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Original Research

A network analysis of depressive symptoms in adults with and without diabetes: findings from the Irish longitudinal study on ageing

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Abstract

Objectives: This study aimed to estimate networks of depressive symptoms among Irish adults with and without diabetes at two time points and compare between the two groups at each time point using data from the Irish Longitudinal Study on Ageing (TILDA).

Methods: Participants were from Wave 1 (2009–2011) and Wave 4 (2016) of TILDA, with $n = 639$ participants with diabetes and $n = 7{,}837$ without diabetes at Wave 1, and $n = 1{,}151$ with diabetes and $n = 4{,}531$ without diabetes at Wave 4. Depressive symptoms were measured using the 8 items of the Center for Epidemiologic Studies Depression Scale. Network psychometric analysis was used to examine symptom centrality, symptom-level associations, and network comparisons at each time point.

Results: Stable, strongly connected networks emerged for people with and without diabetes at both time points. The symptoms of feeling depressed, feeling like everything's an effort, not enjoying life, feeling sad, and couldn't get going were the most central nodes in all networks, which did not differ between people with and without diabetes. However, for people with diabetes, the network was more densely connected at Wave 4, when the sample was predominately people with newly diagnosed diabetes. Furthermore, the relationship between 'felt lonely' and 'couldn't get going' and between 'not enjoying life' and 'sad' was significantly stronger for people with diabetes than for those without.

Conclusions: This study provides a more detailed understanding of the structure of depressive symptoms at two time points in older Irish adults with and without type 1 or type 2 diabetes.

Keywords: Cohort study; diabetes; depression; network analysis

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Introduction

Diabetes is among the most common chronic conditions worldwide and can lead to disability, complications, and a reduced life expectancy (Heald et al., 2020, Vos et al., 2020). The worldwide prevalence of diabetes in 2021 was 10.5% among 20–79-year-olds, with projections that the prevalence would rise to 12.2% by 2024 (Sun et al., 2022). Depression is the most common mental illness worldwide, a growing public health challenge (Liu et al., 2020), and a condition for which people with diabetes are at an increased risk (Nouwen et al., 2010). There is a two to three times higher incidence of depression in people with diabetes compared to people without diabetes (Roy & Lloyd 2012). For those living with diabetes, depression is associated with difficulties in keeping up with diabetes management and treatment (Gonzalez et al., 2008), macro- and microvascular complications (de Groot et al., 2001, Lustman et al., 2000), higher health care costs (Egede et al., 2016), accelerated cognitive decline (Schmitz et al., 2018), and early mortality (Katon et al., 2005, Zhang et al., 2005, Black et al., 2003).

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While symptoms of depression include feelings of sadness and worthlessness, insomnia/hypersomnia, loss of interest or pleasure, and suicidal ideation (APA 2013), there is considerable heterogeneity in the depressive symptoms experienced by individuals (Fried 2017, Wakefield & Schmitz 2013) as well as evidence that individual depressive symptoms differ in their risk factors, associations with biomarkers, impact on functioning, and responsiveness to antidepressants (Fried & Nesse 2015). The heterogeneity in depressive symptomology across individuals may limit our understanding of the association between depression and diabetes prevalence and outcomes. Currently, little is known about the structure of depressive symptomology, in terms of the role and importance of specific symptoms and symptom interactions, in people with diabetes. To improve our ability to tailor depression prevention and intervention efforts for people with diabetes, an exploration of specific symptoms and the depressive symptom structure in people with diabetes, and how it differs to those without diabetes, is necessary.

Network psychometrics allows for the underlying symptom structure of mental health conditions, such as depression, to be explored, visualised, and compared between groups (Borsboom & Cramer 2013). Network theory posits that psychological constructs like depression are heterogeneous, dynamic, and complex systems where symptoms are interconnected and influence one another

(e.g. 'fatigue' and 'difficulty concentrating' directly impacting one another) (Cramer et al., 2016). Symptom-level interactions are key to conceptualising psychopathology in network theory (Borsboom & Cramer 2013).

A limited number of prior studies have examined depressive symptom networks in the context of diabetes. One previous study examined the depressive symptom networks of individuals with diabetes, heart disease, stroke, and cancer, before and after diagnosis (Airaksinen et al., 2020). They found that although the mean level of depressive symptoms increased after diagnoses, these changes were not reflected in the depressive network structure. Recent research, also examining depressive symptoms in individuals before and after diagnosis of type 2 diabetes or hypertension, found a significant increase in depressive symptom connectivity (Wan et al., 2022). However, in both studies depressive symptoms were scored using binary values (1 for yes, and 0 for no), and therefore the network models may suffer from a lack of specificity of the strength of depressive symptom interactions. A recent study explored the symptom structure of diabetes distress, depressive, and anxiety symptoms in adults with type 2 diabetes (McInerney et al., 2022) and found regimen and physician-related symptoms to be central to diabetes distress. Feelings of failure were found to be potential bridges (i.e. symptoms of one condition strongly connected to another condition) between diabetes distress and depression, and symptoms related to worry and trouble relaxing to be potential bridges between anxiety and depression, as well as diabetes distress. However, this study was limited to only one time point and did not investigate depressive symptom centrality alone. Furthermore, these prior studies did not directly compare depressive symptom networks in people with and without diabetes. Comparing the depressive symptom interactions and centrality in the networks of those with and without diabetes may lead to a better conceptualisation of the structure of depressive symptomology in people with diabetes.

The present study aimed to identify the depressive symptoms that are most central among those with diabetes and compare depressive symptom networks between those with and without diabetes. Comparisons were made between those with and without diabetes at two time points, using data from the baseline assessment (2009–2011) and the Wave 4 follow-up assessment (2016) of The Irish Longitudinal Study on Ageing (TILDA). We hypothesised that there would be differences in depressive symptom networks between those with and without diabetes at both time points. Specifically, we hypothesised that depressive symptom centrality (i.e. which symptoms are most highly connected) would differ between those with and without diabetes, and that the overall connectivity within the networks would demonstrate heightened connectivity among individuals with diabetes compared to those without.

Method

Participants

Data were from TILDA, a large nationally representative prospective cohort study of ageing aimed at assessing the health, social, and economic circumstances of the older adult, community-living population in the Republic of Ireland (Kearney et al., 2011). Data collection for Wave 1 was carried out between 2009 and 2011 and 8,175 adults aged 50 and over and 329 younger spouses/partners of participants ($N = 8507$) were interviewed (TILDA 2019). Wave 4 data collection was carried out between January and December 2016 and included 5,715 TILDA respondents. Detail on sampling, study design, and the TILDA cohort profile has been published elsewhere (Kearney et al., 2011, Whelan & Savva 2013). Ethical approval for all waves of the TILDA study was obtained from the Trinity College Dublin Faculty of Health Sciences Research Ethics Committee (Kearney et al., 2011). Access to the TILDA dataset was obtained from the Irish Social Science Data Archive.

For the present study, participants were included if they had complete data on depression and diabetes status at baseline (Wave 1). The analysis examining follow-up data (detailed below) was further refined to those with complete data on depression and diabetes status at Wave 4. The final samples for the present study were $n = 639$ participants with diabetes and $n = 7{,}837$ without diabetes at Wave 1, and $n = 1{,}151$ diabetes with diabetes and $n = 4{,}531$ without diabetes at Wave 4. Between Wave 1 and Wave 4, there were $n = 1{,}010$ new cases of diabetes. Due to drop-out and having missing data on depression or diabetes status, $n = 498$ people with diabetes present in our sample at Wave 1 are not present at Wave 4. As there are five to seven years between data collection at Wave 1 and Wave 4, the sample with diabetes at Wave 4 is predominately represented by people with relatively newly diagnosed diabetes.

Measures

Depressive symptoms were assessed using the Centre for Epidemiological Studies Depression Scale (CES-D) (Radloff 1977). Respondents rate how often they have felt each depressive symptom in the past week on a 4-point Likert scale, from 'Rarely or None of the Time (Less than 1 Day)' (score of 0) to 'Most or all of the time (5–7 days)' (score of 3) (Briggs et al., 2018, Radloff 1977). While the 20-item CES-D was available at Wave 1, at the Wave 4 follow-up, the 8-item CES-D (CES-D-8), which uses 8 items of the original 20-item scale, was used to screen for depressive symptoms. Therefore, for comparability across waves, we used CES-D-8 at Wave 1 and Wave 4. Previous research compared the CES-D-8 to the CES-D-20 in the TILDA cohort and found the CES-D-8 to be a valid and reliable measure of depressive symptoms in this sample (Briggs et al., 2018). Internal consistency was good for the sample with ($\alpha = .83$) and without ($\alpha = .81$) diabetes at Wave 1, acceptable for those with diabetes at Wave 4 ($\alpha = .79$), and good for those without diabetes at Wave 4 ($\alpha = .8$).

Diabetes status was determined by a positive response to 'Do you have diabetes or high blood sugar?'

Statistical analysis

Network analyses were conducted in RStudio (Version 2022. 12.0 + 353). The mean, standard deviation, and polychoric correlations were examined for all items. Item informativeness was quantified by examining item standard deviations. In line with previous network analysis research (Marchetti 2019), an item with a standard deviation 2.5 SDs below the mean standard deviation (*MSD*) was deemed to be poorly informative. An item redundancy test, from the R package *networktools 1*.20 (Jones 2018), was used to test for overlapping pairs of items. Two items were deemed to be measuring the same construct (i.e. to be redundant) if the polychoric correlations between each of those items and all other items were statistically different in less than 25% of the cases (Jones 2018). Networks of depressive symptoms were estimated for people with and without diabetes at Wave 1, respectively. These networks were then compared using the Network Comparison Test (described in detail below). These analyses were then repeated for the Wave 4 data.

A network consists of nodes, which represent the variables of interest (i.e. items on the CES-D-8), connected by edges, representing the relationships between nodes (Borsboom & Cramer 2013). In this study, the edges represent partial polychoric correlations, that is the correlation between two CES-D-8 items, when controlling for all other items in the network (Borsboom & Cramer 2013). Edge thickness and colour saturation reflect the edge weight (i.e. the strength of the relationship between two nodes), such that the thicker and more saturated the edge, the higher the absolute weight (Epskamp et al., 2012). Negative relationships are denoted with a red edge and positive relationships are denoted with a blue edge (Epskamp et al., 2012).

A Gaussian Graphical Model was estimated, with extended Bayesian Information Criterion model selection (Foygel & Drton 2010) to examine pairwise associations between nodes, controlling for all other correlations in the network. A polychoric correlation matrix was estimated as input, as the data were ordinal, using the cor_auto function in *qgraph* (Epskamp et al., 2017) and the R package *lavaan* (Rosseel 2012). To estimate many parameters with relatively small datasets, as is needed when estimating psychological networks, a form of regularisation is necessary. To estimate a more interpretable network and to limit the number of spurious edges, the 'least absolute shrinkage and selection operator' (LASSO; (Tibshirani 1996), a regularisation technique, was used (using the graphical LASSO (glasso; Friedman et al., 2008) with the *glasso* package (Friedman et al., 2022). To control the balance between a model with more (sensitivity) and fewer (specificity) edges estimated, a hyperparameter must be set. In line with suggestions by Foygel & Drton (2010), the hyperparameter was set to 0.5, to estimate a more parsimonious network. The Fructerman-Reingold algorithm was used to visualise the network, which places the nodes with higher centrality at the centre of the network. Further detail on the estimation of regularised partial correlations network can be found elsewhere (Epskamp et al., 2018).

Once the networks were estimated and visualised, centrality indices were examined and reported. The centrality index of strength signifies the sum of absolute edge weights directly connecting one node to other nodes in the network (Epskamp et al., 2018). The index of one-step expected influence allows for positive edges to outweigh negative, thus, signifies the non-absolute sum of the edges directly connecting one node to others in the network (Robinaugh et al., 2016).

In order to have confidence in the interpretation of network indices, a post hoc bootstrapping framework was used to assess the stability and accuracy of the networks. The non-parametric 2500-boostrapped confidence intervals (CIs) for each edge weight were inspected to assess the variability of edge weights (Epskamp et al., 2018). Wide bootstrapped CIs indicate that caution should be exercised in intercepting the strength, but not the presence or direction, of an edge (Epskamp et al., 2018). The stability of the networks was also investigated using subset bootstrapping and by computing a correlation stability coefficient (CS-coefficient) (Epskamp et al., 2018). A CS-coefficient above 0.25 was considered interpretable and above 0.5 was considered highly stable (Epskamp et al., 2018).

To compare networks between people with and without diabetes at each wave, the *NetworkComparisonTest* package was used (van Borkulo et al., 2015). Global strength invariance (i.e. the difference in the absolute sum of network edge weights, that is the overall connectivity of the network) and network invariance (i.e. the possible edge weight differences between networks) were examined.

Results

Sample characteristics are presented in Table 1. The item means and standard deviations, and polychoric correlations between items, were calculated and inspected for each group at both waves. Means and standard deviations for depressive symptoms in each network are reported in Table 2. Polychoric correlations for people with and without diabetes at Wave 1, and for people with and without diabetes at Wave 4, are presented in Supplementary Tables 1–4, respectively.

Item informativeness was examined and no item was found to be poorly informative (i.e. 2.5 SD below the *MSD*: Wave 1 people with diabetes $MSD = 0.44 \pm 0.78$; Wave 1 people without diabetes $MSD = 0.37 \pm 0.71$; Wave 4 people without diabetes $MSD = 0.43 \pm 0.73$; and Wave 4 people without diabetes$MSD = 0.4 \pm 0.7$). The redundancy test suggested no reductions (i.e. no item was found to be measuring the same construct as another). Therefore, all items were included in the analysis.

The networks of CES-D-8 items for people with and without diabetes at Wave 1 and Wave 4 are displayed in Figure 1. Node strength is presented in Figure 2. Expected influence is presented in Supplementary Figure 1. For those with diabetes at wave 1 and 4, respectively, the estimated network had 75% (21/28) non-zero edges, and 86% (24/28) non-zero edges. For those without diabetes at wave 1 and 4, respectively, the estimated network had 86% (24/28) non-zero edges, and 82% (23/28) non-zero edges. These indicate highly connected depressive symptom networks overall.

Network stability among those with diabetes

At wave 1, the bootstrapped CIs around the estimated edge weights were inspected and some were found to overlap, suggesting that edge weight order should be interpreted with caution. However, five edges were significantly different to most other edges in the network (Fig. 3). Case-dropping subset bootstrapping indicated that node strength ($CS[cor = 0.7] = 0.516$) and expected influence ($CS[cor = 0.7] = 0.673$) were above the threshold of 0.5 to be considered highly stable. At wave 4, while many estimated edge weights are overlapping and therefore, their order should be interpreted with caution, three edge weights were significantly different from almost all others, namely, Not happy (Dep4) to Not enjoying life (Dep6), Everything's an effort (Dep2) to Couldn't get going (Dep8), and Felt lonely (Dep5) to Sad (Dep7). Node strength ($CS[cor = 0.7] = 0.59$) and expected influence ($CS[cor = 0.7] = 0.75$) were above the cut-off to be considered stable (Fig. 3).

Network stability among those without diabetes

At wave 1, inspection of the bootstrapped CIs around the estimated edge weights indicated that, while some were overlapping, the edge between Not happy (Dep4) and Not enjoying life (Dep 6) was significantly different to all other edges (Fig. 3). The network was highly stable, with the CS coefficients for strength and expected influence being at the highest level tested ($CS[cor = 0.7] = 0.75$) and therefore, above the cut-off to be considered interpretable (0.5). At wave 4, similarly, while many bootstrapped CIs overlap (Fig. 3), some edge weights were significantly different from almost all other edge weights, namely, Not happy (Dep4) to Not enjoying life (Dep6); Everything's an effort (Dep2) to Couldn't get going (Dep8); Felt lonely (Dep5) to Sad (Dep7); Depressed (Dep1) to Everything's an effort (Dep2); and Depressed (Dep1) to Sad (Dep7). The network was highly stable, with the CS coefficients for strength and expected influence being at the highest level tested

Table 1. Descriptive statistics for the sample

	Those with diabetes at Wave 1 ($n = 639$)	Those without diabetes at Wave 1 ($n = 7,837$)	Those with diabetes at Wave 4 ($n = 1151$)	Those without diabetes at Wave 4 ($n = 4531$)
Age Group, *n* (%)				
<50	7 (1.1)	311 (4.1)	0 (0)	0 (0)
50–64	260 (40.7)	4393 (56.1)	535 (46.5)	1736 (38.3)
65–74	227 (35.5)	1923 (24.5)	402 (34.9)	1638 (36.2)
75+	143 (22.4)	1190 (15.2)	214 (18.6)	1157 (25.5)
Missing	2 (.3)	9 (.1)	0 (0)	0 (0)
Age, mean ± *SD*	66.4 ± 8.933	62.67 ± 9.384	66.44 ± 8.232	68.36 ± 8.601
Sex, *n* (%)				
Male	369 (57.7)	3405 (43.4)	428 (37.2)	2075 (45.8)
Female	270 (42.3)	4432 (56.6)	723 (62.8)	2456 (54.2)
Education, *n* (%)				
Primary/None	261 (40.8)	2246 (28.7)	275 (23.9)	1058 (23.4)
Secondary	236 (37)	2187 (40.7)	455 (39.5)	1796 (39.6)
Tertiary	142 (22.2)	2401 (30.6)	421 (36.6)	1677 (37)
Don't know	0 (0)	3 (.0)	0 (0)	
Do you currently smoke?				
Yes	111 (17.4)	1446 (18.5)	155 (13.5)	510 (11.3)
No	528 (82.6)	6390 (81.5)	996 (86.5)	4020 (88.7)
Missing	0 (0)	1 (.0)	0 (0)	1 (0)
Physical activity level				
Low	278 (43.5)	2388 (30.5)	435 (37.8)	1660 (36.6)
Moderate	206 (32.2)	2686 (34.3)	360 (31.3)	1495 (33)
High	148 (23.2)	2690 (34.3)	331 (28.8)	1261 (27.8)
Missing	7 (1.1)	73 (.9)	25 (2.2)	115 (2.5)
Body mass index				
0–24.99	35 (5.5)	1331 (17)	307 (26.7)	1507 (33)
25–29.99	147 (23)	2421 (30.9)	476 (41.4)	18,858 (41)
30–39.99	212 (33.2)	1714 (21.9)	283 (24.6)	911 (20.1)
40+	36 (5.6)	122 (1.6)	36 (3.1)	42 (.9)
Missing	209 (32.7)	2249 (28.7)	49 (4.3)	213 (4.7)
Marital status				
Married/cohabiting	428 (67)	5526 (70.5)		
Never married	58 (9.1)	730 (9.3)		
Separated/divorced	38 (5.9)	511 (6.5)		
Widowed	115 (18)	1070 (13.7)		
Hypertension				
Not hypertensive	222 (34.7)	3322 (42.4)		
Hypertensive	202 (31.6)	2350 (30)		
Missing	215 (33.6)	2165 (27.6)		
Alcohol consumption				
Heavy	135 (21.1)	1640 (20.9)		
Light/moderate	155 (24.3)	36.2 (2838)		
Non-drinker	191 (29.9)	1640 (20.9)		
Missing	158 (24.7)	1732 (22.1)		

Table 2. Mean scores on the centre for epidemiological studies depression 8-item (CES-D-8) scale for each item. Scores ranged from zero to three

	Those with diabetes: Wave 1	Those without diabetes: Wave 1	Those with diabetes: Wave 4	Those without diabetes: Wave 4
	mean (± SD)	*mean* (± SD)	*mean* (± SD)	*mean* (± SD)
1. I felt depressed	0.32 (.69)	0.25 (.6)	0.26 (.6)	0.24 (.58)
2. I felt that everything I did was an effort	0.42 (.79)	0.29 (.66)	0.34 (.69)	0.3 (.65)
3. My sleep was restless	0.74 (1)	0.65 (.93)	0.83 (1.02)	0.74 (.95)
4. I was happy	0.53 (.88)	0.47 (.82)	0.46 (.72)	0.44 (.73)
5. I felt lonely	0.32 (.68)	0.28 (.65)	0.32 (.69)	0.3 (.66)
6. I enjoyed life	0.44 (.81)	0.39 (.78)	0.40 (.71)	0.41 (.72)
7. I felt sad	0.4 (.71)	0.34 (.65)	0.46 (.72)	0.41 (.7)
8. I could not get going	0.36 (.7)	0.26 (.6)	0.34 (.66)	0.34 (.65)

(CS[cor = 0.7] = 0.75) and therefore, well above the cut-off to be considered interpretable (0.5; Fig. 3).

Network comparison

First, the networks were investigated to determine if they differed in terms of connectivity (i.e. if one network is more strongly connected than the other). At Wave 1, results from the global strength invariance test indicated that the difference in global strength between the depression networks for people with and without diabetes was not significant ($S = 0.07$, $p = .39$), where S refers to the difference in global strength between the networks. Next, the network invariance test was used to investigate whether the edges differed between networks. Results suggested that there was at least one edge that differed between the networks ($M = 0.19$, $p = .03$). Therefore, we performed exploratory post hoc testing of all the edges in the network to determine which edges differed between the networks. There were two edges that differed significantly between the networks at Wave 1, between Felt lonely (Dep5) and Couldn't get going (Dep8) ($E = 0.19$, $p = 0.00$) and between Not enjoying life (Dep6) and Sad (Dep7) ($E = 0.19$, $p = 0.00$), where E refers to the value of the edge weight difference between the networks. The edge between Felt lonely (Dep5) and Couldn't get going (Dep8) and the edge between Not enjoying life (Dep6) and Sad (Dep7) were significantly stronger for those with diabetes than those without diabetes.

The network comparison test indicated that the Wave 4 networks were not different between people with and without diabetes in terms of global strength ($S = 0.01$, $p = .8$) and edge weights ($M = 0.12$, $p = .01$).

Discussion

The present study estimated and compared networks of depressive symptoms in a cohort of adults with and without diabetes at each of two time points, approximately five to seven years apart. This study provides a more detailed understanding of depressive symptom interactions in older Irish adults with and without type 1 or type 2 diabetes. To our knowledge, this is the first study to investigate the network structure of CES-D-8 items using the 4-point response scale for people with diabetes and compare them to people without diabetes. Understanding the differences in depressive symptomology between people with and without diabetes may allow for more tailored, and thus effective, clinical treatment. We identified the most highly connected and influential symptoms in the depressive networks, and differences in the strength of symptom relationships between people with and without diabetes. Across the networks estimated, four symptoms emerged with consistently high node strength in all networks, that is, for people with and without diabetes and at all time points. These were feeling depressed, feeling like everything's an effort, feeling sad, and couldn't get going. Similar results were found when we examined the expected influence of each item. That these symptoms were consistently the most strong and influential may suggest that they are core components of depressive symptomology as measured by the CES-D-8. For people without diabetes, two of the nodes highest in node strength were the same at both time points (feeling depressed and feeling like everything's an effort) while for people with diabetes, feeling like everything's an effort was the only one to remain in the three most central items at Wave 4.

The symptoms of restless sleep, not feeling happy, and feeling lonely were consistently amongst the symptoms lowest in strength and expected influence. In particular, restless sleep was the node lowest in strength and expected influence, across all networks. This suggests that restless sleep may be a peripheral symptom of depression, as measured by the CES-D-8. According to network theory, the most central symptoms trigger and maintain the depressive network (Borsboom 2017). Therefore, targeting poor sleep alone through clinical interventions may not significantly decrease the connectivity or strength of the overall depressive network compared to targeting other, stronger, and more influential symptoms. These findings contradict recent research on non-pharmacological sleep interventions, which showed their effectiveness in reducing depression severity, especially in clinical populations (Gee et al., 2019). However, there were notable differences as the present study was observational and focused on specific populations.

The connectivity of the networks (i.e. how strongly or densely connected the networks are) were also compared between people with and without diabetes at each wave in the present study. The network comparison test determined that the networks were not significantly different between people with and without diabetes in terms of connectivity, at either wave. However, for people with diabetes, the depressive network at Wave 4 was more highly connected (86%; 24/28 non-zero edges) than the depressive network at Wave 1 (75%; 21/28 non-zero edges). Those with diabetes at Wave 4 were predominately (87.74%) people with relatively new (within

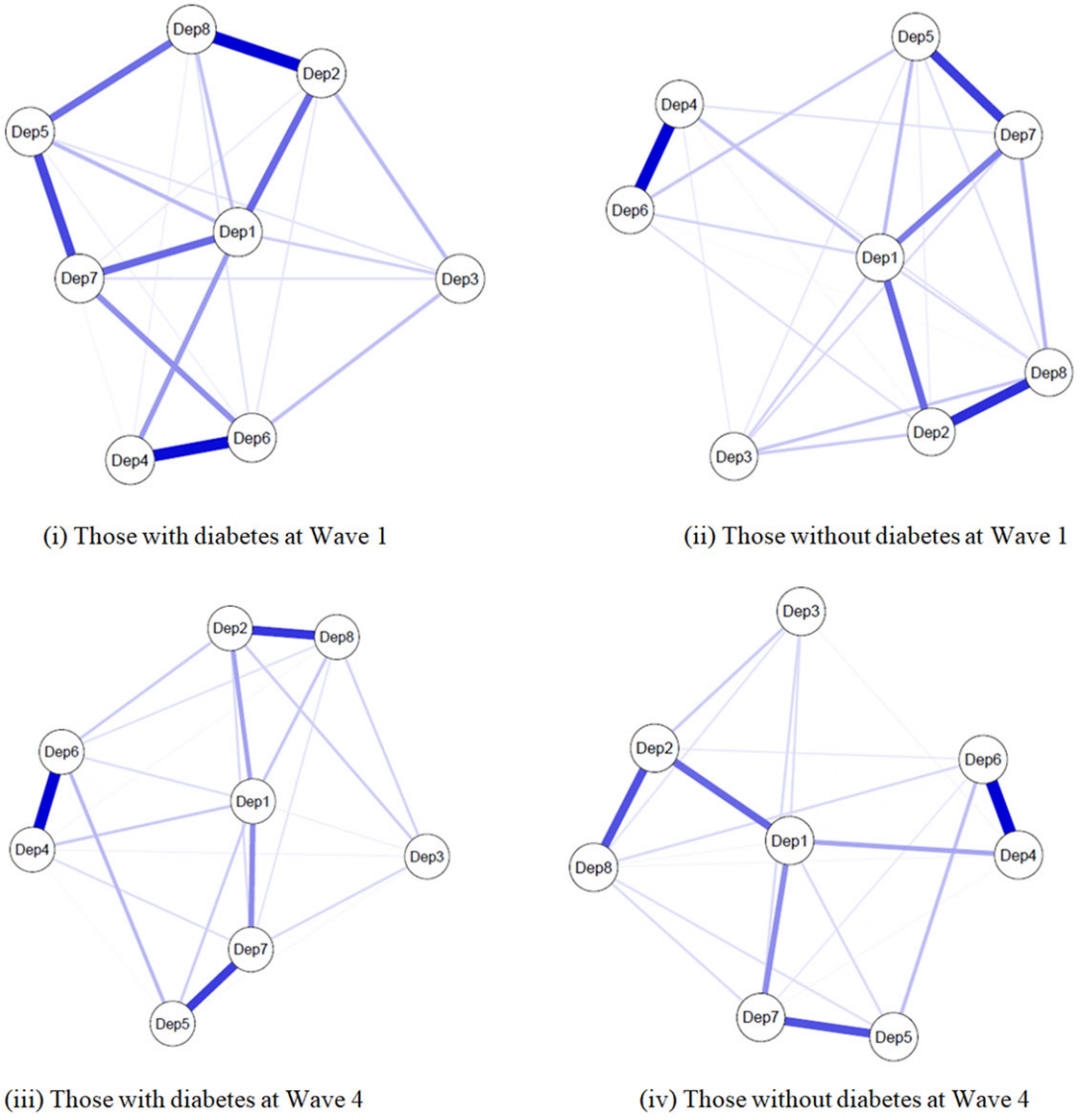
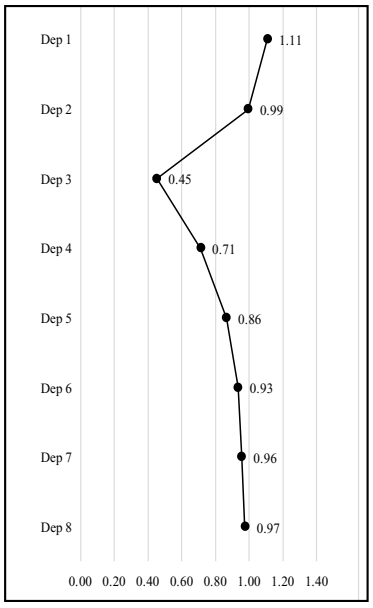


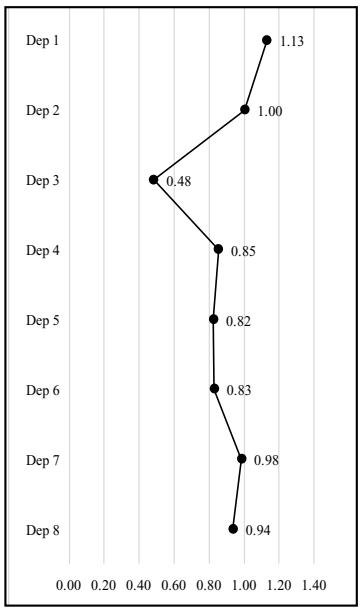
Figure 1. Network of depressive symptoms for people with (i) and without (ii) diabetes at wave 1 and with (iii) and without (iv) diabetes at wave 4. Line thickness and colour denote the strength and direction, respectively, of polychoric correlations between symptoms. Blue lines indicate positive correlations, and red indicate negative. The thicker the line, the stronger the correlation between two symptoms. Dep1 indicates I felt depressed; Dep2, I felt that everything I did was an effort; Dep3, my sleep was restless; Dep4, I was happy; Dep5, I felt lonely; Dep6, I enjoyed life; Dep7, I felt sad; Dep8, I could not get going. For those with diabetes at wave 1 (i), the node highest in node strength was depressed (Dep1), followed by everything's an effort (Dep2) and couldn't get going (Dep8). The order of the three nodes highest in expected influence was depressed (Dep1), couldn't get going (Dep8) and everything's an effort (Dep2). For those without diabetes at wave 1 (ii), the nodes highest in node strength were: depressed (Dep1), everything's an effort (Dep2) and sad (Dep7). The nodes highest in expected influence were: depressed (Dep1), everything's an effort (Dep2), and sad (Dep7). For those with diabetes at wave 4 (iii), the nodes highest in strength were sad (Dep7), not enjoying life (Dep6), and everything's an effort (Dep2). The nodes highest in expected influence were depressed (Dep1), sad (Dep 7), and everything's an effort (Dep2). For those without diabetes at wave 4 (iv), the nodes highest in node strength were depressed (Dep1), not enjoying life (Dep6), and everything's an effort (Dep2). The nodes highest in expected influence were depressed (Dep1), sad (Dep7), and everything's an effort (Dep2).

the last 5–7 years) diagnoses of diabetes. This is in line with recent research by Wan et al. (2022), which found a statistically significant increase in depressive symptom connectivity in the 2 years following diagnosis. In contrast, Airaksinen et al. (2020) found the connectivity of depressive symptoms remained unchanged before and after diagnosis (Airaksinen et al., 2020). However, Airaksinen et al. (2020) used a binary measure of depressive symptoms, which may have impacted the sensitivity of their findings. The network theory of psychopathology proposes that a more densely connected network is indicative of stronger reinforcing feedback loops between symptoms, important to the progression and maintenance of psychopathology (Borsboom 2017, van Borkulo et al., 2015). Our sample was between five and seven years older at Wave 4 than at Wave 1 and predominately people with newly diagnosed diabetes. Therefore, the increased connectivity between these time points could suggest an increase in the reactivity and self-reinforcing nature of the depressive profile for people with diabetes as they age, or in the aftermath of diagnosis. There is also evidence that the density of a network's connectivity may render it more responsive to treatment (Esfahlani et al., 2017, Peralta et al., 2020). Still, more research is necessary to test and confirm the clinical implications of network indices.

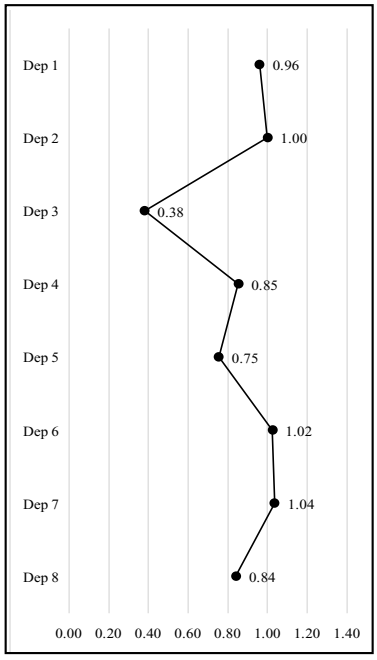
Furthermore, our analyses identified two edges, or relationships between symptoms, that were significantly different between the networks for people with and without diabetes at Wave 1. The



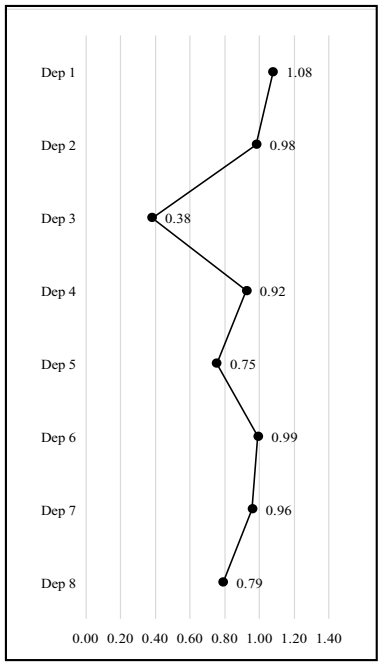
(i) Those with diabetes at Wave 1



(ii) Those without diabetes at Wave 1



(iii) Those with diabetes at Wave 4



(iv) Those without diabetes at Wave 4

Figure 2. Depressive symptom strength scores for people with (i) and without diabetes (ii) at wave 1, as well as for people with (iii) and without diabetes (iv) at wave 4. Dep1 indicates I felt depressed; Dep2, I felt that everything I did was an effort; Dep3, my sleep was restless; Dep4, I was happy; Dep5, I felt lonely; Dep6, I enjoyed life; Dep7, I felt sad; Dep8, I could not get going.

relationship between 'felt lonely' and 'couldn't get going' was significantly stronger for people with diabetes than for those without. Perceived loneliness has been shown to be significantly predictive of higher HbA1c in people with self-reported diabetes, after controlling for demographics, depression, and number of chronic illnesses (Huang et al., 2022). Diabetes self-management behaviours appear to be impacted by levels of social support (Koetsenruijter et al., 2016, Strom & Egede 2012). Our findings suggest that the link between feeling lonely and the somatic symptom of not being able to 'get going' might be an important pathway for both clinicians and researchers to explore to better understand the mechanisms underlying the relationship between loneliness and diabetes management. Results of the network comparison test also indicated that the relationship between 'not enjoying life' and 'Sad' was significantly stronger for people with diabetes than those without at Wave 1. These findings highlight the

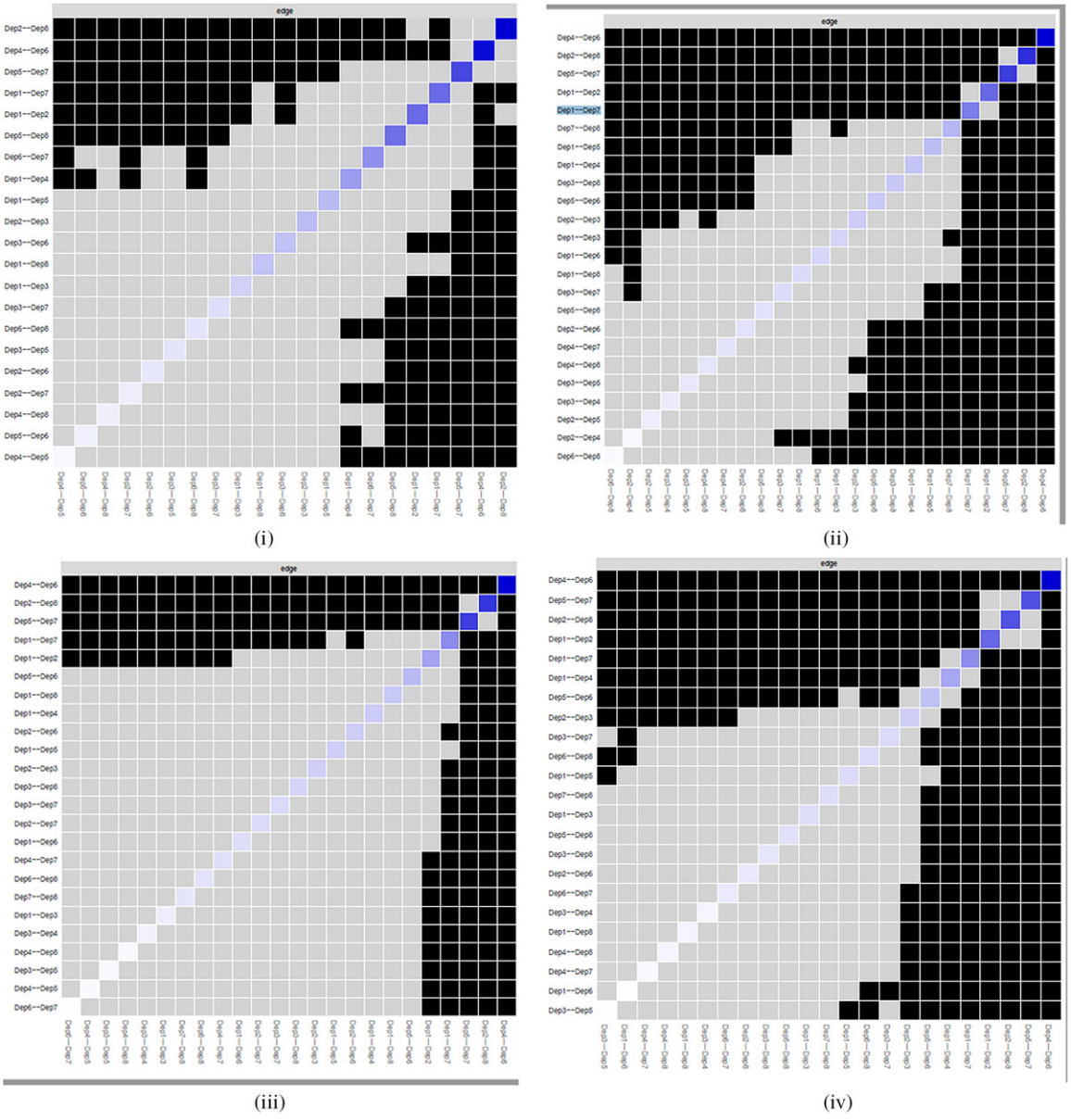


Figure 3. Bootstrapped edge weight confidence intervals for people with (i) and without diabetes (ii) at wave 1, as well as for people with (iii) and without diabetes (iv) at wave 4. Dep1 indicates I felt depressed; Dep2, I felt that everything I did was an effort; Dep3, my sleep was restless; Dep4, I was happy; Dep5, I felt lonely; Dep6, I enjoyed life; Dep7, I felt sad; Dep8, I could not get going.

capability of network analyses to provide unique insights into the structure of mental health conditions and associations between symptoms, which may lead to more personalised clinical care.

Strengths and limitations

To our knowledge, this was the first study to compare depressive networks between people with and without diabetes at two time points. Our findings highlight differences in individual symptom relationships between those with and without diabetes. As the TILDA dataset is a nationally representative prospective study of adults over 50 living in Ireland, the findings should be generalisable to the population of Ireland. By taking a symptom-level approach, this study highlights individual symptoms and symptom relationships that could be targeted as part of a personalised approach to mental health treatment in the future.

The study has several limitations. First, the findings may not be generalisable beyond the predominantly White and older adults living in Ireland who were included in the TILDA dataset. Second, the data collection took place between 2009 and 2016, and changes in diabetes technology and healthcare services since then may affect the applicability of the results to the present day. Third, confounding factors were not accounted for in the network analysis; only the depressive symptom structure was modelled. It is possible that connections between nodes and node strength can be explained by factors not modelled in the network. While our focus was on the crude structure of depressive symptoms in people with diabetes, future research should use datasets with much larger numbers of people with diabetes, and with diabetes specific data, to consider factors such as complications, diabetes duration, HbA1c levels, and demographics. Fourth, while there was a significant difference in edge weights between people with and without

diabetes at Wave 1, this difference did not persist at Wave 4, possibly due to sample size limitations. Additionally, the study did not focus on diagnosed clinical depression. In a study using the network comparison test to compare depressive networks in pregnant women, there was a difference in global strength (connectivity) but not in network structure between women with and without depression (Santos et al., 2017). Future research should further explore differences between clinical and non-clinical populations. At present, our findings should be interpreted in relation to depressive symptomology in the general, non-clinical population. Finally, although we used polychoric correlations to preserve information on data severity and order, there is currently no established 'gold standard' for handling ordinal psychological data in network analysis (Epskamp 2017).

Conclusion

The present study highlights the symptoms which may be central to depressive symptomology in adults over 50 living in Ireland with and without diabetes. Findings suggest that specific symptom relationships, namely, between 'felt lonely' and 'couldn't get going' and between 'not enjoying life' and 'sad', were significantly stronger for people with diabetes than for those without. As such, the present paper identifies key areas of symptom-level inquiry for researchers and clinicians working with older adults in Ireland with diabetes. Furthermore, clinicians could consider utilising questionnaires, such as the CES-D-8, as a tool to supplement a full clinical interview and gain a more in-depth understanding of each individual's unique disease burden.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/ipm.2024.10.

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Competing interests. None.

Ethical standards. The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committee on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008.

References

Airaksinen J, Gluschkoff K, Kivimäki M, Jokela M (2020). Connectivity of depression symptoms before and after diagnosis of a chronic disease: a network analysis in the US health and retirement study. *Journal of Affective Disorders* **266**, 230–234.

APA. (2013). *Diagnostic and Statistical Manual of Mental Disorders: DSM-5*. American Psychiatric Association: Washington, DC.

Black SA, Markides KS, Ray LA (2003). Depression predicts increased incidence of adverse health outcomes in older Mexican Americans with type 2 diabetes. *Diabetes Care* **26**, 2822–2828.

Borsboom D (2017). A network theory of mental disorders. *World Psychiatry* **16**, 5–13.

Borsboom D, Cramer A (2013). Network analysis: an integrative approach to the structure of psychopathology. *Annual Review of Clinical Psychology* **9**, 91–121.

Briggs R, Carey D, O'halloran A, Kenny R, Kennelly S (2018). Validation of the 8-item centre for epidemiological studies depression scale in a cohort of community-dwelling older people: data from the irish longitudinal study on ageing (TILDA). *European Geriatric Medicine* **9**, 121–126.

Cramer AO, Van Borkulo CD, Giltay EJ, Van Der Maas HL, Kendler KS, Scheffer M, Borsboom D (2016). Major depression as a complex dynamic system. *PloS one* **11**, e0167490.

De Groot M, Anderson R, Freedland KE, Clouse RE, Lustman PJ (2001). Association of depression and diabetes complications: a meta-analysis. *Psychosomatic Medicine* **63**, 619–630.

Egede LE, Bishu KG, Walker RJ, Dismuke CE (2016). Impact of diagnosed depression on healthcare costs in adults with and without diabetes: United States, 2004–2011. *Journal of Affective Disorders* **195**, 119–126.

Epskamp S (2017). *Network Psychometrics, Discussion: The Road Ahead*. University of Amsterdam: Amsterdam, Netherlands.

Epskamp S, Borsboom D, Fried EI (2018). Estimating psychological networks and their accuracy: a tutorial paper. *Behavior Research Methods* **50**, 195–212.

Epskamp S, Costantini G, Haslbeck J, Cramer AO, Epskamp MS, Rsvgtipsdevice S (2017). *Package 'qgraph'*.

Epskamp S, Cramer AOJ, Waldorp LJ, Schmittmann VD, Borsboom D (2012). qgraph: Network Visualizations of Relationships in Psychometric Data. *Journal of Statistical Software* **48**, 1–18.

Esfahlani FZ, Sayama H, Visser KF, Strauss GP (2017). Sensitivity of the positive and negative syndrome scale (PANSS) in detecting treatment effects via network analysis. *Innovations in clinical neuroscience* **14**, 59–67.

Foygel R, Drton M (2010). Extended Bayesian information criteria for Gaussian graphical models. *Advances in Neural Information Processing Systems* 23.

Fried E (2017). Moving forward: how depression heterogeneity hinders progress in treatment and research. *Expert Review of Neurotherapeutics* **17**, 423–425.

Fried E, Nesse R (2015). Depression sum-scores don't add up: why analyzing specific depression symptoms is essential. *BMC Medicine* **13**, 72.

Friedman J, Hastie T, Tibshirani R (2008). Sparse inverse covariance estimation with the graphical lasso. *Biostatistics* **9**, 432–441.

Friedman J, Hastie T, Tibshirani R (2022). *Package 'Glasso': Graphical Lasso: Estimation of Gaussian graphical models*. R Package version, 1. [R Package]. Retrieved from http://mirrors.nic.cz/R/web/packages/glasso/

Gee B, Orchard F, Clarke E, Joy A, Clarke T, Reynolds S (2019). The effect of non-pharmacological sleep interventions on depression symptoms: a meta-analysis of randomised controlled trials. *Sleep Medicine Reviews* **43**, 118–128.

Gonzalez JS, Peyrot M, Mccarl LA, Collins EM, Serpa L, Mimiaga MJ, Safren SA (2008). Depression and diabetes treatment nonadherence: a meta-analysis. *Diabetes Care* **31**, 2398–2403.

Heald AH, Stedman M, Davies M, Livingston M, Alshames R, Lunt M, Rayman G, Gadsby R (2020). Estimating life years lost to diabetes: outcomes from analysis of national diabetes audit and office of national statistics data. *Cardiovascular Endocrinology & Metabolism* **9**, 183–185.

Huang Y-C, Cho E, Kuo H-J, García AA (2022). The influences of depression and loneliness on A1C among middle-aged and older adults with diabetes. *Psychology, Health & Medicine* **28**, 1540–1548.

Jones P (2018). Networktools: tools for identifying important nodes in networks. *R Package Version* **1**, 10–1155.

Katon WJ, Rutter C, Simon G, Lin EHB, Ludman E, Ciechanowski P, Kinder L, Young B, Von Korff M (2005). The association of comorbid depression with mortality in patients with Type 2 diabetes. *Diabetes Care* **28**, 2668–2672.

Kearney PM, Cronin H, O'regan C, Kamiya Y, Savva GM, Whelan B, Kenny R (2011). Cohort profile: the irish longitudinal study on ageing. *International Journal of Epidemiology* **40**, 877–884.

Koetsenruijter J, Van Eikelenboom N, Van Lieshout J, Vassilev I, Lionis C, Todorova E, Portillo MC, Foss C, Serrano Gil M, Roukova P, Angelaki A, Mujika A, Knutsen IR, Rogers A, Wensing M (2016). Social support and self-management capabilities in diabetes patients: an international observational study. *Patient Education and Counseling* **99**, 638–643.

Liu Q, He H, Yang J, Feng X, Zhao F, Lyu J (2020). Changes in the global burden of depression from 1990 to 2017: findings from the global burden of disease study. *Journal of Psychiatric Research* **126**, 134–140.

Lustman PJ, Anderson RJ, Freedland KE, De Groot M, Carney RM, Clouse RE (2000). Depression and poor glycemic control: a meta-analytic review of the literature. *Diabetes Care* **23**, 934–942.

Marchetti I (2019). Hopelessness: a network analysis. *Cognitive Therapy and Research* **43**, 611–619.

Mcinerney AM, Lindekilde N, Nouwen A, Schmitz N, Deschênes SS (2022). Diabetes distress, depressive symptoms, and anxiety symptoms in people with Type 2 diabetes: a network analysis approach to understanding comorbidity. *Diabetes Care* **45**, 1715–1723.

Nouwen A, Winkley K, Twisk J, Lloyd CE, Peyrot M, Ismail K, Pouwer F, for the European Depression in Diabetes (EDID) Research Consortium (2010). Type 2 diabetes mellitus as a risk factor for the onset of depression: a systematic review and meta-analysis. *Diabetologia* **53**, 2480–2486.

Peralta V, Gil-Berrozpe GJ, Librero J, Sánchez-Torres A, Cuesta MJ (2020). The symptom and domain structure of psychotic disorders: a network analysis approach. *Schizophrenia Bulletin Open* **1**, sgaa008.

Radloff LS (1977). The CES-D scale: a self-report depression scale for research in the general population. *Applied Psychological Measurement* **1**, 385–401.

Robinaugh DJ, Millner AJ, Mcnally RJ (2016). Identifying highly influential nodes in the complicated grief network. *Journal of Abnormal Psychology* **125**, 747–757.

Rosseel Y (2012). Lavaan: an R package for structural equation modeling and more. Version 0.5-12 (BETA). *Journal of Statistical Software* **48**, 1–36.

Roy T, Lloyd CE (2012). Epidemiology of depression and diabetes: a systematic review. *Journal of Affective Disorders* **142**, S8–S21.

Santos H, Fried EI Asafu-Adjei J, Ruiz RJ (2017). Network structure of perinatal depressive symptoms in Latinas: relationship to stress and reproductive biomarkers. *Research in Nursing & Health* **40**, 218–228.

Schmitz N, Deschênes SS, Burns RJ, Danna SM, Franco OH, Ikram MA, Kivimäki M, Singh-Manoux A, Tiemeier H (2018). Cardiometabolic dysregulation and cognitive decline: potential role of depressive symptoms. *The British Journal of Psychiatry* **212**, 96–102.

Strom JL, Egede LE (2012). The impact of social support on outcomes in adult patients with Type 2 diabetes: a systematic review. *Current Diabetes Reports* **12**, 769–781.

Sun H, Saeedi P, Karuranga S, Pinkepank M, Ogurtsova K, Duncan BB, Stein C, Basit A, Chan JCN, Mbanya JC, Pavkov ME, Ramachandaran A, Wild SH, James S, Herman WH, Zhang P, Bommer C, Kuo S, Boyko EJ, Magliano DJ (2022). IDF diabetes atlas: global, regional and country-level diabetes prevalence estimates for 2021 and projections for 2045. *Diabetes Research and Clinical Practice* **183**, 109119.

Tibshirani R (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological)* **58**, 267–288.

TILDA (2019). *The Irish Longitudinal study on Ageing (TILDA) Wave 1, 2009-2011*. Irish Social Science Data Archive: Dublin, Ireland. www.ucd.ie/issda/data/tilda/wave1.

Van Borkulo C, Boschloo L, Borsboom D, Penninx BW, Waldorp LJ, Schoevers RA (2015). Association of symptom network structure with the course of depression. *JAMA Psychiatry* **72**, 1219–1226.

Vos T, Lim SS, Abbafati C, Abbas KM, Abbasi M, Abbasifard M, Abbasi-Kangevari M, Abbastabar H, Abd-Allah F, Abdelalim A (2020). Global burden of 369 diseases and injuries in 204 countries and territories, 1990-2019: a systematic analysis for the global burden of disease study 2019. *The Lancet* **396**, 1204–1222.

Wakefield JC, Schmitz MF (2013). When does depression become a disorder? Using recurrence rates to evaluate the validity of proposed changes in major depression diagnostic thresholds. *World Psychiatry* **12**, 44–52.

Wan C, Feng W, Ma R, Ma H, Wang J, Huang R, Zhang X, Jing M, Yang H, Yu H (2022). Association between depressive symptoms and diagnosis of diabetes and its complications: a network analysis in electronic health records. *Frontiers in Psychiatry* **13**, 966758.

Whelan BJ, Savva GM (2013). Design and methodology of the irish longitudinal study on ageing. *Journal of the American Geriatrics Society* **61**, S265–S268.

Zhang X, Norris SL, Gregg EW, Cheng YJ, Beckles G, Kahn HS (2005). Depressive symptoms and mortality among persons with and without diabetes. *American Journal of Epidemiology* **161**, 652–660.