with my life
21.LS4-gotten important things
22.LS5-change almost nothing
23.Positive
24.Negative
25.Good
26.Bad
27.Pleasant
28.Unpleasant
29.Happy
30.Sad
31.Afraid
32.Joyful
33.Angry
34.Contented
35.FS1-purposeful and meaningful life.
36.FS2-social relationship
37.FS3-daily activities
38.FS4-contribute to the wellbeing of others
39.FS5-capable in important activity

40.FS6-good person and live a good life
41.FS7-optimistic about my future
42.FS8- People respect me
43.WEMWBS1-optimistic about the future
44.WEMWBS2-useful
45.WEMWBS3-relaxed
46.WEMWBS4-deal with problems well
47.WEMWBS5-think clearly
48.WEMWBS6-feel close to other people
49.WEMWBS7-make up my own mind

Figure 2. The centrality of estimated whole-sample network.



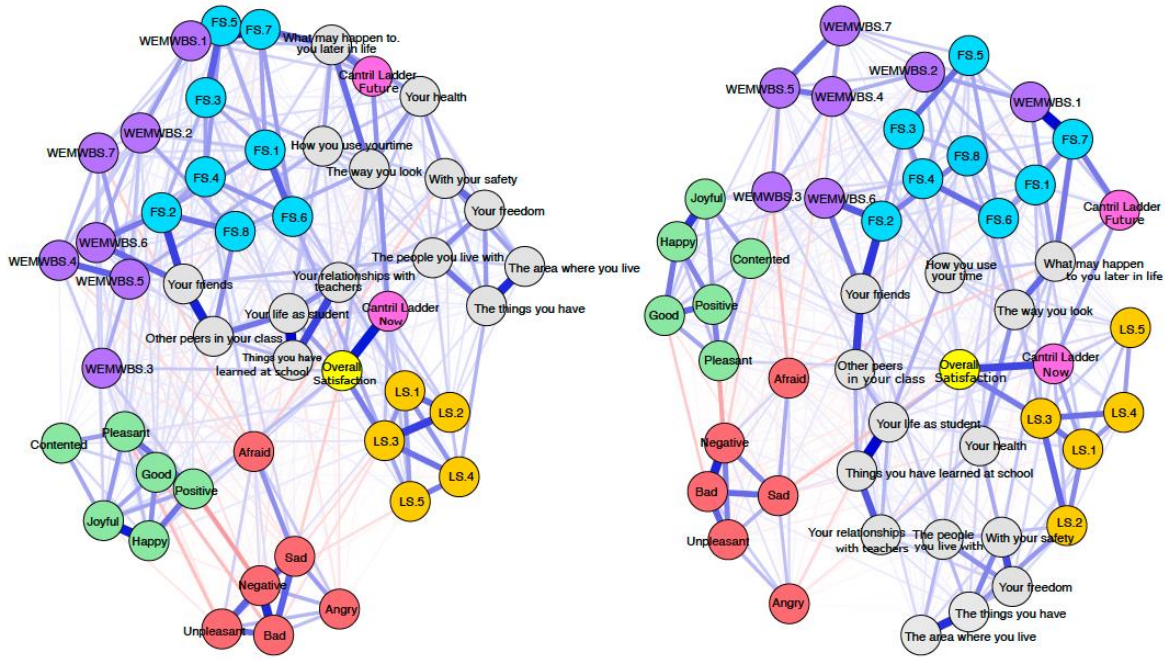
Network accuracy and stability

The bootstrapped confidence intervals (CIs) of the estimated edge weights revealed narrowed intervals (see Appendix 4), suggesting high accuracy in network estimation. The stability of node strength and edge weights was assessed using a case-dropping bootstrap procedure. The centrality stability (CS) coefficient for node strength and edges was 0.75, exceeding the recommended cutoff of 0.5, indicating a highly stable network. This suggests that up to 75% of the data could be removed while still maintaining a correlation of 0.7 with the original dataset at 95% certainty, further supporting the robustness of the estimated network structure. For both 11-14 and 15-18 age group, the network also demonstrated high stability, with centrality and edge weight CS-coefficients of 0.75, indicating that up to 75% of cases could be dropped while still retaining a correlation of at least 0.7 with the original network in 95% of bootstrap samples.

Network Comparison Test (NCT) Results

We compared the networks for early adolescents (11-14 years) and middle adolescents (15-18 years) using the Network Comparison Test (NCT; van Borkulo et al., 2017) with 5,000 permutations. First, we assessed global strength and found no significant difference between the two age groups ($S = 0.4268$, $p = 0.161$), indicating that the overall level of connectivity among wellbeing indicators is comparable in early and middle adolescence.

Figure 3. The networks of early adolescents and middle adolescents



Next, the network invariance test revealed a significant difference in overall structure ($m = 0.1029$, $p = 0.0249$), demonstrating that, despite similar global strength, the specific configuration of connections varies by age. Edge-weight comparisons highlighted several of these age-linked shifts: the association between Overall Life Satisfaction and Pleasant was stronger in the older group ($p = 0.00020$), the link between Your Friends and Your Relationships with Teachers was stronger in the younger group ($p = 0.00020$), and the connection between The Things You Have and LS2 ('conditions are excellent') was again stronger in older adolescents ($p = 0.00040$). These differences point to changes in how particular aspects of wellbeing relate to one another across adolescence.

When we examined node centrality, three indicators: Bad, WEMWBS-1 ('optimistic about the future'), and WEMWBS-3 ('relaxed'), showed significantly higher strength centrality in the 15-18-year-old network than in the 11-14-year-old network (all $p < 0.01$). This suggests that negative affect and future-orientation and calmness play a more dominant role in the wellbeing network of older adolescents. Conversely, the single-item Cantril

Ladder (Now) was significantly more central for younger adolescents ($p = 0.042$), indicating that their momentary global life evaluation is more pivotal in early adolescence.

Discussion

This study applied psychometric network analysis to a large, cross-national sample of 6,445 students (11-18 years) drawn from 24 countries, modelling the interplay among 49 indicators of SWB (life satisfaction, affect) and PWB (flourishing and positive mental functioning). To our knowledge, this is one of the first studies to include eight distinct wellbeing measures which span from hedonic to eudaimonic constructs and incorporate both single-item and multi-item questionnaires within a multinational context.

We first estimated a pooled network to examine the structure of adolescent wellbeing across the full sample and identify its most central components. Overall life satisfaction, satisfaction with life as a student, and optimism about the future emerged as the most central and interconnected elements within a moderately dense and highly stable network. We then used a Network Comparison Test to explore developmental differences between early (ages 11-14) and middle (15-18) adolescence. While the overall strength of connections was similar across age groups, the structure of the network and the centrality of specific nodes, such as negative affect, relaxation, and future optimism, shifted significantly with age. In the sections that follow, we interpret these findings in light of developmental theory, highlight implications for policy and educational practice, and note limitations and directions for future research.

Across all analyses and all groups (whole sample, 11-14, 15-18), Overall Satisfaction consistently emerged as the most central node, across strength, closeness, and betweenness centrality. And similarly, for LS3 (“I’m satisfied with my life”) was among the top hubs. Their high centrality reflects close ties to a range of other wellbeing indicators, suggesting

adolescents' general life satisfaction is tightly interconnected with many other components, serving as a key integrative "hub". This finding aligns with previous research emphasizing the foundational role of overall life satisfaction in youth wellbeing (Blasco-Belled et al., 2024; OECD, 2021; Vieta-Piferrer et al., 2024). This study has implications for simple monitoring and confirms a single general life satisfaction item can effectively summarize broad adolescent wellbeing in a multi-country dataset.

Another life satisfaction related item Cantril Ladder (Now) was consistently among the top three nodes across all samples for closeness centrality, but its strength and betweenness centrality was much lower than that of Overall Satisfaction and LS3. This suggests while many aspects of wellbeing are efficiently connected to present life evaluation through Cantril ladder, these connections are not as strong or numerous as those anchored by the other two global satisfaction measures. This may be due to a more abstract and evaluative nature of the Cantril ladder which ask participants to rank themselves on a hypothetical ladder which potentially reducing its integration with other wellbeing indicators.

Although affective experiences are often treated as core elements of wellbeing, our findings reveal distinct roles for individual emotions within the broader adolescent wellbeing network. While negative affect items such as Angry, Contented, Afraid, Unpleasant were consistently peripheral in our network, the item 'sad' exhibited a high betweenness centrality. This suggests that sadness plays a bridging or mediating role within the wellbeing structure, even though it is not the most directly connected node. Notably, Wang et al. (2023) also identified sadness as central, alongside other negative moods like anxiety and worry, in their network of Chinese high school students, though their use of a distress-oriented scale and an older, more homogeneous sample. Together, these findings point out the unique role of sadness in adolescent wellbeing networks across different contexts, emphasizing its importance as both a potential bridge and a target for intervention. By contrast, positive

emotions such as happy and joyful, which were central in previous network studies (e.g., Vieta-Piferrer et al., 2024; Blasco-Belled et al., 2024), were less prominent in our analysis. One likely reason is the inclusion of setting-specific indicators, particularly satisfaction with student life, which showed stronger centrality and may displace more general affective states in adolescent populations.

Our findings reveal a clear developmental shift: wellbeing in early adolescence is anchored in present-focused experiences, particularly school satisfaction, while in middle adolescence it increasingly depends on emotion regulation and future-oriented thinking. Although the overall connectivity of the networks remained stable across age groups echoing prior findings by Blasco-Belled et al. (2024) and Vieta-Piferrer et al. (2024), the structure and prominence of specific nodes changed meaningfully with age.

In early adolescence (11-14), life as a student ranked among the most central components of wellbeing, alongside overall life satisfaction and LS3 ("I'm satisfied with my life"), underscoring the importance of day-to-day school experiences during this stage. By middle adolescence (15-18), optimism about my future rose in centrality, signalling a shift toward future-oriented appraisal. This reordering of central nodes reflects growing cognitive capacities for goal-setting, abstract reasoning, and identity exploration (Shulman & Nurmi, 2010). At the same time, emotional regulation became more influential: relaxed mood and low negative affect (e.g., not feeling "bad") gained strength, while momentary life evaluation (e.g., Cantril Ladder "Now") declined. These changes suggest that as adolescents mature, sustaining wellbeing increasingly requires managing internal states and maintaining a sense of forward-looking purpose, even under mounting academic and social pressures (Putwain et al., 2021). In this context, feeling relaxed may reflect the absence of stress or anxiety which are unmeasured yet salient factors in middle adolescence that have been shown to shape network structure (Wang et al., 2023). Taken together, these patterns support developmental

theory and suggest age-sensitive priorities for intervention: for younger adolescents, enhancing present satisfaction and school engagement; for older adolescents, cultivating optimism and emotional resilience to navigate transitional demands.

Finally, our network also revealed coherent clusters, around academic life, future orientation, positive and negative affect, and social relationships, while showing strong cross-domain linkages that connect subjective and psychological wellbeing. For example, overall life satisfaction bridged cognitive evaluations, emotional states, and eudaimonic traits like meaning and purpose. These patterns reinforce the idea that hedonic and eudaimonic wellbeing are not independent domains but form an integrated system during adolescence, as supported by prior network studies (Blasco-Belled et al., 2024). Importantly, the network structure was highly stable, with strong bootstrap metrics and narrow edge confidence intervals, suggesting that similar patterns would likely emerge in comparable samples. Our findings build on prior evidence from Wang et al. (2023), who found stable wellbeing network structures across gender and residential context. We extend this evidence by demonstrating network stability across a much larger and more diverse sample, spanning 15 countries and covering ages 11 to 18, and by incorporating a broader range of wellbeing indicators. It is worth noting as highlighted by Shukla et al. (2022), pooled networks can mask local variations. Future work should complement global analyses with context-specific network models to capture cultural nuance and tailor interventions more effectively.

Implications for policy, practice, and research

Our findings offer clear guidance for how adolescent wellbeing can be measured, supported, and better understood in both policy and applied settings. Most notably, overall life satisfaction emerged as the most central node across all network metrics making it a powerful structural hub. If practical constraints limit the use of longer scales, this single-item

measure ("Overall, how satisfied are you with your life?") provides a reliable and informative summary of adolescents' broader wellbeing.

Beyond this, the strong centrality of school-related satisfaction and student experiences across a diverse international sample highlights their relevance as core monitoring indicators. Policies aiming to improve adolescent wellbeing should therefore invest in both the present-day context by fostering positive school climates and peer relationships and the future-facing capacities adolescents develop, such as optimism, hope, and purpose. Notably, future orientation became more central in mid-adolescence, suggesting that efforts to build goal-setting and resilience skills become increasingly important with age. Moreover, the selection of specific wellbeing measures is not merely a methodological decision but also reflects deeper assumptions about what constitutes healthy adolescent development. Different tools emphasize distinct element, such as affective balance, autonomy, or relational connectedness, and their use can signal varying priorities across policy, cultural, or developmental frameworks. Thus, while core indicators such as life satisfaction and school engagement should anchor national and international wellbeing strategies, flexibility for local adaptation remains essential, given cultural variation in which components matter most (Shukla et al., 2022).

In relation to intervention, strategies should focus on the most central and developmentally relevant network nodes. For younger adolescents, boosting daily satisfaction (particularly with school and peer relationships) may yield broad improvements across their wellbeing system. For older adolescents, fostering future-oriented thinking, emotional regulation, and stress coping may be more impactful. Targeted interventions could include mentoring programs, goal-setting workshops, or classroom environments designed to build calm and connection. The bridging role of sadness in our network also suggests it may be a key early marker of vulnerability. Addressing sadness through counselling or social-

emotional learning could improve not only mood but also broader wellbeing domains due to its linking role.

Our findings also highlight measurement considerations. While network diagnostics confirmed no problematic multicollinearity, we did observe semantic overlap between items such as “good” and “positive” or “bad” and “negative.” These pairs, while statistically distinct, may represent overlapping constructs that could be refined in future measurement work. Moreover, based on our observations, terms like “contented”, may not resonate with younger respondents and should be replaced with more developmentally appropriate alternatives. These refinements can improve both the accuracy and accessibility of youth wellbeing assessments.

Given our international sample, future work should build on this by conducting culturally grounded network analyses. While our findings were robust across 24 countries, pooled analyses may mask important context-specific differences. Comparative studies, such as those from Children’s Worlds, PISA, and HBSC, have shown that the timing and pace of adolescent wellbeing changes vary across countries (Marquez et al., 2024); network models could help determine whether the structure of wellbeing shifts in parallel. In addition to cultural variation, longitudinal designs are needed to track how adolescent wellbeing networks evolve over time and to test directional hypotheses, such as whether optimism fosters later life satisfaction or vice versa. Exploring individual-level moderators, including gender, migrant background, neurodiversity, and sexuality, will further illuminate who experiences these shifts most strongly and why. Finally, experience sampling methods, which capture real-time fluctuations in adolescents’ emotions and thoughts, could offer rich insight into the dynamic interplay of wellbeing components in daily life.

Limitations

Several limitations should be acknowledged when interpreting these findings. First, the sample, although large and multinational, was drawn exclusively from IB schools. IB students may differ from national-system peers in socioeconomic status, academic motivation, or school climate, which could limit generalisability. Future studies should replicate the network structure in more socio-economically and academically diverse settings.

Second, data was collected mostly from early adolescents (age 11-14) in some countries, whereas the opposite (age 15-18) was observed in others. Thus, the age-related differences observed in this study may partly be explained by cross-cultural differences.

Third, all variables were assessed via self-report in a single online session. Common-method variance, social-desirability bias, and transient mood states may have inflated certain associations. Incorporating longitudinal designs or experience-sampling designs would help validate the observed network patterns.

Fourth, although the survey was administered in three languages and rigorous translation/back-translation procedures were used, we did not formally test measurement invariance across language versions. Differential item functioning could still influence item correlations and, by extension, the pooled network structure. Future work should conduct invariance tests (e.g., multi-group CFA or alignment methods) to ensure that items operate equivalently across languages before aggregating data.

Fifth, the network analyses are entirely cross-sectional, precluding causal inference. Partial-correlation networks capture contemporaneous associations rather than temporal influence. Although the Network Comparison Test reveals age-group differences in network architecture, longitudinal network modelling or intensive time-series approaches (e.g., dynamic vector autoregression) are needed to establish directionality and within-person change.

Sixth, despite controlling for school, country, language, gender, and age, other contextual factors, such as socioeconomic status, pandemic-related disruptions, or family functioning, were not modelled and could confound specific edges or centralities. Furthermore, while we opted not to exclude countries with smaller subsamples to retain the breadth of cross-cultural representation, we acknowledge that these imbalances may limit the generalizability of findings to individual countries. Future work with larger within-country samples could explore cultural variation in wellbeing network structures using multigroup or multilevel network modeling approaches.

Finally, item selection was deliberately comprehensive, but this breadth increases redundancy risk and estimation complexity. Although Unique Variable Analysis and multicollinearity checks were conducted, alternative item sets or dimension-reduced networks may yield slightly different configurations. Taken together, these limitations temper the generalisability and causal interpretation of our results, while pointing to clear avenues for methodological refinement in future research.

Conclusions

In sum, our network analysis indicates that adolescent wellbeing is best understood as a dynamic, interconnected system, rather than a set of isolated traits. Within this system, overall life satisfaction, school-related satisfaction, and optimism about the future consistently emerged as central hubs which reinforcing the foundational role of both present experiences and future-oriented thinking.

While these core connections remain stable from early to middle adolescence, we observed meaningful developmental shifts: the rising centrality of negative affect (bad), emotional calm (relaxed), and future optimism, alongside a decline in momentary life

evaluation. These changes underscore the importance of age-sensitive strategies for monitoring and supporting adolescent wellbeing.

By mapping how subjective and psychological wellbeing components interact and shift with age, this study offers actionable insights and precise targets for measurement, policy, and intervention. A network approach moves beyond description to reveal how specific wellbeing components function together, offering a developmentally grounded roadmap for intervention, monitoring, and future research.

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Declaration of interest statement

The authors have no conflicts of interest to declare.

References

Ambrosetti, E., Bettin, G., Cela, E., & Paparusso, A. (2023). Subjective well-being and school outcomes among children of immigrants and natives in Italy. *Population, Space and Place*, *29*(4), e39. https://doi.org/10.1002/psp.2639

Black, L., Farzinnia, R., Humphrey, N., & Marquez, J. (2024). Variation in global network properties across risk factors for adolescent internalizing symptoms: Evidence of cumulative

effects on structure and connectivity. *Psychological Medicine*, *54*(4), 687–697. https://doi.org/10.1017/S0033291723002362

Blasco-Belled, A. (2023). Character strengths and mental health as complex systems: A network analysis to identify bridge strengths. *Current Psychology*, *42*(29), 25832–25842. https://doi.org/10.1007/s12144-022-03598-7

Blasco-Belled, A., González-Carrasco, M., & Casas, F. (2024). Changes in the network structure of well-being components in adolescents in the school context: A 2-year longitudinal study. *Journal of School Psychology*, *102*, 101255. https://doi.org/10.1016/j.jsp.2023.101255

Borsboom, D. (2017). A network theory of mental disorders. *World Psychiatry*, *16*(1), 5–13. https://doi.org/10.1002/wps.20375

Bortes, C., Ragnarsson, S., Strandh, M., & Petersen, S. (2021). The Bidirectional Relationship Between Subjective Well-Being and Academic Achievement in Adolescence. *Journal of Youth and Adolescence*, *50*(5), 992–1002. https://doi.org/10.1007/s10964-021-01413-3

Bringmann, L. F., Elmer, T., Epskamp, S., Krause, R. W., Schoch, D., Wichers, M., Wigman, J. T. W., & Snippe, E. (2019). What do centrality measures measure in psychological networks? *Journal of Abnormal Psychology*, *128*(8), 892–903. https://doi.org/10.1037/abn0000446

Burger, J., Isvoranu, A.-M., Lunansky, G., Haslbeck, J. M. B., Epskamp, S., Hoekstra, R. H. A., Fried, E. I., Borsboom, D., & Blanken, T. F. (2023). Reporting standards for psychological network analyses in cross-sectional data. *Psychological Methods*, *28*(4), 806–824. https://doi.org/10.1037/met0000471

Campbell, O. L. K., Bann, D., & Patalay, P. (2021). The gender gap in adolescent mental health: A cross-national investigation of 566,829 adolescents across 73 countries. *SSM - Population Health*, *13*, 100742. https://doi.org/10.1016/j.ssmph.2021.100742

Campbell, S., & Osborn, T. L. (2021). Adolescent psychopathology and psychological wellbeing: A network analysis approach. *BMC Psychiatry*, *21*(1), 333. https://doi.org/10.1186/s12888-021-03331-x

Cantril, H. (1965). *The Pattern of Human Concerns*. Rutgers University Press,.

Cárdenas, D., Lattimore, F., Steinberg, D., & Reynolds, K. J. (2022). Youth well-being predicts later academic success. *Scientific Reports*, *12*(1), 2134. https://doi.org/10.1038/s41598-022-05780-0

Casas, F. (2011). Subjective Social Indicators and Child and Adolescent Well-being. *Child Indicators Research*, *4*(4), 555–575. https://doi.org/10.1007/s12187-010-9093-z

Casas, F., Bello, A., González, M., & Aligué, M. (2012). Children's subjective wellbeing: Spanish findings from the International Survey of Children's Well-Being. *Child Indicators Research*, *5*(4), 609–628.

Casas, F., & González-Carrasco, M. (2019). Subjective Well-Being Decreasing With Age: New Research on Children Over 8. *Child Development*, *90*(2), 375–394. https://doi.org/10.1111/cdev.13133

Casas, F., & González-Carrasco, M. (2021). Analysing Comparability of Four Multi-Item Well-being Psychometric Scales Among 35 Countries Using Children's Worlds 3rd Wave 10 and 12-year-olds Samples. *Child Indicators Research*, *14*(5), 1829–1861. https://doi.org/10.1007/s12187-021-09825-0

Casas, F., González-Carrasco, M., Oriol, X., & Malo, S. (2022). Economic and Children's Subjective Well-Being Indicators at the National Level in 35 Countries. *Child Indicators Research*, *15*(5), 1539–1563. https://doi.org/10.1007/s12187-022-09918-4

Christensen, A. P., Golino, H., & Silvia, P. J. (2020). A Psychometric Network Perspective on the Validity and Validation of Personality Trait Questionnaires. *European Journal of Personality*, *34*(6), 1095–1108. https://doi.org/10.1002/per.2265

Clarke, T. (2020). Children's wellbeing and their academic achievement: The dangerous discourse of 'trade-offs' in education. *Theory and Research in Education*, *18*(3), 263–294. https://doi.org/10.1177/1477878520980197

Dalege, J., Borsboom, D., Van Harreveld, F., Waldorp, L. J., & Van Der Maas, H. L. J. (2017). Network Structure Explains the Impact of Attitudes on Voting Decisions. *Scientific Reports*, *7*(1), 4909. https://doi.org/10.1038/s41598-017-05048-y

De Neve, J.-E., & Oswald, A. J. (2012). Estimating the influence of life satisfaction and positive affect on later income using sibling fixed effects. *Proceedings of the National Academy of Sciences*, *109*(49), 19953–19958. https://doi.org/10.1073/pnas.1211437109

Diener, E., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The Satisfaction With Life Scale. *Journal of Personality Assessment*, *49*(1), 71–75. https://doi.org/10.1207/s15327752jpa4901_13

Diener, E., Lucas, R. E., & Oishi, S. (2002). Sujective well-being: The science of happiness and life satisfaction. In *Handbook of positive psychology* (pp. 463–473). Oxford University Press.

Diener, E., Suh, E. M., Lucas, R. E., & Smith, H. L. (1999). Subjective well-being: Three decades of progress. *Psychological Bulletin*, *125*(2), 276–302. https://doi.org/10.1037/0033-2909.125.2.276

Diener, E., Wirtz, D., Tov, W., Kim-Prieto, C., Choi, D., Oishi, S., & Biswas-Diener, R. (2010). New Well-being Measures: Short Scales to Assess Flourishing and Positive and Negative Feelings. *Social Indicators Research*, *97*(2), 143–156. https://doi.org/10.1007/s11205-009-9493-y

Duncan, M. J., Patte, K. A., & Leatherdale, S. T. (2021). Mental Health Associations with Academic Performance and Education Behaviors in Canadian Secondary School Students. *Canadian Journal of School Psychology*, *36*(4), 335–357. https://doi.org/10.1177/0829573521997311

Efron, B. (1979). Bootstrap Methods: Another Look at the Jackknife. *The Annals of Statistics*, *7*(1). https://doi.org/10.1214/aos/1176344552

Ehrhart, I. C., Parker, P. E., Weidner, W. J., Dabney, J. M., Scott, J. B., & Haddy, F. J. (1975). Coronary vascular and myocardial responses to carotid body stimulation in the dog. *The American Journal of Physiology*, *229*(3), 754–760. https://doi.org/10.1152/ajplegacy.1975.229.3.754

Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods*, *50*(1), 195–212. https://doi.org/10.3758/s13428-017-0862-1

Fuhrmann, D., Van Harmelen, A.-L., & Kievit, R. A. (2022). Well-Being and Cognition Are Coupled During Development: A Preregistered Longitudinal Study of 1,136 Children and Adolescents. *Clinical Psychological Science*, *10*(3), 450–466. https://doi.org/10.1177/21677026211030211

Geijsen, A. J. M. R., & Bartels, M. (n.d.). *Wellbeing as a catalyst: Teenage wellbeing is associated with positive social, health and lifestyle outcomes in early adulthood*. osf.io/preprints/psyarxiv/7hr5k_v1

Goodman, A., Joshi, H., Nasim, B., & Tyler, C. (2015). *Social and emotional skills in childhood and their long-term effects on adult life*. https://www.eif.org.uk/report/social-and-emotional-skills-in-childhood-and-their-long-term-effects-on-adult-life

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (Eighth edition). Cengage.

Hevey, D. (2018). Network analysis: A brief overview and tutorial. *Health Psychology and Behavioral Medicine*, *6*(1), 301–328. https://doi.org/10.1080/21642850.2018.1521283

Höltge, J., Cowden, R. G., Lee, M. T., Bechara, A. O., Joynt, S., Kamble, S., Khalanskyi, V. V., Shtanko, L., Kurniati, N. M. T., Tymchenko, S., Voytenko, V. L., McNeely, E., &

VanderWeele, T. J. (2023). A systems perspective on human flourishing: Exploring cross-country similarities and differences of a multisystemic flourishing network. *The Journal of Positive Psychology*, *18*(5), 695–710. https://doi.org/10.1080/17439760.2022.2093784

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning* (Vol. 112, No. 1). New York: springer.

Marquez, J., Taylor, L., Boyle, L., zhou, wanying, De Neve, J.-E., & World Happiness Report. (2024). *Child and Adolescent Well-Being: Global Trends, Challenges and Opportunities* (Version v1.0) [Application/pdf]. University of Oxford. https://doi.org/10.18724/WHR-91B0-EK06

Marsman, M., Borsboom, D., Kruis, J., Epskamp, S., Van Bork, R., Waldorp, L. J., Maas, H. L. J. V. D., & Maris, G. (2018). An Introduction to Network Psychometrics: Relating Ising Network Models to Item Response Theory Models. *Multivariate Behavioral Research*, *53*(1), 15–35. https://doi.org/10.1080/00273171.2017.1379379

OECD. (2021). *Measuring What Matters for Child Well-Being and Policies*. OECD. https://doi.org/10.1787/e82fded1-en

Orben, A., & Przybylski, A. K. (2019). The association between adolescent well-being and digital technology use. *Nature Human Behaviour*, *3*(2), 173–182. https://doi.org/10.1038/s41562-018-0506-1

Putwain, D. W., Loderer, K., Gallard, D., & Beaumont, J. (2020). School-related subjective well-being promotes subsequent adaptability, achievement, and positive behavioural conduct. *British Journal of Educational Psychology*, *90*(1), 92–108. https://doi.org/10.1111/bjep.12266

Putwain, D. W., Stockinger, K., Von Der Embse, N. P., Suldo, S. M., & Daumiller, M. (2021). Test anxiety, anxiety disorders, and school-related wellbeing: Manifestations of the same or

different constructs? *Journal of School Psychology*, *88*, 47–67. https://doi.org/10.1016/j.jsp.2021.08.001

Robinaugh, D. J., Hoekstra, R. H. A., Toner, E. R., & Borsboom, D. (2020). The network approach to psychopathology: A review of the literature 2008–2018 and an agenda for future research. *Psychological Medicine*, *50*(3), 353–366. https://doi.org/10.1017/S0033291719003404

Ryff, C. D. (1989). Happiness is everything, or is it? Explorations on the meaning of psychological well-being. *Journal of Personality and Social Psychology*, *57*(6), 1069–1081. https://doi.org/10.1037/0022-3514.57.6.1069

Ryff, C. D., Boylan, J. M., & Kirsch, J. A. (2021). Eudaimonic and Hedonic Well-Being: An Integrative Perspective with Linkages to Sociodemographic Factors and Health. In M. T. Lee, L. D. Kubzansky, & T. J. VanderWeele (Eds.), *Measuring Well-Being* (1st ed., pp. 92–135). Oxford University PressNew York. https://doi.org/10.1093/oso/9780197512531.003.0005

Ryff, C. D., & Keyes, C. L. M. (1995). The structure of psychological well-being revisited. *Journal of Personality and Social Psychology*, *69*(4), 719–727. https://doi.org/10.1037/0022-3514.69.4.719

Savahl, S., Adams, S., & Hoosen, P. (2023). The Subjective and Psychological Well-Being of Children in South Africa: A Population-Based Study. *Applied Research in Quality of Life*, *18*(5), 2315–2347. https://doi.org/10.1007/s11482-023-10187-8

Savahl, S., Casas, F., & Adams, S. (2021). The Structure of Children's Subjective Well-being. *Frontiers in Psychology*, *12*, 650691. https://doi.org/10.3389/fpsyg.2021.650691

Sawyer, S. M., Azzopardi, P. S., Wickremarathne, D., & Patton, G. C. (2018). The age of adolescence. *The Lancet Child & Adolescent Health*, *2*(3), 223–228. https://doi.org/10.1016/S2352-4642(18)30022-1

Shukla, M., Wu, A. F. W., Lavi, I., Riddleston, L., Hutchinson, T., & Lau, J. Y. F. (2022). A network analysis of adolescent mental well-being during the coronavirus pandemic: Evidence for cross-cultural differences in central features. *Personality and Individual Differences*, *186*, 111316. https://doi.org/10.1016/j.paid.2021.111316

Shulman, S., & Nurmi, J.-E. (2010). Understanding emerging adulthood from a goal-setting perspective: Understanding Emerging Adulthood from a Goal-Setting Perspective. *New Directions for Child and Adolescent Development*, *2010*(130), 1–11. https://doi.org/10.1002/cd.277

Solmi, M., Radua, J., Olivola, M., Croce, E., Soardo, L., Salazar De Pablo, G., Il Shin, J., Kirkbride, J. B., Jones, P., Kim, J. H., Kim, J. Y., Carvalho, A. F., Seeman, M. V., Correll, C. U., & Fusar-Poli, P. (2022). Age at onset of mental disorders worldwide: Large-scale meta-analysis of 192 epidemiological studies. *Molecular Psychiatry*, *27*(1), 281–295. https://doi.org/10.1038/s41380-021-01161-7

Stewart-Brown, S., Platt, S., Tennant, A., Maheswaran, H., Parkinson, J., Weich, S., Tennant, R., Taggart, F., & Clarke, A. (2011). The Warwick-Edinburgh Mental Well-being Scale (WEMWBS): A valid and reliable tool for measuring mental well-being in diverse populations and projects. *Journal of Epidemiology & Community Health*, *65*(Suppl 2), A38–A39. https://doi.org/10.1136/jech.2011.143586.86

Stewart-Brown, S., Tennant, A., Tennant, R., Platt, S., Parkinson, J., & Weich, S. (2009). Internal construct validity of the Warwick-Edinburgh Mental Well-being Scale (WEMWBS): A Rasch analysis using data from the Scottish Health Education Population Survey. *Health and Quality of Life Outcomes*, *7*(1), 15. https://doi.org/10.1186/1477-7525-7-15

Taylor, L., De Neve, J.-E., DeBorst, L., & Khanna, D. (2022). *Well-being in education in childhood and adolescence.* International Baccalaureate Organisation.

https://www.ibo.org/research/wellbeing-research/well-being-in-education-in-childhood-and-adolescence-2022/

Tejada-Gallardo, C., Blasco-Belled, A., & Alsinet, C. (2022). Changes in the network structure of mental health after a multicomponent positive psychology intervention in adolescents: A moderated network analysis. *Applied Psychology: Health and Well-Being*, *14*(3), 987–1003. https://doi.org/10.1111/aphw.12363

Tennant, R., Hiller, L., Fishwick, R., Platt, S., Joseph, S., Weich, S., Parkinson, J., Secker, J., & Stewart-Brown, S. (2007). The Warwick-Edinburgh Mental Well-being Scale (WEMWBS): Development and UK validation. *Health and Quality of Life Outcomes*, *5*(1), 63. https://doi.org/10.1186/1477-7525-5-63

Van Borkulo, C. D., Van Bork, R., Boschloo, L., Kossakowski, J. J., Tio, P., Schoevers, R. A., Borsboom, D., & Waldorp, L. J. (2023). Comparing network structures on three aspects: A permutation test. *Psychological Methods*, *28*(6), 1273–1285. https://doi.org/10.1037/met0000476

Vieta-Piferrer, J., Oriol, X., & Miranda, R. (2024). Longitudinal Associations Between Cyberbullying Victimization and Cognitive and Affective Components of Subjective Well-Being in Adolescents: A Network Analysis. *Applied Research in Quality of Life*, *19*(5), 2967–2989. https://doi.org/10.1007/s11482-024-10363-4

Wang, S., Zhao, S., Guo, Y., Huang, C., Zhang, P., She, L., Xiang, B., Zeng, J., Zhou, F., Xie, X., & Yang, M. (2023). A network analysis of subjective well-being in Chinese high school students. *BMC Public Health*, *23*(1), 1249. https://doi.org/10.1186/s12889-023-16156-y

Wang, Y., Li, W., Liu, X., Zhang, Q., Lu, D., & Chen, Z. (2024). Emphasizing symbolic capital: Its superior influence on the association between family socioeconomic status and adolescent subjective well-being uncovered by a large-scale multivariate network analysis. *Frontiers in Psychology*, *15*, 1335595. https://doi.org/10.3389/fpsyg.2024.1335595

Wasil, A. R., Gillespie, S., Park, S. J., Venturo-Conerly, K. E., Osborn, T. L., DeRubeis, R. J., Weisz, J. R., & Jones, P. J. (2021). Which symptoms of depression and anxiety are most strongly associated with happiness? A network analysis of Indian and Kenyan adolescents. *Journal of Affective Disorders*, *295*, 811–821. https://doi.org/10.1016/j.jad.2021.08.087

Zhou, W. (2024, May 7). Evaluating the Wellbeing of Adolescents on a Global Scale. https://doi.org/10.17605/OSF.IO/24P7V

Zhou, W., & McLellan, R. (2021). Examining Social Status Profiles with Gender, School Attended, SES, Academic Achievement and Wellbeing in Urban China. *Journal of Youth and Adolescence*, *50*(7), 1464–1477. https://doi.org/10.1007/s10964-021-01454-8

Appendix

Appendix 1

VIF for each variable:

	Variable	VIF
0	const	1.000087
1	Overall Satisfaction	3.023596
2	Cantril Ladder (now)	2.234814
3	Cantril Ladder (future)	1.613175
4	The people you live with	1.583486
5	Your life as student	2.439353
6	Things you have learned at school	1.910655
7	Other peers in your class	1.720235
8	Your friends	1.796759
9	The area where you live	1.502358
10	The things you have	1.738353
11	How you use your time	1.668891
12	With your safety	1.598125
13	Your freedom	1.768268
14	The way you look	1.740616
15	What may happen to you later in life	2.192569
16	Your health	1.672327
17	Your relationships with teachers	1.625115
18	LS-1	2.190502
19	LS-2	2.076604

20	LS-3 2.885477
21	LS-4 1.742763
22	LS-5 1.588369
23	Positive 2.312418
24	Negative 2.100740
25	Good 2.007192
26	Bad 2.043766
27	Pleasant 1.914027
28	Unpleasant 1.662810
29	Happy 2.228420
30	Sad 1.761135
31	Afraid 1.227960
32	Joyful 1.960906
33	Angry 1.247452
34	Contented 1.317176
35	FS-1 2.270227
36	FS-2 2.100896
37	FS-3 1.906362
38	FS-4 1.534580
39	FS-5 1.684989
40	FS-6 2.225370
41	FS-7 2.425218
42	FS-8 1.696875
43	WEMWBS-1 1.944100
44	WEMWBS-2 1.756028

45	WEMWBS-3	1.492478
46	WEMWBS-4	1.469470
47	WEMWBS-5	1.684842
48	WEMWBS-6	1.674953
49	WEMWBS-7	1.449779

Appendix 2

Table. Sample characteristics by country.

Country	Respondents	Number of schools	Age 11-14	Age 15-18	Boy	Girl	Other
United Arab Emirates	451	2	65.6%	34.4%	46.3%	49.0%	4.7%
Argentina	202	1	56.4%	43.6%	43.6%	56.4%	0.0%
Armenia	135	1	0.0%	100.0%	42.2%	57.0%	0.7%
Austria	72	1	62.5%	37.5%	52.8%	45.8%	1.4%
Bahrain	303	1	62.7%	37.3%	44.9%	50.8%	4.3%
Bangladesh	132	2	79.6%	20.5%	53.0%	44.7%	2.3%
Canada	1202	2	61.7%	38.3%	41.1%	56.4%	2.5%
China	156	1	80.8%	19.2%	48.1%	43.6%	8.3%
Germany	437	3	43.9%	56.1%	43.5%	53.8%	2.8%
Denmark	300	2	30.0%	70.0%	43.3%	54.0%	2.7%
Ecuator	109	1	42.2%	57.8%	58.7%	41.3%	0.0%
Egypt	155	1	80.0%	20.0%	54.8%	40.6%	4.5%
Estonia	272	1	48.9%	51.1%	42.3%	53.3%	4.4%
United Kingdom	95	2	0.0%	100.0%	20.0%	74.7%	5.3%
Ghana	64	1	7.8%	92.2%	40.6%	59.4%	0.0%
India	755	4	75.2%	24.8%	49.1%	48.7%	2.1%
Japan	139	2	50.4%	49.6%	48.9%	45.3%	5.8%
Mexico	98	1	91.8%	8.2%	60.2%	39.8%	0.0%
The Netherlands	94	1	28.7%	71.3%	52.1%	43.6%	4.3%
Other	163	1	66.3%	33.7%	41.1%	54.6%	4.3%
Russia	145	1	49.7%	50.3%	40.0%	53.8%	6.2%
Slovakia	82	1	53.7%	46.3%	56.1%	36.6%	7.3%
Sweden	312	2	42.0%	58.0%	44.9%	52.9%	2.2%
Turkey	572	4	4.4%	95.6%	45.3%	52.3%	2.5%

Appendix 3

Network Stability and Centrality Results by Age Group

Ages 11–14

Sampling levels tested:

- nPerson range: 836 (75% drop) to 3,176 (5% drop)

Network stability:

- The centrality stability (CS) coefficient for both edge weights and node strength was 0.75, exceeding the recommended minimum of 0.5. This indicates that up to 75% of cases could be dropped while retaining a correlation of at least 0.7 with the original network in 95% of bootstrap samples, supporting strong network robustness.

Strongest edges:

- *Your Life as a Student – Things You Have Learned at School*: 0.337
- *Cantril Ladder (Now) – Overall Satisfaction*: 0.305
- *WEMWBS-1 ("optimistic about the future") – FS7 ("optimistic about my future")*: 0.334

Strongest negative edges:

- *Negative – Positive*: –0.113
- *Bad – Good*: –0.074
- *Pleasant – Unpleasant*: –0.071

Node centrality:

- **Strength centrality:** Highest for *Overall Satisfaction*, *LS3 ("satisfied with my life")*, and *Your Life as a Student*; lowest for *Contented*, *Angry*, and *The Area Where You Live*.
- **Betweenness centrality:** Highest for *Overall Satisfaction* (4.99), *Positive*, and *LS3* (2.01); lowest for *Contented*, *Angry*, and *The Area Where You Live*.

- **Closeness centrality:** Highest for *Overall Satisfaction*, *Cantril Ladder (Now)*, and *LS3*; lowest for *Contented*, *Angry*, and *Unpleasant*.

These results highlight the central importance of life satisfaction and school experience in the wellbeing network of younger adolescents.

Ages 15–18

Sampling levels tested:

- nPerson range: 776 (75% drop) to 2,947 (5% drop)

Network stability:

- The CS coefficient for both edge weights and node strength was 0.75, indicating robust stability as in the younger group.

Strongest edges:

- *Your Life as a Student – Things You Have Learned at School*: 0.389
- *WEMWBS-1 – FS7*: 0.385
- *Bad – Negative*: 0.325

Strongest negative edges:

- *Negative – Positive*: –0.120
- *Afraid – WEMWBS-3 ("relaxed")*: –0.080
- *Pleasant – Unpleasant*: –0.106

Node centrality:

- **Strength centrality:** Highest for *Overall Satisfaction*, *LS3 ("satisfied with my life")*, and *FS7 ("optimistic about my future")*; lowest for *Angry*, *Contented*, and *Afraid*.
- **Betweenness centrality:** Highest for *Overall Satisfaction*, *LS3*, and *Sad*; lowest for *Contented*, *LS5 ("change almost nothing")*, and *The Area Where You Live*.

- **Closeness centrality:** Highest for *Overall Satisfaction*, *LS3*, and *Cantril Ladder (Now)*; lowest for *Contented*, *Angry*, and *Unpleasant*.

Appendix 4: bootstrap of CIs of estimated edge weight