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Maintaining Well-Being During the COVID-19 Pandemic: A Network Analysis of Well-Being Responses from British Youth

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Abstract
COVID-19 has significant impacts on young peoples' lives and emotions. Understanding how young people maintain well-being in the face of challenges can inform future mental health intervention development. Here we applied network analysis to well-being data gathered from 2532 young people (12-25 years) residing in the UK during the COVID-19 pandemic to identify the structure across well-being and crucially, its central defining features. Gender and age differences in networks were also investigated. Across all participants, items emerged in two clusters: 1) optimism, positive self-perception, and social connectedness, and 2) processing problems and ideas. The two central features of well-being were: "I've been dealing with problems well" and "I've been thinking clearly". There were minimal age and gender differences. Our findings suggest that the perception of being able to process problems and ideas efficiently could be a hallmark of well-being, particularly in the face of challenging circumstances. These findings contrast with pre-pandemic studies that point to positive affect as central aspects of well-being networks. Future interventions that encourage problem-solving and mental flexibility could be useful in helping young people maintain well-being during times of stress and uncertainty.

Keywords well-being; young people; COVID-19; network analysis; resilience; coping

The COVID-19 pandemic continues to pose multiple challenges, adding to levels of stress globally (Serafini et al., 2020). Young people may be especially susceptible to the long-term impact of stress, given that youth reflects a period when many mental illnesses emerge, consolidate and become chronic (Paus et al., 2008; Romeo, 2013). Identifying those reporting poor mental health and intervening early to attenuate negative outcomes is a priority. However, from a public health preventative perspective it is also crucial to promote positive outcomes at the population level, such as good mental well-being. Mental well-being is the positive aspect of mental health (2001) and is known to protect against long-term mental health problems, for example, by reducing emotional distress and increasing exposure to protective factors (e.g. academic achievement, positive interpersonal relationships) (Saxena et al., 2006). Identifying how young people maintain well-being despite the challenges and stressors associated with the pandemic could inform the development of future universal programs designed to promote positive mental health. This information can be used to guide countries during this pandemic but can also be used more generally in population-based resilience programs post-pandemic. Here, we used a network approach to identify the core features of well-being in adolescents and young adults (12-25 years) in the UK across various lockdown phases of the pandemic.

"Well-being" refers to the capacity to flourish under "normal" circumstances as well as the ability to be resilient and recover from challenging

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circumstances (Galderisi et al., 2015). Well-being is often divided into two behavioural dimensions: affective ("feeling good") and functional ("functioning well") (Vittersø, 2013). Latent variable approaches to youth well-being have identified several higher-order (latent) factors e.g. positive affect and optimism, positive self-perceptions, the ability to process, engage and persevere with tasks and problems, and social connectedness (Arslan & Coşkun, 2020; Kern et al., 2016). These distinct factors purportedly capture common variance across well-being items. However, these approaches, while recognising that items form clusters together, can be limited in their explanatory power, by failing to capture all possible interactions or paths between items, missing out on quantifying any causal, mutually reinforcing effects. By specifying direct links ("edges") between all items ("nodes"), network analysis can also quantify how influential ("central") items are, by their capacity to activate or be activated by other items (Costantini et al., 2015). As central items are more influential, it has been argued that they reflect more optimal targets for intervention (Fried et al., 2017).

To our knowledge, there have been two studies that have analysed the network structure of well-being items, both conducted before the pandemic. The first study included data across 4 large population-based cohorts (Stochl et al., 2019). Of these, one cohort comprised adolescents and young adults (14-25 year olds) and one involved adolescents only (12-16 year olds). On the whole, findings across all 4 cohorts were similar, suggesting minimal age differences. There were also minimal gender differences. Across all participants, positive self-perception and positive affect emerged as the key features (central items) of well-being. The second study was conducted only in children and young people from China (aged 6-18 years) (Zeng et al., 2019); a partial replication of the earlier UK findings by Stochl et al. was reported. Although positive affect and optimism emerged as being central to youth well-being, engagement was also a key feature. While informative regarding well-being in general, neither datasets inform a second aspect of well-being: the ability to be resilient and recover from more challenging circumstances.

In the present study, we applied network analysis to well-being data collected from young people (12-25 years) during the COVID-19 pandemic from May to December 2020. Our primary interest was to inform interventions to mitigate the damaging emotional impact of COVID-19 on young peoples' mental health but these data are also crucial to post-pandemic positive mental health or resilience interventions too. We investigated how well-being items clustered and which items were most central in all participants. Given we used the (short) Warwick–Edinburgh Mental Well-being Scale (Bartram et al., 2013; Tennant et al., 2007), we expected that items will cluster in terms of affective and functioning dimensions of well-being. Tentatively, we hypothesised that positive affect would emerge as a central item, given pre-pandemic network findings. However, as the core features of well-being may vary during times of stress, other items may also emerge as central features. We also compared whether centrality and clustering parameters would vary across males and females and across adolescents (12-18 years) and young adults (19-25 years). Based on minimal gender differences in the previous UK study (Stochl et al., 2019), we expected no differences in findings between males and females. Although neither the UK (Stochl et al., 2019) nor the China study (Zeng et al., 2019) explicitly explored age differences, prior (non-network) studies suggest that there may be mean level differences between adolescents' and young adults' deployment of specific coping strategies (Skinner & Zimmer-Gembeck, 2007). How this translates to which items are the most central feature of well-being is unknown.

Method

Participants and Procedure

The study was approved by the Psychiatry, Nursing and Midwifery Research Ethics Committee at Kings College London (ref: HR-19/20-18868). Anyone aged between 12 and 25 residing in the UK at the time of data collection in the UK was eligible to take part. Participants were recruited via several methods: advertising within UK schools, colleges and Universities, research advertisement websites, social media and charities. All participants aged 16 or over provided informed consent. For participants under 16, informed assent/consent was provided by participants and their parent/guardian respectively. The study was set up in response to the global COVID-19 pandemic, utilising an online survey to understand and monitor the emotional impact of the pandemic in young people. Data collection began on 12th May 2020 and ended on 2nd December 2020. The study, which consisted of a battery of measures including well-being, negative affect, anhedonia, loneliness, boredom, worries, and coping strategies was administered through the online platform, Qualtrics. Participants were offered vouchers for their time spent taking part in this and subsequent follow-up surveys. 4872 respondents clicked on the survey link. Respondents were removed from the data if they: 1) did not complete any survey measures other than initial demographic information (n=1932); 2) were duplicate responses (n=33); 3) did not meet age criteria (n=13); 4) had a survey completion time <5 minutes (n=41); 5) were not in the UK (n=48); 5) showed other evidence of careless /inauthentic responding (n=245); or 6) had missing data on key variables for this analysis (n=28). This allowed N=2532 for the final analysis.

Measures

Demographic Information. We measured participants' age, gender, ethnicity (using response options that corresponded to ONS-recommended harmonised country-specific questions for England, Wales, Scotland and Northern Ireland), educational level, socioeconomic status (SES; indexed by highest qualification obtained by either parent), and country of current residence.

Warwick – Edinburgh Mental Wellbeing Scale (WEMWBS). Given practical considerations of administering several online measures to young people, the short-version of the WEMWBS was used. Consisting of 7 items, this scale captures the concept of well-being as reflecting functional and affective aspects (although more items relate to functioning) and is robust and valid in community youth settings (Bartram et al., 2013; Tennant et al., 2007). Each item is rated between 1 (none of the time) and 5 (all of the time).

Analysis

Network analysis quantifies links ("edges") between observed items ("nodes") of a measure; thus it informs the overall structure of items, clusters ("communities") of items, and items that are more connected ("central") (Costantini et al., 2015). All analyses were performed by various packages within the statistical software, R, version 1.2.5033-1(Team, 2013): "qgraph version 1.6.5" (Epskamp et al., 2012), "bootnet version 1.4.3" (Epskamp et al., 2018)"NetworkComparisonTest version 2.2.1" (van Borkulo et al., 2016) and "NetworkToolbox version 1.4.0" (Christensen, 2018). The Gaussian graphical model (GGM, (Costantini et al., 2015)), an undirected weighted network, was estimated based on partial Spearman correlations between observed variables. To infer the characteristics of interest (i.e. relationships between nodes, clusters among nodes, the most central items), we evaluated the network structure using measures taken from graph theory (Müller et al., 2012). When estimating the GGM, we employed GLASSO regularisation ("graphical least absolute shrinkage and selection operator", (Tibshirani, 1996) to ensure the sparsity (fewer edges) of the model with the Extended Bayesian Information Criterion (EBIC, (Chen & Chen, 2008)) to select the best-fitting model.

These analyses yielded 4 sets of information. First, while GGMs were estimated and plotted for all participants (and for each subgroup), the accuracy of edge weights was also evaluated. This step allowed for the assessment of the overall network structures. Second, centrality indices representing the degree to which a node influences or can be influenced by other nodes were estimated for each item. We focused on two centrality indices: strength and closeness (Newman, 2010) as these were stable in the present analysis. Strength suggests how strongly and frequently a node is directly associated (has edges) with other nodes. Closeness is indexed by the lengths of paths from any one node in the network to itself and calculated by the inverse sum of distances of the focal node to all other nodes based on their shortest paths (Costantini et al., 2015). Betweenness is the number of shortest paths passing through a specific node (Costantini et al., 2015), but as the index was not reliably estimated from the current dataset, it was not presented here. Third, the communities within the networks were detected using the Louvain algorithm (Rubinov & Sporns, 2011) on edge weights, which identifies nodes that cluster together. The Louvain algorithm optimises modularity, defined as the comparison between the edges' density of a community/cluster and edges' density outside this community/cluster, through moving each node to different communities/clusters (Blondel et al., 2008). This algorithm has been used in previous studies and shown good performance (Miers et al., 2020). Finally, to explore gender and age group differences, network comparisons across genders and age groups (12-18 and 19-25) were conducted. 18 years was selected as the cut-off because it reflected the median value within our age range. Network comparison analyses with Bonferroni correction were conducted on the global strength of the networks, which is the total sum of all edge weights (partial Spearman correlations) and reflects how tightly linked the entire network is, and on the centrality indices, across the different groupings with 5000 iterations.

To mitigate against any potential sample size limitations, we applied bootstrapping procedures to enhance the reliability of network parameters (Epskamp et al., 2018). 95% confidence intervals (CI) of edge weights were obtained through a bootstrapping method, involving repeatedly estimating a model under sampled data and the statistic of interest (Team, 2013). To investigate the stability of centrality indices, correlation stability (CS) coefficients were calculated by case dropping bootstrap methods. Here, the centrality measures are recalculated for different sub-portions of the data after dropping a random percentage of cases. The CS coefficient is defined as the amount of cases that can be dropped while still maintaining a high correlation (higher than .7) with the original centrality estimate (Epskamp et al., 2018). This coefficient should not drop below 0.25 and ideally be above 0.5 to justify robust interpretation of centrality indices.

Results

Participant Characteristics

The mean age of participants was 18.4 (SD 3.6), and there were more females (70.1%) than males (29.9%). Proportions of individuals in different ethnic groups was as follows: 62.6% White/Caucasian, 8.2% Mixed/multiple ethnic groups, 20.6% Asian/Asian British, 4.1% Black/African/Caribbean, 2.4% other ethnicities, and 2.1% prefer not to say. In terms of parental educational level, 2.9% reported parents with primary level qualifications, 13.4% with GCSE or equivalent, 18.7% with A level or equivalent, 39.5% with Higher level degree or equivalent, 19% with Masters and 6.4% with PhD.

The female group was older than the male group (Mean(SD)male = 17.6 (3.6), Mean(SD)female = 18.7 (3.6), t(2531) = 7.21, p < .001, d = .31, CI [0.81, 1.41]). There were also more males in the adolescent age group compared to the young adult age group (male ratioadolescence = 35.1%, male ratioadult = 22.1%, c2 =48.91, p < .001).

Network Structure Across all Participants

The estimated network of 7 items represented as nodes is presented in Figure 1a, where thicker lines reflect stronger partial correlations between items and all items are positively correlated. Two clusters were identified. The first cluster comprised 3 items: item 1 ("*I've been feeling optimistic about the future*"), item 2 ("*I've been feeling useful*") and item 6 ("*I've been feeling close to other people*"). The second cluster consisted of the remaining items: item 3 ("*I've been feeling relaxed*"), item 4 ("*I've been dealing with problems well*"), item 5 ("*I've been thinking clearly*") and item 7 ("*I've been able to make up my own mind about things*"). The centrality analysis showed items 4 and 5 had the highest standardised strength and closeness, each estimated with high stability (CS-coefficient values for strength and closeness were both 0.75, see Table 1).

Gender Differences of Well-Being Networks

There were no significant differences in overall global strength in the networks of males and females, $p = .48$. Both male and female group networks clustered in the same way as those of the whole sample (Figure 1b). Centrality analyses (i.e. strength and closeness) showed that items 4 and 5 had the highest strength and closeness across *both* males and females, resembling that across all participants. Strength indices were mostly stable in both gender groups (see Table 1) but the CS-coefficients for closeness in males showed only acceptable stability (CS-coefficient = .44), suggesting caution when interpreting male-only results. Of note, additional analyses on age-matched groups were similar to the unmatched groups with no gender differences in overall global strength, clusters and centrality analysis.

Age Differences of Well-Being Networks

The network comparison test showed no significant global network strength difference between groups, $p = .3$. Both age groups showed the same two clusters as those of the whole group network (Figure 1c). Centrality indices (i.e. strength and closeness) were stable in both age groups (Table 1). Items 4 and 5 had the highest strength in both groups. In terms of closeness, item 5 ("*I've been thinking clearly*") had the highest closeness in the adolescent group (12-18 years) whereas in young adults (19-25 years), item 4 ("*I've been dealing with problems well*") had the highest closeness.

Of note, due to differences in the proportion of males to females across age groups, we repeated analyses with gender-matched groups, which yielded similar results to unmatched groups.

Discussion

The outbreak of COVID19 and government measures to mitigate infection rates have meant new daily routines for many young people (changes in educational, occupational, social and recreational activities), uncertainties over the physical health and morbidity of themselves, family members/friends/acquaintances, and wider society, and an exacerbation over any existing stressors (e.g. family dynamics, over-crowded housing) (Janssen et al., 2020). As well-being can protect against future distress and mental health problems (Saxena et al., 2006), understanding how individuals maintain well-being in the face of these challenges at a developmental juncture typically associated with the emergence of persistent lifelong psychiatric symptoms (Paus et al., 2008) is important for prevention. Although sparse, pre-pandemic data (Stochl et al., 2019; Zeng et al., 2019) are consistent in showing that experiences of positive affect (e.g. feeling cheerful) are at the centre of well-being networks, and that this is true across genders and across ages (children, young people, adults). Our findings taken during the pandemic revealed a different set of key features, which related to functional aspects of well-being, notably, processing problems and ideas (i.e. "I've been dealing with problems well" and "I've been thinking clearly"). Well-being items could be differentiated into two distinct clusters. The first included items about optimism, positive self-perception, and social connectedness, while the second broadly related to processing problems/ideas. Consistent with a previous UK study, we found no

Table 1. Correlation stability coefficients of networks for all participants, each gender group and each age group.

	n	Strength	Closeness
All	2532	0.75	0.75
Gender			
male	757	0.75	0.44
female	1775	0.75	0.67
Age			
Adolescents	1517	0.75	0.67
Young adults	1015	0.75	0.36

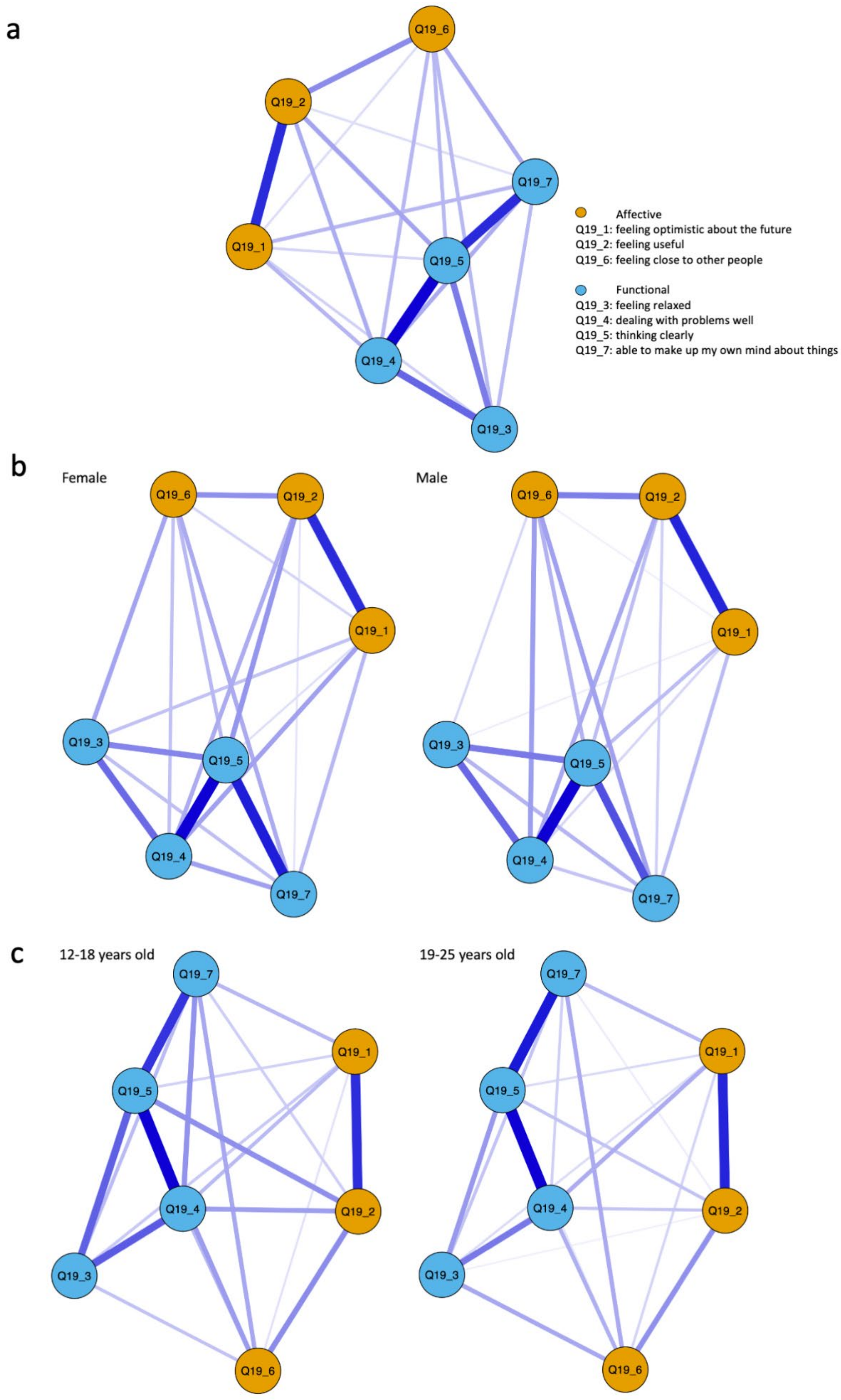
gender differences in global network strength, clusters and central items but subtle age differences on central items only were found. There were no age differences in items reflecting the highest strength; that is, both clear thinking and problem-solving were equally strongly associated with other items across adolescents and young adults. In terms of closeness (how quickly an item can affect other items or be affected by other items), clear thinking had the highest closeness index in adolescents (12-18 years) but problem-solving emerged as being closest to other items in young adults (19-25 years). Each of these findings are discussed.

Although direct comparisons between our study findings and the two previous studies are somewhat constrained by the use of different well-being measures, developmental differences (with the UK study, (Stochl et al., 2019)) and cultural differences (with the Chinese study, (Zeng et al., 2019)), nonetheless, the broad pattern of findings around central items is different between those collected pre-pandemic and ours collected during lockdown – a time of stress and uncertainty. While both pre-pandemic studies identified positive mood as a key feature of well-being, pandemic data indicated that a functional aspect of well-being, notably processing problems and ideas, became more prominent. In network analyses, being prominent means that these items have more strong connections with other items. Once activated, these items may also be likely to quickly influence other items and be quickly influenced in turn. Within the concept of well-being, this suggests that under conditions of stress and uncertainty, being able to problem-solve and think clearly could impact other affective aspects of well-being including optimism, positive self-perception and feeling connected to others. That these findings differ from pre-pandemic findings suggests that the emotional challenges posed by the pandemic requires more than the experience of positive affect to maintain well-being. Indeed, being able to manage and control feelings that emerge specifically to stress and uncertainty by thinking clearly and problem-solving appear to be important. Future studies may wish to differentiate whether it is objective abilities or simply the perception of being able to think clearly and problem-solve that is important to resilience.

Nonetheless, these findings suggest that therapeutic techniques encouraging problem-solving and thinking more clearly (or nurturing the perception of these cognitive capacities) could nurture resilient outcomes to challenging situations. These findings are useful for dealing with stressful life events more generally. However, these skills need to be directed at problems that are carefully selected, not just for personal salience but are also within control and achievable. While our findings suggest that such interventions may be applicable to males and females, somewhat different intervention targets could benefit adolescents and young adults. Adolescents who are struggling may benefit more from instruction around thinking clearly (sustained, flexibly, being able to ignore distractors), while struggling young adults could be more receptive to guidance over solving the problems that they are facing.

Beyond findings on the centrality of items, our data also shed light on the network structure of items during the pandemic. In network analysis, clusters within networks may not necessarily suggest that these items have conceptual equivalence, as they perhaps do in factor analysis. Instead, clusters point to more dense patterns of inter-connection or co-activation within a subset of items. We identified two clusters. The first pertained to items mapping onto the affective aspects of well-being: optimism, positive self-perception and connectedness with others while the second cluster mapped more onto functional aspects of well-being, specifically, cognitive-processing of problems, ideas and decisions. At first glance, the items of the first cluster appear more heterogeneous, but given the restrictions, changes and uncertainty of the pandemic,

Figure 1. Network clusters of well-being items for: a) all participants; b) two gender groups, and c) two age groups.



may have been re-defined together because they are all more difficult to achieve. Yet, their differentiation from processing problems and ideas are also somewhat consistent with previous research. For example, Stohl and colleagues reported that items around processing problems and ideas were highly related but distinct from items of self-perception (which were themselves highly related), and from items of relationships with others (again highly related to each other). Although feeling relaxed also feels more "affective" in nature compared to the more "cognitive" aspects of the second cluster, it may be that it co-activates with these items more because feeling relaxed is important for cognitive processing such as thinking clearly, decision-making and problem-solving, an association that is especially evident during mindfulness meditation (Jay Lynn et al., 2006; Tarrasch, 2015).

There are some study limitations. First, as we used a different measure to previous studies, our findings are not directly comparable. Specifically, we used the 7-item Warwick-Edinburgh Mental Well-being Scale (WEMWBS), whereas the previous study of British sample used the 14-item version and the study involving Chinese adolescents used the 20-item Chinese version of Engagement, Perseverance, Optimism, Connectedness, and Happiness scale (EPOCH). The 7-item scale we used contains fewer affective well-being items compared to the 14-item scale, and the WEMWBS considers two behavioural dimensions of well-being rather than the more in-depth EPOCH, which measures five clusters of well-being. Differences between these measures (and their underlying constructs) means it is difficult to attribute discrepancies between findings to differences in environmental circumstances (pre and during the pandemic). Another concern about measurement is our reliance on self-reported items only; this means that for some of the key features of well-being reflect perceptions rather than objective capacity to use these skills. Second, because it is challenging to incorporate continuous age differences as a moderator into network analysis, to assess age differences we divided the sample into those above and below the median value. 18 years was the median in our sample, however, it is also a transitional juncture where some 18 year olds have begun University and others are still in secondary school, adding to the heterogeneity of the adolescent sample. Third, not all young people experienced the COVID-lockdown to the same degree of impact; some may have experienced greater bereavements, different levels of restrictions with varied lockdown rules and tiers occurring in different geographic locations. Finally, our sample may not be representative of the UK population in terms of SES (based on parental educational qualifications) and ethnicity. Compared to reports from the Office for National Statistics, our sample had higher SES, contained a lower proportion of participants describing themselves as belonging to a White ethnic group, and a higher proportion belonging to a minority ethnic group (Office for National Statistics, 2018).

In closing, our findings suggest that the perception of being able to process problems and ideas efficiently could be a hallmark of well-being, particularly in the face of challenging circumstances. Tentatively, developing interventions that encourage (perceptions of or actual) problem-solving and mental flexibility could be useful in helping young people maintain well-being during times of stress and uncertainty, either during later phases of the pandemic or even post-pandemic.

Additional Information

Supplementary Materials

Supporting information includes network analysis results (centrality graphs and bootstrapping results for all participants, see FigS1, gender groups, see FigS2, and age groups, see FigS3) and R code for network analysis and comparison, see SRcode.docx. Supplementary materials for this article can be viewed here: https://osf.io/4s76g/

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Conflict of Interest

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

Ethical Approval

This study was approved by the research ethics committee of King's College London (reference: HR-19/20-18250)

Data Availability

Data and study materials are available upon request.

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