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The "central" importance of loneliness in mental health: A network psychometric study

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Loneliness is linked to negative mental health outcomes like depression and social anxiety. However, it is unclear how loneliness and these conditions are connected. This study aims to address two questions: (a) Are there pathways connecting loneliness to these conditions? (b) What symptoms play a role in these pathways? Using network analyses, the study examined a representative sample of 962 adults from the UK (mean age = 46, females = 492). The network analysis revealed four dimensions: depression, social anxiety and two dimensions for loneliness (isolation and social connectedness). Two distinct pathways were identified for the transmission of symptoms between loneliness, social anxiety and depression. The depression-isolation pathway involved a node representing the perceived loss of social connections. The social anxiety-social connectedness pathway was characterised by intimate interaction contexts. These findings suggest that loneliness is associated with different symptom pathways, potentially contributing to comorbidity between loneliness, social anxiety and depression.

Keywords: Loneliness; Perceived social isolation; Social anxiety; Depression; Network psychometrics.

Forming connections is a human need (Baumeister & Leary, 1995). Loneliness may arise when this need is not met (Perlman & Peplau, 1981). Loneliness is associated with mental health problems like social anxiety and depression (Heinrich & Gullone, 2006), but the nature of this association is not clear. Loneliness, social anxiety and depression are broad constructs that encompass diverse mental experiences. The current study investigates if there are specific links between particular aspects of loneliness, social anxiety and depression using a network psychometric approach.

Loneliness, social anxiety and depression are distinct yet highly related constructs, as suggested by both qualitative and quantitative research (Perlman & Peplau, 1981). For instance, Fung et al. (2017) conducted a study on social anxiety, loneliness and depression, employing factor analysis on questionnaire responses from around 1000 undergraduate students. The results indicated that social anxiety and loneliness are partially independent traits and separate from depression. Further, loneliness has been found to predict anxiety and depression beyond autoregressive effects in longitudinal studies (Bayat et al., 2021; Matthews et al., 2016).

Loneliness, social anxiety and depression are complex concepts encompassing diverse mental experiences. For instance, regarding loneliness, Weiss (1973) distinguished between different types of loneliness, such as lack of close relationships versus not feeling part of a group. Factor analyses of the UCLA Loneliness Scale have identified multiple dimensions, including lacking close personal relationships ("isolation") and not belonging to a social group ("social connectedness," McWhirter, 1990; Shevlin et al., 2015). Regarding the association of subdimensions of loneliness with mental health constructs, Shevlin et al. (2015) found that the isolation subdimension of loneliness had a strong connection with general psychopathology, while social connectedness had moderate links. This indicates that there may be specific links with mental health for particular aspects of loneliness.

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Beyond the construct level, additional insight could be gained by investigating the link between specific indicators of depression, anxiety and depression. The traditional view of psychiatric conditions sees mental disorders as latent constructs expressed through specific symptoms (Borsboom, 2017; Robinaugh et al., 2020). For instance, depression is characterised by dysphoria, loss of interest, changes in weight, negative self-perception and suicidal ideation (DSM). Similarly, loneliness is marked by feelings of isolation, lack of meaningful relationships and social disengagement (Russell, 1996). In this view, symptoms serve as indicators of an underlying condition, and their information is typically combined into a single score (e.g., by counting symptoms or averaging questionnaire subscales). In contrast, network psychometrics interprets the relation between symptoms and disorders as mutually reinforcing clusters (Borsboom, 2017; Fried et al., 2017; Robinaugh et al., 2020). It suggests that symptoms within a specific mental health condition have a causal effect on one another, leading to clustering, instead of clustering being solely due to a common underlying cause as proposed in the traditional view. These causal webs are more interconnected within constructs, but comorbidity can be explained by certain symptoms exerting a causal influence on symptoms in other constructs (referred to as a bridge node; Jones et al., 2021). From a network psychometrics perspective, the strong association between loneliness and mental health constructs can be attributed to bridges between specific symptoms within each construct. Identifying these associations is crucial for understanding how symptom activation spreads between constructs. Previous studies have examined networks involving loneliness, generalised anxiety disorder (GAD) and depression. While social anxiety and loneliness are inherently interpersonal, GAD is not. Thus, it is crucial to test a psychometric network that incorporates social anxiety. Additionally, social anxiety symptoms may have a distinct relationship with loneliness compared to other mental health constructs, as it has been found to predict future loneliness, unlike paranoia and depression (Lim et al., 2016). No prior network analysis has included both these constructs, and this study aims to fill that gap.

The current study applied psychometric network analysis to identify any symptoms linking loneliness, social anxiety and depression. Given the strong association previously found between these conditions, we hypothesised that indicators of loneliness would be central nodes in the network, acting as bridges between the three conditions.

PARTICIPANTS AND METHODS

Procedure

Participants were recruited online through the research participant platform Prolific.co. Prolific.co maintains a panel of research participants who complete screening questions, allowing researchers to recruit based on selection criteria. For this study, a representative sample of the UK population was recruited to address the limited representativeness of previous studies that relied on convenience samples of university students. Prolific.co creates representative samples in terms of age, gender and ethnicity using UK Census Bureau and Office for National Statistics data. Participants had to be over 18 years old to register on Prolific.co and participate in the study. Compensation of £7.50 per hour was provided, resulting in a payment of £1.25 for the 10-minute study duration, following the recommended hourly rate for online studies at the time. The study used Qualtrics XM (Qualtrics, Provo, UT), an online survey platform.

Participants completed a questionnaire on demographic information, including age, sex, ethnicity and history of psychiatric disorders. They were also asked if they were completing the study alone or with others. Next, participants were presented with three questionnaires in a randomised order: the UCLA Loneliness Scale Version 3 (Russell, 1996), the Social Anxiety Interaction Scale (Mattick & Clarke, 1998) and the depression subscale of the Depression Anxiety Stress Scale (Lovibond & Lovibond, 1995). The UCLA-LS consists of 20 items rated on a 4-point Likert scale (Russell, 1996), with excellent reliability in the current sample (Cronbach's alpha: 0.95). The SIAS includes 20 items rated on a 5-point Likert scale (Lindner & Martell, 2013; Mattick & Clarke, 1998), with excellent reliability in the current sample (Cronbach's alpha: 0.96). The DASS-D has 14 items rated on a 4-point Likert scale, displaying excellent reliability in the current sample (Cronbach's alpha: .96). An instructed response item was included to identify careless responders (Meade & Craig, 2012).

Participants

A total of 1018 participants completed the study. Based on the instructed response item attention check, 16 participants were excluded. In addition, 40 participants were flagged as potential careless responders based on their longest string of responses ($n = 6$), low even-odd correlation ($n = 21$) and/or high Mahalanobis distance for summed questionnaire scores ($n = 15$). The main analyses were run excluding these participants. The final sample consisted of 962 participants. There was no significant difference between the final sample and the potentially careless responders in age, sex or ethnicity (see Table 1). The group of participants who met criteria for careless responding included a higher proportion of mental health diagnoses and had higher scores on the depression questionnaire (see Table 1).

TABLE 1
Descriptive statistics for the main analysis sample (final) and participants who met criteria for careless responding (careless)

	Final (n = 962)	*Careless (n = 40)*	*p*
Age, mean (*SD*)	46.0 (15.8)	42.9 (16.5)	.164
Sex, *n* (%)			
Female	492 (51.1)	26 (46.4)	.181
Male	467 (48.5)	29 (51.8)	
Other	1 (0.1)		
Decline to answer	2 (0.2)		
Ethnicity, *n* (%)			
White	802 (83.4)	48 (85.7)	.929
Asian	79 (8.2)	5 (8.9)	
Black	40 (4.2)	1 (1.8)	
Mixed	21 (2.2)	1 (1.8)	
Other	20 (2.1)	1 (1.8)	
Mental health diagnosis, *n* (%)			
Yes	341 (35.6)	29 (52.7)	.028*
No	607 (63.4)	25 (45.5)	
Not known	10 (1.0)	1 (1.8)	
Declined to answer	0 (0.0)	0 (0.0)	
DASS-D, mean (*SD*)	18.5 (18.9)	40.1 (25.8)	<.001***
SIAS, mean (*SD*)	28.7 (17.4)	32.8 (18.4)	.085
UCLA-LS, mean (*SD*)	47.8 (12.3)	45.1 (13.2)	.109

Note: Statistical comparisons were based on chi-square tests and independent *t*-tests. DASS-D = Depression and Anxiety Stress Scale Depression score; SIAS = Social Interaction Anxiety Scale; UCLA-LS = UCLA Loneliness Scale. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Statistical analysis

All statistical analyses were carried out in R v4.1.2 in April 2023. The anonymised data and analysis code are available via the Open Science Framework: https://osf.io/n28t9/?view_only=73ad725e43114ac0a07dc4f6b3d04ac0.

Factor analysis

It is often difficult to interpret network psychometric analyses. In this study, we attempted to relate the results of network psychometric analysis to previous factor analytic studies by associating nodes with construct-level labels. To this end, we obtained the joint factor structure of loneliness, social anxiety and depression. An exploratory factor analysis (EFA) was conducted using the psych package v2.2.3 for R (Revelle, 2016). Due to the non-normal distribution of item responses, principal axis factoring with oblique rotation (direct oblimin) was used. Polychoric correlations were employed to account for the limited response range. Several indices, including eigenvalue, very simple structure (CSS), minimum average partial (MAP), Bayesian Information Criterion (BIC) and Extended Bayesian Information Criterion (BIC), were calculated to determine the optimal number of factors. Parallel analysis with 10,000 random permutations was also performed.

Additionally, exploratory graph analysis (EGA) was applied as a novel method known for providing a superior factor solution in simulation studies (Golino et al., 2020). The EGAnet package v1.0.1 was used for EGA, constructing a psychometric network using glasso regularisation or a triangulated maximally filter graph (TMFG) approach (Golino et al., 2020). The network was then divided into modules using the Louvain or Walktrap algorithm. The results of EGA were evaluated based on graph construction and community detection algorithms. Permutation testing with 10,000 permutations was conducted to assess the stability of the solutions.

Network psychometrics

The aim of the study was to examine the associations between nodes representing loneliness, social anxiety and depression using network psychometric analysis. Network estimation was performed using the estimateNetwork function of the bootnet package v1.5 (Epskamp et al., 2018), with non-parametric bootstrapping and 10,000 bootstrap samples for edge estimate accuracy. Network visualisation was done using the qgraph package v1.9.2 (Epskamp et al., 2012). Different network construction methods implemented in bootnet, including optimal Gaussian graphical model, sparse Gaussian graphical model with graphical lasso, high-dimensional undirected graph estimation and unregularised methods were compared. The use of various network construction algorithms was motivated by uncertain nature of real-world data, particularly psychological variables. Unlike simulated networks, empirical networks lack a definitive ground truth, making it challenging to determine a single optimal algorithm.

Employing multiple algorithms allowed us to comprehensively explore potential network structures and assess robustness. This approach enhances the reliability and validity of our findings.

Additional network models were run, incorporating potentially confounding variables such as age, gender, history of mental health conditions and circumstances during questionnaire completion (alone, with company or in public). Mixed Graphical Models (MGMs) were used for estimating models with categorical, ordinal and continuous variables.

The resulting networks were characterised using established measures of node influence, including betweenness, closeness and expected influence (Borsboom et al., 2021; Robinaugh et al., 2016). Nodes bridging between the loneliness, social anxiety and depression factors identified in the factor analyses were identified using equivalent measures, such as bridge-betweenness, bridge-closeness and bridge-expected influence (Jones et al., 2021). All measures were calculated with 10,000 permutations and case-wise deletion using bootnet. Influential nodes were defined as nodes with influence measures at least 1 standard deviation above the mean across all nodes.

RESULTS

Questionnaire scores and influence of demographic factors

Regarding the questionnaire scores, on the loneliness questionnaire, 586 participants (60.91%) showed elevated scores potentially indicative of high loneliness (total score >43), 292 (30.35%) moderate loneliness (total score 28–43) or for low loneliness (total score <28, 306 [31.81%], Lee et al., 2019). For the social anxiety questionnaire, 344 participants (35.76%) showed elevated social anxiety symptoms (total score >34, Rodebaugh et al., 2006). In terms of depression scores, 663 participants (68.92%) met elevated score criteria (total score >16, Evans et al., 2021). Men reported higher loneliness scores than women, as shown in Table 2. Participants who reported a diagnosis of or treatment for a mental health condition had higher self-ratings of depression, social anxiety and loneliness (see Table 2). Younger participants reported higher self-ratings of depression, social anxiety and loneliness (see Table 2). There were no significant associations between ethnicity or being alone when filling in the questionnaires and the scores of depression, social anxiety or loneliness.

Factor analysis

Exploratory factor analysis

EFA was conducted to determine the optimal number of factors for the loneliness, social anxiety and depression questionnaires. Bivariate correlations between the items were positive but not redundant ($0.10 \leq r \leq 0.95$, see Figure S1). The indicators did not agree on the number of factors, with the Kaiser-Guttman criterion suggesting four factors and MAP and parallel analysis favouring seven factors (see Table S1). The four-factor solution explained 67% of the variance, while the 7-factor solution explained

TABLE 2
Influence of extraneous variables on total questionnaire scores

	DASS-D		*SIAS*		*UCLA-LS*	
Age, β	−0.19	<.001***	−0.26	<.001***	−0.21	<.001***
Sex, mean (*SD*)						
Female	17.9 (18.2)	.352	29.2 (17.6)	.289	46.9 (12.2)	.02*
Male	19.0 (19.6)		28.1 (17.0)		48.8 (12.4)	
Ethnicity, mean (*SD*)						
Asian	17.1 (17.1)	.188	27.9 (16.5)	.983	49.6 (13.4)	.311
Black	13.1 (18.3)		27.9 (17.8)		47.6 (13.2)	
Mixed	13.9 (12.9)		30.2 (19.5)		46.7 (10.9)	
Other	22.5 (21.4)		38.6 (16.9)		52.4 (12.5)	
White	18.8 (19.1)		28.7 (17.3)		47.6 (12.2)	
Situation, mean (*SD*)						
Alone	18.5 (19.0)	.392	28.5(17.1)	.571	48.0 (12.3)	.104
Company	16.0 (17.9)		30.4 (19.9)		45.3 (12.6)	
Public	22.0 (16.2)		30.4 (19.9)		51.2 (9.5)	
Mental health, *n* (%)						
Yes	28.7 (21.4)	<.001***	36.2 (17.7)	<.001***	53.0 (11.7)	<.001***
No	12.4 (14.1)		24.5 (15.6)		44.7 (11.6)	
Not known	24.6 (15.1)		23.6 (14.2)		54.6 (9.9)	
Declined to answer	42.5 (35.5)		36.2 (23.8)		57.5 (13.5)	

Note: Values represent the mean and standard deviation (in brackets) in each group for categorical variables and the standardised beta-coefficient for continuous variables. Statistical comparisons were based on *t*-tests or one-way ANOVA. DASS-D = Depression and Anxiety Stress Scale Depression score; SIAS = Social Interaction Anxiety Scale; UCLA-LS = UCLA Loneliness Scale. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

70.97% of the variance. Considering the balance between complexity and interpretability, the four-factor solution based on the Kaiser-Guttman criterion was chosen (see Supporting Information for the seven-factor solution).

In the four-factor solution, the first factor, labelled "social anxiety," explained 24.34% of the variance and loaded heavily on items from the social anxiety questionnaire and Item 17 of the loneliness questionnaire ("How often do you feel shy?," see Figure S2 for factor loadings). The second factor, labelled "depression," explained 21.58% of the variance and loaded strongly on all items of the depression questionnaire. The third factor, labelled "social connectedness," explained 17.06% of the variance and loaded prominently on positive items of the loneliness questionnaire and items from the social anxiety questionnaire related to socialising. The fourth factor, labelled "isolation" explained 4.02% of the variance and loaded significantly on the negative items of the loneliness questionnaire.

Exploratory graph analysis

EGA was used as an alternative network-based method to characterise the factor structure of the loneliness, social anxiety and depression questionnaires. Two network construction methods (glasso, TMFG) and two community detection algorithms (Louvain, Walktrap) were compared. Bootstrap analysis with 1,000 resamples showed that the glasso regularisation with the Louvain algorithm yielded a more stable solution, indicated by a smaller confidence interval (glasso-Louvain: 4 [3.94, 4.06]) and higher consistency across bootstrap repetitions (99.9% for glasso-Louvain). The bootstrap analysis confirmed excellent stability of all items in the four-factor solution (Golino et al., 2020).

In the four-factor solution, separate factors were identified for the items of the depression questionnaire and the social anxiety questionnaire. The "social anxiety" factor also included Item 17 of the loneliness questionnaire. Another factor consisted of the negatively phrased items of the loneliness questionnaire, similar to the "isolation" factor in the four-factor EFA solution. The fourth factor comprised the positively phrased items of the loneliness and social anxiety questionnaires, resembling the "social connectedness" factor in the EFA four-factor solution.

Network psychometric analysis

We constructed psychometric networks using multiple algorithms and created a consensus network by including edges present across all methods (representation of networks using particular algorithms are shown in Figures S5–S9). The resulting network, shown in Figure 1 and Figure S1, represents regularised partial correlations between factor scores or items, with edge weights ranging from −0.03 to 0.62. The stability of the network was assessed using the ggmModSelect algorithm, yielding a Bootstrap Confidence Interval (BCI) with 440 non-zero edges and a centrality stability (CS) coefficient of 0.67.

Node measures were used to identify highly influential nodes, defined as having metric scores at least 1 standard deviation above the mean on at least two influence indices. Four items from the loneliness questionnaire, one item from the social anxiety questionnaire and one item from the depression questionnaire met this criterion (Figures 1 and 2). D09 ("I feel downhearted and blue"), S20 ("I am unsure whether to greet someone I know only slightly"), U17 ("How often do you feel shy?") and U20 ("How often do you feel that there are people you can turn to?") were identified as highly influential nodes (marked with a square in Figure 1). S05 ("I find it easy to make friends my own age"), U02 ("How often do you feel that you lack companionship?"), U05 ("How often do you feel part of a group of friends?"), U07 ("How often do you feel you are no longer close to anyone?") were identified as highly influential bridge nodes (marked with a diamond in Figure 1). U07 and S05 met the criteria for general and bridge measures, indicating their high importance. These findings were consistent across most network construction methods.

Including covariates (age, sex, ethnicity, mental health diagnosis and situation during questionnaire completion) did not alter the network structure, except for a negative association between age and item S12 (at ease at parties). Node metrics could not be computed for the network with covariates due to limited connections with the main network, except for age's association with S12. The inclusion of age as a node did not affect the network measures.

DISCUSSION

The goal of this exploratory study was to examine the links between indicators of loneliness, social anxiety and depression. One particular loneliness symptom, UCLA-LS item 07 ("How often do you feel that you are no longer close to anyone?"), emerged as a highly influential bridge node, connecting multiple pathways to the depression community. This finding suggests that loneliness-related items may play a central role as bridge nodes in the network, aligning with our initial expectations. Additionally, we identified two influential bridge nodes within the social anxiety community, linking to multiple nodes in the social connectedness community.

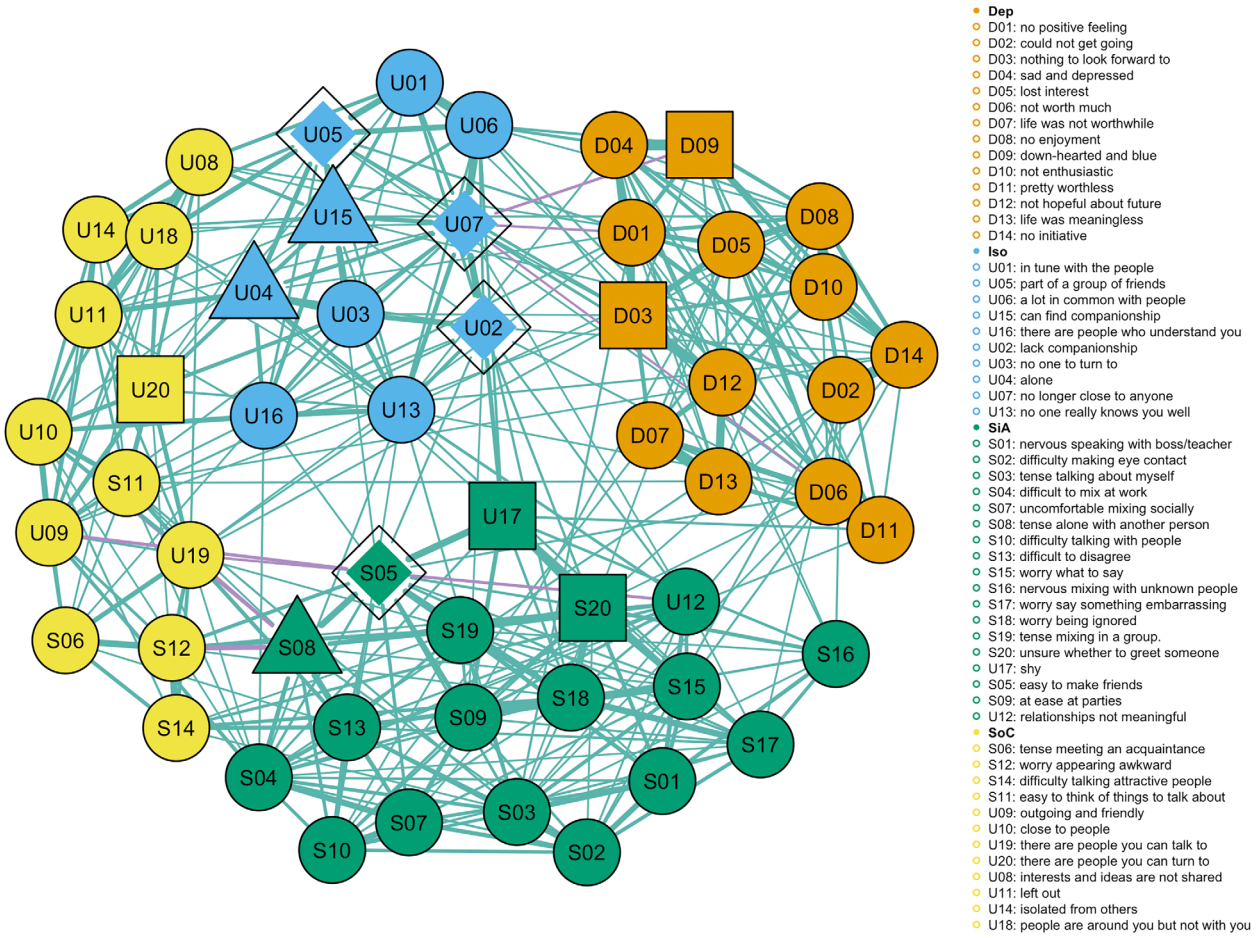

Figure 1. Consensus network. *Note:* The consensus network, indicating the grouping according to exploratory graph analysis (EGA), is displayed with edges colour-coded. The legend provides a shortened description of item content. Nodes exceeding 1 standard deviation above the mean for two or more influence measures are denoted by a square, while nodes meeting the same criterion for bridge influence measures are marked with a triangle. Nodes fulfilling both regular and bridge influence criteria are represented by a diamond. All edges in the network were positive. The purple edges highlighted in the figure are discussed in detail in the main text. Dep = depression; Iso = isolation; SoA = social anxiety; SoC = social connectedness; D = Depression and Anxiety Stress Scale Depression score; S = Social Interaction Anxiety Scale; U = UCLA Loneliness Questionnaire.

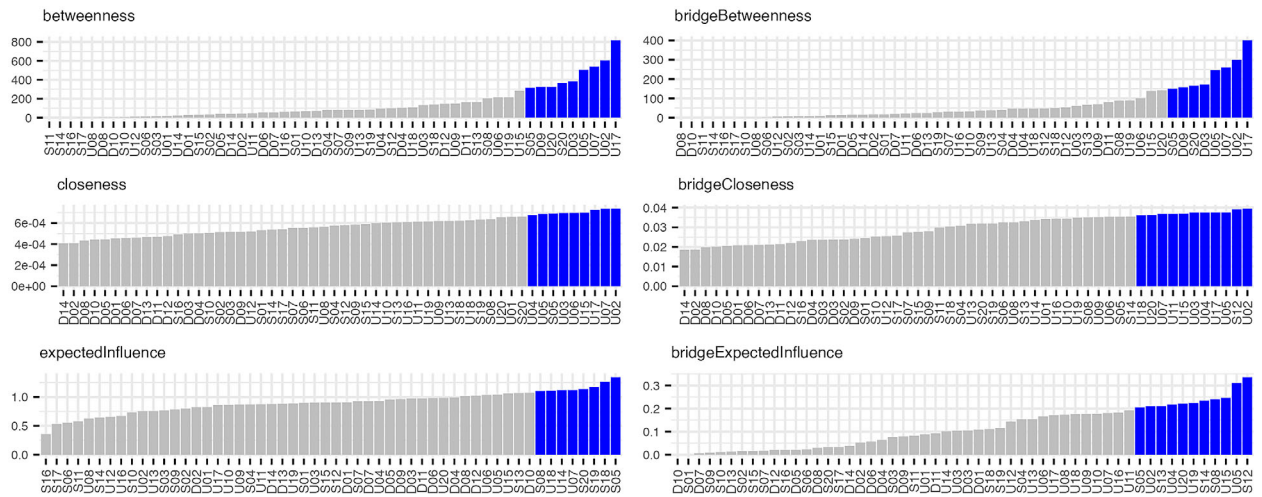

Figure 2. Overview of influential nodes. *Note:* The ranking of nodes on centrality (left) and bridge centrality (right) measures is shown. Nodes that are 1 standard deviation above the mean across all nodes are highlighted in blue.

Loneliness, social anxiety and depression questionnaires form four separable communities

In our initial step, our goal was to determine if loneliness, social anxiety and depression formed distinct communities to align our network psychometric analyses with previous factor analytic studies. Through factor analysis and community detection methods, we successfully established the separability of these constructs, consistent with previous studies (Fung et al., 2017). This finding is valuable from a network perspective as it suggests that different causal mechanisms connect the clusters of symptoms within separate communities.

The depression items formed a tightly clustered community without any overlap. The loneliness and social anxiety items, overall, formed distinct communities aligned with their conceptual constructs. However, at the boundaries, there was notable overlap among certain items. For instance, four items from the Social Interaction Anxiety Scale (SIAS) were located within the social connectedness community, while two items from the UCLA-Loneliness Scale were clustered with the social anxiety community. This indicates that the communities had distinct cores but became blurred at their edges. Loneliness, specifically, formed two distinct communities labelled as isolation and social connectedness here, which differs from some previous research that identified a single dimension of loneliness (e.g., Fung et al., 2017). This discrepancy may be attributed, in part, to the use of EGA that has been shown to produce more stable factor solutions in simulation studies (Golino et al., 2020). The convergence of this method with EFA across multiple indicators suggests that the four-factor solution is a robust characterisation of our data (Steegen et al., 2016).

It is important to note that all the algorithms employed a "hard clustering" approach, which means they assigned each node to a single community. However, this approach may not accurately capture nodes that could belong to more than one community. For instance, fuzzy algorithms like clique percolation have been suggested as alternatives to identify nodes with potential multiple community assignments (Blanken et al., 2018). However, these algorithms are less well established in network psychometrics and can be more difficult to tune and interpret. Instead, we focus on bridge metrics to identify nodes that act as intermediaries between different communities.

Loneliness symptoms have central influence across the psychometric network

Our network psychometric analysis revealed that loneliness symptoms play a central role in the combined network of loneliness, social anxiety and depression. They exhibited high graph measures of betweenness, closeness and expected influence, indicating their influential position within the network. Loneliness symptoms showed distinct connections with nodes representing social anxiety and depression. Conversely, the social anxiety and depression communities had pathways connecting to different loneliness communities. Specifically, depression nodes connected with the loneliness community of isolation, while anxiety connected with the loneliness community of social connectedness. These findings align with previous research demonstrating the relationship between loneliness and social anxiety and depression (Lim et al., 2016, Owczarek et al., 2022). It suggests that the pathways through which comorbidity can spread between loneliness and the two mental disorders are specific to the dimension of loneliness. This contributes to the growing evidence highlighting the association between loneliness and depression, as well as loneliness and social anxiety (Lim et al., 2016).

Specific transmission pathways between loneliness and mental health constructs

The isolation-depression pathway

We now delve into the specific bridge nodes to translate the abstract network concepts into psychological understanding. Network psychometric results are often difficult to interpret due to the dense information contained in the graph. In this section, we want to highlight a few connections that emerged as important for the links between loneliness, social anxiety and depression. We identified a prominent bridge node that connects the isolation community and the depression community, which is loneliness item U07 (How often do you feel that you are no longer close to anyone?). This item exhibits connections with multiple nodes in the depression community (specifically nodes: D01, D09). Connections between U07 with D01 and D09 were still observed in the network that including age, sex and ethnicity as covariates, indicating the robust association of these nodes. U07 stands out within its community because it suggests a loss of connection, indicating that there was a time when the person was once close to someone. The high influence of this node aligns with the evolutionary explanation of depression proposed in the Unified Model of Depression (Beck & Bredemeier, 2016). According to this perspective, depression is an adaptive response to the perceived loss of a valuable resource necessary for survival. Research has shown that stressful life events, including the perceived loss of social connections, can trigger depression (Cacioppo & Cacioppo, 2018; Kendler et al., 1999; Slavich et al., 2009). Therefore, feeling no longer close to anyone can be perceived as a scarcity in social resources, and the depressive response may be an evolutionary programme to conserve energy until vital social resources are regained.

It's important to note that from the cross-sectional network analysis, we cannot determine the direction of causality. However, we hypothesise that this loneliness symptom primarily triggers the manifestation of depression symptoms. This hypothesis aligns with the evolutionary explanation of depression and is supported by previous research indicating that loneliness predicts future depression, while depression does not predict future loneliness (Lim et al., 2016). Testing this hypothesis could be explored in future studies, such as applying network analysis to longitudinal data to unravel causal influences.

The social connectedness — Social anxiety pathway

Within the social anxiety community, we identified two influential bridge nodes that connect to the social connectedness community. The first influential bridge node pertains to the perceived ease of forming new friendships, specifically among peers of the same age (S05: "I find it easy to make friends my own age"). This node stands out as it explicitly references the formation of new friendships. It connects to the social connectedness community through nodes S12 ("I worry about expressing myself in case I appear awkward"), U09 ("How often do you feel outgoing and friendly?") and U19 ("How often do you feel that there are people you can talk to?"). This bridge node may play a crucial role in the transmission between communities because individuals who perceive an ability to form new friendships may believe that they can establish new connections even if their current friendships are not successful. This self-confidence could shape their perception of the social environment, as they may feel more capable of finding people to talk to in various social situations. Consequently, having this self-confidence could serve as a protective factor against transmission between communities, while its absence may pose a risk factor.

The second influential bridge node represents a symptom related to feeling tense when alone with one other person (S08: "I feel tense if I am alone with just one other person"). This item emphasises one-on-one interactions and bridges into the social connectedness community through connections with items U10 ("How often do you feel close to people?"), U19 ("How often do you feel that there are people you can talk to?") and S12 ("I worry about expressing myself in case I appear awkward"). This suggests that this specific form of interaction, concerning the presence of only one person, plays a significant role in the transmission of activation between social anxiety and loneliness. Perhaps one-on-one interactions pose particular challenges because they require heightened focus on the interaction partner.

Overall, both bridges between social anxiety and social connectedness revolve around intimate interpersonal contexts, namely friendships and one-on-one interactions. There is substantial overlap in their cross-community pathways, with edges connecting to "feeling that you have people to talk to" and "worrying about expressing oneself in case one appears awkward." It is reasonable to view these bridges as two lanes of the same comorbidity pathway.

The loss pathway and the intimacy pathway

The main pathways of activation between mental health constructs are associated with different loneliness communities. The loss pathway extends from the isolation community to the depression community, while the intimacy pathway spans from the social connectedness community to the social anxiety community. This indicates that distinct aspects of loneliness may play a mechanistic role in the spread of activation between loneliness and these mental health constructs.

Furthermore, these pathways are characterised by different psychological constructs. The loss pathway, linking depression and isolation, emphasises a negative change leading to a deficit in social connections. In contrast, the intimacy pathway, connecting social anxiety and social connectedness, highlights situations in which close connections are formed.

The activation profiles of these pathways also differ. The loss pathway exhibits a fanning profile, with a single main node in the loneliness community connecting to multiple nodes in the depression community. On the other hand, the intimacy pathway displays a dual-lane profile, with two overlapping routes for activation to spread.

Therefore, it is crucial to consider not only specific symptoms that are closely associated with different mental health constructs but also the underlying psychological processes driving the activation (e.g., loss of connection or intimate interactions). These pathways may correspond to different phases of loneliness. The social withdrawal phase of loneliness may be more closely linked to depression, while the re-attachment phase may be more associated with social anxiety. Future longitudinal research should examine temporal effects by following individuals across different phases of loneliness.

LIMITATIONS

Several limitations should be considered when interpreting the findings. Firstly, the use of retrospective measures may not capture real-time emotional experiences accurately, relying on recollection and semantic knowledge. Future studies could incorporate experiential momentary assessment for direct measures (Robinson & Clore, 2002). Another limitation is the lack of specificity in some questionnaire items, combining different mechanisms and hindering the disentanglement of specific variables.

For instance, an item asking about forming new relationships does not differentiate between general friendships or friendships specifically with peers. Future research should include more specific items to establish causal pathways in psychometric network analysis. Furthermore, the study relied on cross-sectional, group-level data, limiting the determination of the direction of influence and generalizability to individuals (Fisher et al., 2018). Further, measures of network centrality may not adequately capture causal influence and may not replicate across datasets (Bringmann et al., 2019). To establish causal associations and identify causal primacy, longitudinal data and experimental manipulations, such as mood induction techniques, are needed. In addition, participants in the current studied were recruited via an online platform that provides monetary incentives for participation. Consequently, the sample may be biased towards a greater number of unemployed people or people from lower socioeconomic background (Vanhove et al., 2021), which could influence the rates of loneliness and mental health concerns. Addressing these limitations in future research will enhance the understanding of the dynamics and causal interactions within the network.

CONCLUSION

In conclusion, this exploratory study used factor and psychometric network analysis to examine the relationship between loneliness, depression and social anxiety. The findings revealed four distinct communities formed by these constructs, as indicated by factor and community detection analysis. Loneliness symptoms emerged as influential bridge nodes in the network, connecting to depression and social anxiety. Specifically, loneliness item U07 (How often do you feel that you are no longer close to anyone?) served as a significant bridge between the loneliness (isolation) community and the depression community, reflecting a loss of connection and linking to nodes related to low mood and self-worth. These results highlight the importance of considering loneliness in relation to depression and social anxiety, despite its absence from diagnostic systems and limited assessment in clinical settings. Further investigation is needed to understand causal mechanisms, emphasising the role of loneliness in the assessment of depression and social anxiety.

ETHICAL COMPLIANCE

The study adhered to the Declaration of Helsinki and the British Psychological Society's ethics guidelines for internet-mediated research. Approval was obtained from the local research ethics committee at Royal Holloway, University of London (REC ID: 3076). All participants provided written informed consent before participating.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Figure S1. Correlations between all questionnaire items based on polychoric correlations. Please find the full correlation matrix with numerical values on the Open Science Framework repository that accompanies this paper.

Figure S2. EFA factor loading for the 4-factor solution. Blue colours indicate positive loading, red values indicate negative loading. The error indicated 95% bootstrap confidence interval. Only factor loadings with an absolute value above 0.1 are shown. Abbreviations: DASS = Depression and Anxiety Stress Scale, SIAS = Social Interaction Anxiety Scale, UCLALS = UCLA Loneliness Scale, Social Conn = Social Connectedness.

Figure S3. EFA factor loading for the seven-factor solution. Blue colours indicate positive loading, red values indicate negative loading. The error indicated 95% bootstrap confidence interval. Only factor loadings with an absolute value above 0.1 are shown. Abbreviations: DASS = Depression and Anxiety Stress Scale, SIAS = Social Interaction Anxiety Scale, UCLALS = UCLA Loneliness Scale, Emotional Conn = Emotional Connectedness.

Figure S4. Psychometric network with covariates. This network contains covariates as nodes. Namely, the participant's age, sex, ethnicity, situation while completing the questionnaire (alone, in public, or in company), and history of mental health diagnosis were included. The network was constructed using the Mixed Graphical Models (mgm) package to accommodate binary and categorical variables.

Figure S5. Psychometric network constructed using the huge algorithm.

Figure S6. Psychometric network constructed using the MGM algorithm.

Figure S7. Psychometric network constructed using the EBICglasso algorithm.

Figure S8. Psychometric network constructed using the ggmModSelect algorithm.

Figure S9. Psychometric network based on partial correlations without regularisation.

Table S1. Indices used to determine the number of factors in exploratory factor analysis (EFA). The bold values indicate the optimum number of factors for each index. Abbreviations: VSS = very simple structure; MAP = minimum average partial; BIC = Bayesian Information Criterion; EBIC = Extended Bayesian Information Criterion; Kaiser = Kaiser-Guttman Eigen value rule; PAeig = parallel analysis observed eigenvalue; PAsim = parallel analysis simulated eigenvalue.

Table S2. Consistency of high influence nodes across different network construction methods. N: node measure B: bridge measure. Total: Count of how many times a node met the criteria for

high influence, i.e. one standard deviation above the mean for at least two of the influence measures.

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