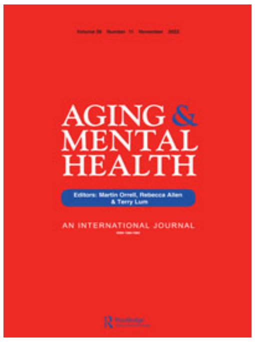

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The use of psychological network analysis in informal dementia care: an empirical illustration

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ABSTRACT

Objective: Theoretical models in informal dementia care have been developed to understand how risk and protective factors interact to cause caregiver's distress. The development of psychological network analysis provides a rich complement to our current models, as explores how different variables (or nodes) are associated using graph theories.

Methods: The present study explored the use of network analysis using data from 125 informal caregivers of their partner with dementia (PwD). The included variables were recipient's dependency, self-efficacy, conflict within the family, dyadic adjustment, and caregiver's distress.

Results: The analysis suggests a complex network of interacting variables. The core variable was not the caregiver's distress but rather their dyadic adjustment with their PwD. Variables were associated with caregiver distress through a large array of direct and indirect pathways and were associated with each other in the form of an asymmetric spider's web.

Conclusion: The results show the complex interplay of variables in a psychological network. The central role of distress suggests a complex and dynamic role, notably through a bidirectional influence with quality of interactions. In the same way, quality of interactions appeared as one of the strongest nodes, its connectivity suggesting a crucial role to consider in our models and interventions.

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Informal care; network analysis; dyadic adjustment; burden; dementia

Introduction

Informal caregivers provide assistance to a relative or friend in need due to a disability, a disease, or any health-related issue that leads to a loss of autonomy (Schulz & Tompkins, 2010). In the daily life, informal caregivers help care-recipients in the daily tasks they can no longer perform autonomously due to their health-related limitations (e.g. doing the groceries or helping for personal hygiene). Overall, it is considered that informal caregivers are pillars in the current healthcare system by allowing numerous individuals with health-related issues to stay at home without only resorting to professional caregivers (Oliva-Moreno et al., 2019).A large part of the current literature on informal care is based on quantitative research, and most of our theoretical models and statistical analysis rely on exploring how multiple variables can represent risk or protective factors of the caregiver's distress. The problem with such approach is that it does not consider that the variables we study are interconnected and have an influence that cannot be summarized only in a unidirectional or sequential fashion. In parallel, developments in network approaches come to change the way we conceive psychological well-being, and as a consequence, analyze our data (Borsboom, 2017; Borsboom & Cramer, 2013). Because providing care in the daily life involves a large set of interacting elements, studies focusing on informal caregivers would greatly benefit from the developments in psychological network research.

The network approach

Network analysis allows the investigation of the association between multiple variables by showing how they interact with each other at the same time in an exploratory fashion (Borsboom, 2017; Hevey, 2018). Beyond this sole methodological fact, this approach questions the way psychopathology and well-being-related concepts are viewed. The starting point of the network approach came from the premise that psychopathological disorders are conceptualized as systems of causally connected symptoms, rather than as effects of a latent disorder(for a brief history of network analysis, see Hevey, 2018). Instead of applying the biomedical paradigm that one central monolithic latent element (the disorder) causes all the symptoms and is distinct from them, what is now called the psycho(patho)logical network approach rather suggests that the disorder itself is only but a system of interconnected and interacting symptoms, where the symptoms constitute the disorder (e.g. one cannot be depressed without depressed mood). As such, the disorder cannot be the cause of the symptom, as it *is* the symptom or, more accurately, a complex network of mutually interacting or even reciprocally reinforcing symptoms (Borsboom, 2017).

What we currently see as risk factors are also viewed as interacting elements to integrate within the network (Borsboom, 2017; Rath et al., 2019). By exploring all possible relationships between different variables at the same time, network analysis can guide researchers and clinicians towards more complex and dynamic thinking about well-being and mental disorders (Bringmann & Eronen, 2018). Network approach does not rely on an *a priori* cause-effect model (e.g. in opposition to structural equation modeling), and therefore provides a new exploratory approach to investigate how variables interact with each other, while highlighting those with the strongest influence in the network (Di Blasi et al., 2021). One of the benefit of this

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approach is to consider the associations between variables based on the partial correlations or predictive values between investigated variables (Hevey, 2018). They provide estimates of the strength of a relationship between variables while controlling for the effect of the other measured variables in the network model (in the same way as multiple regression coefficients), and therefore provides support for conditional causality (see Pearl, 2016).

Network analysis can be used in two main contexts: cross-sectional (one measurement) and intensive longitudinal (multiple intensive measurements) (Borsboom & Cramer, 2013). Cross-sectional networks provide information about the covariation of variables and the typology the network they form. It explores how different stable traits or variables interact with each other, and which variables are more central than others. By doing so, they inform on the potential role of triggering and maintaining factors, which could therefore be targets of interventions (Bringmann et al., 2019). By focusing on central nodes or traits, such intervention would affect other nearby nodes and therefore the entire network. A complementary way of using network analysis is in the context of intensive longitudinal data. In that context, the presence of several consecutive measurements allows the investigation of associations between variables at the same measurement and between measurements, therefore informing on temporal dynamics in the investigated variables (Epskamp, Waldorp, et al., 2018).

A network approach of informal care

To date, and to our knowledge, no published study has ever applied network analysis to the context of informal care. Network analysis could be useful in the context of informal care as providing care to a relative is acknowledged to be a complex experience, involving multiple actors, factors, and variables (Revenson et al., 2016). For now, temporal and sequential models have been and continue to guide our understanding of how informal care affects the caregiver's well-being and what could be a target of intervention (e.g., Gérain & Zech, 2019; Pearlin et al., 1990; Revenson et al., 2016; Sörensen et al., 2006). However, these approaches only consider associations unidirectionally (all variables lead to an endpoint with few feedback loops) and strongly rely on stress-based approaches, where a (set of) stressor(s) is the predictor of a consequence (e.g. primary and secondary stressors lead to increased distress).

In opposition to that, network analysis is an exploratory method that allows to have a different approach and provide new opportunities to explore the information at hand (Hevey, 2018). The benefit of such method in comparison to their multivariate counterparts (e.g. structural equation modeling) is to introduce more dynamic in the models through exploratory means by having no *a priori* conceptual assumption and providing new insights if applied to developing the understanding of informal care. Multiple factors influence caregiver's well-being, whether they are related to the care-recipient, the caregiver, or their social environment (Gérain & Zech, 2019; Pearlin et al., 1990). All these elements interact to form a complex *network* of components that are influenced by each other, and these interactions must therefore be reflected our analysis. Network analysis therefore provides the opportunity to understand how several components and risk factors interact, in order to complexify our understanding, beyond the stress—appraisal—consequence paradigm, and to get closer to the complex reality informal caregivers are facing. In addition, certain forms of networks called Directed Acyclic Graphs (DAGs) also allow drawing causality in exploratory models (Briganti et al., 2022). This method is based in conditional independence (see Pearl, 2016) and suggests causal paths in a network based on how they interact together.

Network analysis also investigates the relative importance of variables rather than only the association between them. For now, our models explore how several variables are associated with specific consequences, and the conclusion that can be taken is that the variable with the strongest association with our outcome consequently is the most important variable (e.g., the role of the appraisal in risk models, Gérain & Zech, 2022; Pearlin et al., 1990; Sörensen et al., 2006). In the network approach, the strength of the association is considered, but alongside the strength of the *variable* itself. This addition implies that the strongest nodes—those that are the most connected with other variables—may draw our interest in different areas than just looking at the strongest predictor taken alone. In the context of informal care, it could help us understand not what the strongest predictor of distress is, but what could be the best leverage to influence the entire psychological network of a caregiver.

Finally, network analysis also uses exploratory tools to investigate the communities in nodes, i.e. nodes that are grouped and vary together (Hevey, 2018). Such approach is particularly relevant in informal care due to the different spheres of life faced by informal caregivers (e.g. personal, care-related, or social) that could be reflected empirically through different communities of variables. The community analysis also defines the variables that constitute bridges between the communities. In the same sense that strong nodes can be considered as highly influential (or at least strongly associated) to other nodes, bridges nodes are the ones that make the strongest connections with nodes *from other communities*.

Objectives

Because of all the elements network analysis can bring to the informal care literature, the present study proposes to re-explore a risk and resource model of informal caregiver well-being by applying network analysis to existing cross sectional data (Wawrziczny et al., 2017).

Presentation of the dataset

Data from this dataset originates from a study which aimed at exploring the determinants of spouse-caregivers distress in the context of dementia through a large set of variables analyzed with a covariance-based structural equation modelling (PLS-PMM, see Vinzi et al., 2010). In this model, variables were grouped into latent variables. Distress was therefore composed of Depression, Health Problems related to care, disrupted schedule due to care, and the psychological distress index. The determinants were grouped in five latent variables: a) preparedness and confidence (self-efficacy, self-esteem, and caregiving preparedness), b) self-rated health (health in general and health in comparison to others), c) care-recipient's impairment (cognitive status, activities of daily living, and instrumental activities of daily living), d) family divergence (family caregiver conflict and lack of support from the family), and e) couple adjustment (degree of agreement and dyadic interactions). All groups were found to directly influence caregiver distress, with exception of couple adjustment, whose impact was mediated by recipient's care impairment.

Network analysis is demanding in terms of statistical power and does not rely on latent variables. Consequently, less variables than in the original study were included but attention was made to select the most representative variables and to represent all four categories of determinants of caregiving distress (i.e. individual characteristics of the caregiver, of the care-recipient, quality of their relationship, and their social context, see Gérain & Zech, 2019). Therefore, self-efficacy (individual), (instrumental) activities of daily living (care-recipient), degree of agreement and dyadic interactions (relationship quality), and family caregiver conflict (social) were chosen as determinants. Depression and health impact of caregiving were selected as indicators of caregiver distress as they were the strongest variables of the latent variable in the original model.

Methods

Participants

Participants were 125 heterosexual spouses of a person with early- and late-onset Alzheimer's disease or related dementia (PWD) that were recruited through the Regional University Hospital Center of Lille, in France. The sample is described in Table 1. They were mostly female ($n = 74$, 59.2%), on average 67.2 years old (SD = 6.5). The recipients were on average 69.3 years old (SD = 5.1), having displayed the first signs of dementia since an average of 7.1 years (SD = 4.5). They had been married for 43 years (SD = 9.6).

Materials

The included variables were caregiver's levels of distress, evaluated through 7-item depression subscale of the Hospital Anxiety and Depression Scale (HDep, e.g. 'I still enjoy the things I used to enjoy', Zigmond & Snaith, 1983) with scores ranging from 0 to 21 (high depression) (α = .75); the perceived impact of caregiving on health was evaluated through the 4-item health problems subscale of the Caregiver Reaction Assessment (CRAh, e.g. 'My health has got worse since I started caring for …', Given et al., 1992) with a total score from 4 to 20 (high impact on health) (α = .75); the severity of the functional autonomy of the PWD as rated by the caregiver were measured by the 9-item of Activities of Daily Living scale (rADL, e.g. eat, dress, and use the toilet, Ducharme et al., 2016; Gendron & Levesque, 1993) with total scores ranging from 9 to 45 (not at all able) (α = .95) and the 4 items of the Instrumental Activities of Daily Living (rIADL) (e.g. telephone, shopping, housekeeping, Lawton & Brody, 1969), with a total score between 4 to 16 (totally unable) (α = .78); self-efficacy was evaluated through the 15 items Self-Efficacy scale that evaluated the perceived confidence regarding dealing with areas of caregiving (e.g. 'dealing with your need to maintain most of your daily activities', Kuhn & Fulton, 2004) with total score from 15 to 75 (extremely confident) (α = .88); the presence of conflict within the family was measured by the 15-item Family Caregiver Conflict Scale (e.g. 'We avoid discussing things about our relative because it results in disagreements' Clark et al., 2003), with a total ranging from 15 (low conflict) to 105 (high conflict) (α = .91); dyadic adjustment was evaluated through the two-dimensional Dyadic Adjustment Scale (DAS) (Antoine et al., 2008) that measures in 10 items the degree of agreement in the couple (e.g. 'We generally agree in the following areas …') and in 6 items the quality of their interactions (e.g. 'We discuss calmly'), with scores from 10 to 60 (high agreement) and 6 to 36 (good relational quality) (α = .92 & .76).

Table 1. Description of the sample ($n = 125$).

	Mean (SD)	N (%)
Caregivers		
Age	67.2 (6.5)	
Gender (Women)		74 (59.2)
Schooling (years)	14.0 (4.3)	
Paid occupation	20.0 (16.0)	
Care-recipients		
Care-recipients' age	69.3 (5.1)	
First signs of dementia	7.1 (4.5)	
Common characteristics		
Income (€/day)	83.3 (34.4)	
Time since marriage	43.0 (9.6)	

Data analysis

The R (version 4.1.3; R Core Team, 2013) software was used for the analyses. Correlation tables were created through the *APA tables* package (Stanley, 2021). The methodology used for network analysis in the present study is based on existing network studies (Bernstein et al., 2019; Blanchard et al., 2020; Burger et al., 2020; Isvoranu et al., 2021; van Zyl, 2021) and takes most of its source in the methodology developed by Epskamp, Borsboom, et al. (2018).

Network analysis involves three steps (Epskamp, Borsboom, et al., 2018; Hevey, 2018): (1) estimation of the statistical model of the data used to build the network, (2) analysis of the weighted network structure using graph theory (e.g. to explore node centrality), and (3) assessment of the accuracy of the network parameters and measures.

Data preparation

One of the assumptions of network analysis is that the data must follow a multivariate normal distribution to perform psychological network analysis on continuous data (Epskamp, Borsboom, et al., 2018). For that reason, a transformation can was applied, the non-paranormal transformation using the *huge* R-package (Jiang et al., 2020) before estimating the GGM, following recommendations in the field (Epskamp, Borsboom, et al., 2018; Hevey, 2018).

As network analysis relies on partial correlation, missing data were deleted listwise.

Estimation method of the network

The present papers mainly focuses on undirected network, where nodes represent variables that are connected through undirected edges (Hevey, 2018). Pairwise Markov Random Fields (PMRF, Costantini et al., 2015) were used to estimate psychological networks through Gaussian Graphical Models (GGM) of partial correlation coefficients between two variables after conditioning for the other variables in the dataset (i.e. the association between the two variables cannot be explained by any other variable/node in the model) (Epskamp, Waldorp, et al., 2018; Lauritzen, 1996).

Due to the relatively small sample size in the present study, a regularization method was used to reduce false-positive rates (i.e. the probability to keep an edge while it is equal to 0). The Least Absolute Shrinkage and Selection Operator (LASSO, Epskamp, Borsboom, et al., 2018; Tibshirani, 1996) was applied to the data. The LASSO regularization penalizes the model by limiting the total sum of absolute parameters values, which leads to drop edges that are close or equal to 0 (i.e. it gives a *conservative* network model). The use of regularization methods is discussed, but appears to remain an appropriate solution for small sample sizes such as in this study (Williams et al., 2019). The LASSO uses a tuning parameter to control the degree to which regularization is applied, and this parameter is to minimize the Extended Bayesian Information Criterion (EBIC, Foygel & Drton, 2010). The EBIC uses a γ operator that dictates how much the EBIC will prefer sparser models. The value set for this study was 0.5, as recommended previously (Hevey, 2018). The Graphical Lasso (glasso) function was used to do so (Friedman et al., 2008). The *qgraph* R-package (Epskamp et al., 2021) uses the glasso in combination with EBIC model selection to estimate regularized GGM.

The *qgraph* R-package was used to visualize the network (Epskamp et al., 2021).The layout of the network is based on the Fruchterman-Reingold algorithm representation (Epskamp, Borsboom, et al., 2018; Fruchterman & Reingold, 1991). The algorithm calculates the optimal layout so that nodes with less strength and less connections are placed further apart, and those with more or stronger connections are placed closer to each other (Hevey, 2018).

Analysis of the network and centrality indices

For the second step, we looked at the structure of the network, but also at the strengths of the connection between two nodes (Epskamp, Borsboom, et al., 2018). The relationship between nodes was evaluated with the *edge weight* that can be positive or negative (sign) and more or less strong (strength), as well as with node distance (which is equal to the sum of the lengths of all edges on the shortest path between two nodes, see Newman, 2010). The importance of individual nodes was assessed through *node strength*, which is the magnitude of direct associations with other nodes (i.e. the addition of the strength of the association of one node with other nodes)(Costantini et al., 2015). Other strength indicators (e.g. closeness and betweenness) were not considered in the present paper due to conceptual interrogation regarding their use in psychological networks (see Bringmann et al., 2019).

Following cases from previous studies, a community analysis –an analysis of the structure of the network (Traag & Bruggeman, 2009)—was performed in order to explore the presence of subnetworks between the variables. In the present study the Exploratory Graph Analysis (EGA) was used, which uses the Walktrap algorithm to find the number of dense subgraphs or communities (for a more detailed presentation, see Golino & Epskamp, 2017). The EGA method was preferred over the Spinglass as it provides more stable outputs (i.e. running multiple times the analysis usually leads to the same results) (Christensen & Golino, 2019; Golino et al., 2020).EGA was applied using the *EGAnet* package (Golino et al., 2021). EGA and associated results were visualized using the *GGally* (Schloerke et al., 2021), *ggplot2* (Wickham et al., 2020), and *qgraph* (Epskamp et al., 2021) packages in R. To understand which variable bridges the different communities, the *bridge* function from the *networktools* R-package was used (Jones, 2020). The role of bridge variables was evaluated through the *bridge strength* indicator, which measures the influence of a node on nodes from other communities through the sum of the absolute value of all edges that exist between a node and all nodes that are not in the same community.

Network accuracy

To ensure the accuracy of the network and estimators, additional analyses can be performed. For edge-weight accuracy, 95% confidence intervals containing the true value of the parameter were estimated using bootstrap (Epskamp, Borsboom, et al., 2018). In the present study, non-parametric bootstrapping was used, which is preferred over the parametric bootstrap due to the use of the LASSO regularization (Hevey, 2018). To estimate the centrality stabilityaccuracy,the *case-dropping subset bootstrap* was used (Epskamp, Borsboom, et al., 2018). The stability is evaluated with a correlation-stability coefficient (CSC), which represents the maximum proportion of cases than can be dropped, such that with a 95% probability the correlation between the original centrality indices and centrality of networks based on subsets is higher than a fixed value (usually cor = 0.7). Values should be above 0.25 and preferably above 0.50. The *bootnet* package was used to compute both the non-parametric and the case-dropping bootstrap; 1000 bootstrap samples were used (Epskamp & Fried, 2020).

Directed acyclic graphs

Finally, directed networks were explored through Bayesian Networks, represented in a Directed Acyclic Graphs (DAGs) (for a description, see Epskamp, Waldorp, et al., 2018; Pearl, 2016). To do so, the *bnlearn* R package was used (Scutari et al., 2021), using the Inductive Causation PC-stable algorithm (Colombo & Maathuis, 2014). No arrows were blacklisted (excluded). The algorithm provides an initial directed model that is not uniquely identified, which means that several edges could be reversed without changing the conditional independence (Briganti et al., 2022). Because of that, the model was then bootstrapped 1000 times to strengthen the conclusion by displaying a stable network in which directed arrows appear most often (Briganti et al., 2022). Arrows that appear in more than half (≥ 50%) of bootstrapped networks were therefore kept in the final model.

Results

The Pearson correlation matrix of the included variable is displayed in Table 2 (before non-paranormal transformation).

Network estimation

The network obtained from the analysis is displayed in Figure 1. The edges represent regularized (undirected) partial correlations between nodes. Blue edges represent positive associations

Table 2. Correlation coefficients between the included variables.

	1	2	3	4	5	6	7
1. rADL							
2. rIADL	.66**						
3. HDep	.33**	.33**					
4. CRAh	.19*	.16	.54**				
5. DASda	-.35**	-.27**	-.31**	-.35**			
6. DASqi	-.33**	-.30**	-.52**	-.48**	.57**		
7. FamC	-.05	.10	.19*	.29**	-.07	-.19*	
8. SE	.08	-.04	-.31**	-.32**	.17	.28**	-.25**

*Note.** $p < .05$. ** $p < .01$. rADL = recipient's Activities of Daily Living. rIADL = recipient's Instrumental Activities of Daily Living. HDep = HADS Depression. CRAh = Caregiver Reaction Assessment – health impact. DASda = Dyadic Adjustment Scale – Degree of Agreement. DASqi = Dyadic Adjustment Scale – Quality of Interactions. FamC = Family Conflict. SE = Self-Efficacy.

whereas red edges represent negative associations. Thicker edges reflect as stronger partial correlation between nodes.

Strong associations appeared between dyadic adjustment—quality of interactions and degree of agreement, recipient's activities of daily living and instrumental activities of daily living, and depression and impact of caregiving on health, to a lower extent, which reflects conceptual convergence between these nodes.

An important association appears between quality of interactions and the indicators of distress (depression and health impact of being a caregiver), as well as between the two subscales of dyadic adjustment (DAS) and activities of daily living (rADL), and between family conflict and the two indicators of distress, to a lower extent. Self-efficacy appears well connected but only to a limited extent with the other nodes. Overall, these results suggest that the indicators of distress (whether depression or health impact of caregiving) are well-connected, but that dyadic adjustment, especially the quality of the interactions, has a comparable connectivity (except for the absence of association with family conflict).

When looking at the centrality indices that explored the influence of each node (see Figure 2a), it appears that quality of interactions, the recipient's activities of daily living and instrumental activities of daily living, as well as depression and impact of caregiving on health are the strongest nodes involved. These results therefore show that the quality of interactions is the most influential node, and the two indicators of distress are less central, with activities of daily living as an intermediate. Degree of agreement in the couple, self-efficacy, and family conflict are more peripheral nodes with less influence.

Community analysis

Based on the associations between nodes, the community analysis aims at exploring if all the nodes in the network function as a unitary network or if there is the presence of communities of nodes covarying together. This analysis suggests that three

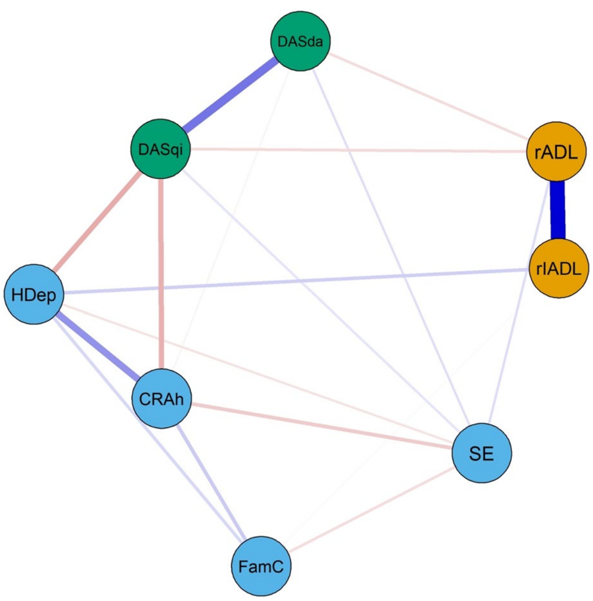

Figure 1. Estimated network.Note: The color of each node reflects its community membership. CRAh = Caregiver Reaction Assessment –health impact. DASda = Dyadic Adjustment Scale – Degree of Agreement. DASqi = Dyadic Adjustment Scale – Quality of Interactions. FamC = Family Conflict. HDep = HADS Depression. rADL = recipient's Activities of Daily Living. rIADL = recipient's Instrumental Activities of Daily Living. SE = Self-Efficacy.

communities appear (see colored nodes in Figure 1): the first focuses on the caregiver and encompasses the distress (CRAh & HDep), self-efficacy, and the presence of conflict within the family. The second focuses on dyadic adjustment and its two dimensions (quality of interactions and degree of agreement). The third encompasses the two dimensions of dependency (rIADL & rADL). The bridge strength analysis (Figure 2b) explores which nodes are the most influential outside of their own community. It showed that the most influential node was the quality of interactions within the couple, followed by depression, activities of daily living, and self-efficacy. This result therefore suggest that the quality of interactions has the biggest sum of edges outside of its community.

Network accuracy

The edge-weight accuracy relies on bootstrapping and helps estimating the true value of the investigated edges identified by the network analysis. The analysis is displayed in Figure 3. As show in the figure, only four edges include 0 in their confidence interval, which means that it cannot be confidently assumed that they are different from 0. This observation is consistent with their exclusion from the network (i.e. no edge displayed).

Finally, the case-dropping bootstrap helps identifying the robustness of the centrality indices used when estimating the model (here, node and bridge strength). When performing the analysis, it appeared that the average correlation for strength and bridge strength was above the .25 threshold (= .36 and .28, respectively), which is supported graphically (Appendix). The strength indicator can therefore be considered valid (Epskamp, Borsboom, et al., 2018).

Directed acyclic graph

The Bayesian Networks represented as Directed Acyclic Graphs (DAGs) display the directed associations between the included nodes following a bootstrap to identify the arrows that are consistent across iterations (Figure 4). Most of arrows seem to converge on quality of interactions and the health impact of caregiving. The impact of family conflict is direct on the latter, whereas the impact of the recipient's activities of daily living is through a worsening of the dyadic interactions. More specifically, the recipient's autonomy diminishes the degree of agreement, which in turn influences the quality of interactions that increase the perceived impact of caregiving in health. The DAG also suggests that depression influences at the same time the quality of interactions and the perceived impact of caregiving on health.

Discussion

The objective of the present study was to make a first attempt in using network analysis in the context of informal dementia care. To do so, a secondary analysis of previously exploited data was performed to have the opportunity to compare the two models used. In the original model, almost all variables were considered as predictors of caregiver distress through direct associations (Wawrziczny et al., 2017). The only exception was that the dyadic adjustment influences the caregiver distress through the recipient's dependency. Aside from that mediation, the model was therefore close to other kinds of risk models in informal dementia care, where variables are expected to

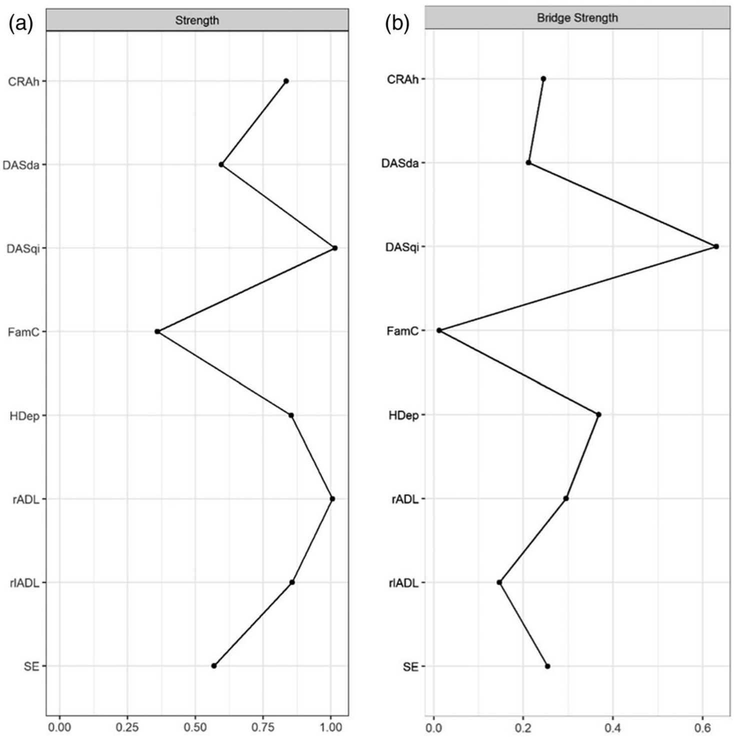

Figure 2. Strength indices of the estimated networks (a) and the bridge strength of the community analysis (b).

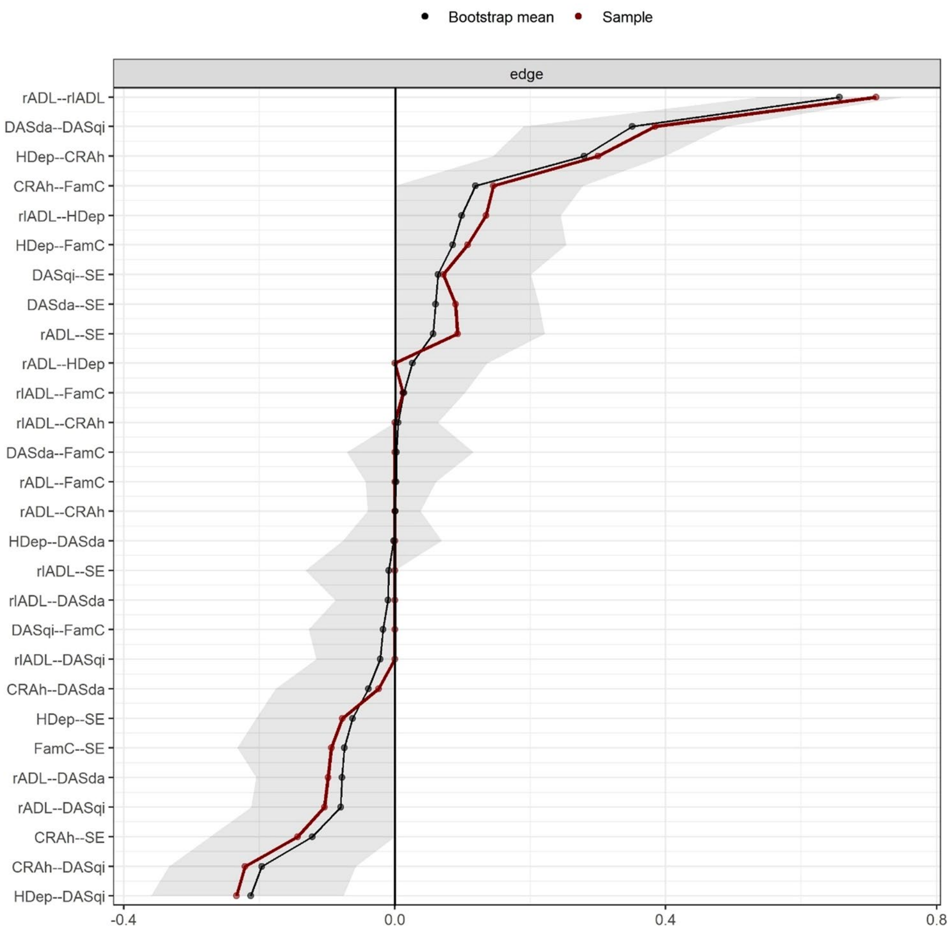

Figure 3. Non-parametric bootstrap of the edges in the estimated network displaying 95% confidence intervals.
Note: Edges different from 0 appear in the network.

influence directly and independently the caregiver distress (e.g. van der Lee et al., 2014). In the present study, as it was expected, distress indicators (depression and impact on health of caregiving) were associated with almost all included variables, which reflects its importance for informal caregivers and in risk models. This result is however coupled with other significant findings.

The centrality of the dyadic adjustment—and particularly of the quality of interactions (QI)—is important on multiple aspects.

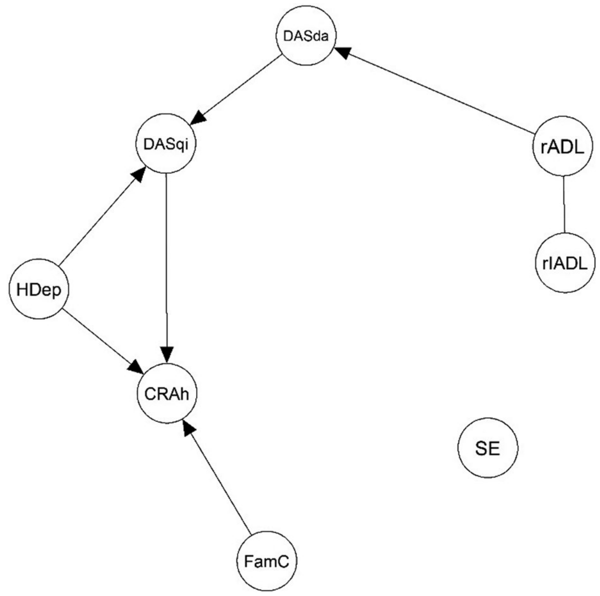

Figure 4. Directed acyclic graph (DAG) of the network.

It suggests that QI is not a mere predictor of distress, but rather an active component that influences distress, but also that is influenced by it (a result that is also supported in the DAGs). This bidirectional association has been suggested in various works (e.g. Gérain & Zech, 2019; Fauth et al., 2012) and supports a vicious circle where increased distress fuels poor QI, and vice versa. In addition, the close ties of dyadic adjustment with the autonomy and results from the DAGs suggest that QI is influenced by autonomy, as supported by the literature that shows how dementia and its consequences influence the dyadic adjustment and interactions (Hellström & Torres, 2021). This importance of QI also echoes works showing that good relationship quality can have a buffer role by moderating the influence caregiving stress on distress (Chunga et al., 2021). The present dataset was focused on the caregiver, but these results highlight the importance of the dyadic components and opens to the necessity to conceive models and interventions that expand to a dyadic paradigm (Bielsten & Hellström, 2019a, 2019b).

In addition, the role of the recipient's dependency is here nuanced. It is often viewed as one mere stressors in theoretical models, but the tentacular impact it can have is here more accurately reflected and echoes original models of caregiver distress (e.g. Pearlin et al., 1990). This reflection is however made with a more dynamic angle that reflects the complexity that one change can have on an entire network. The dynamic in the network is arguably closer to the complex reality of the clinical field, as it reflects the intertwined experience where a small symptomatic change can modify the precarious equilibrium of a single situation.

The conclusions from the connectivity analysis also question the goal of our models. What starts as a model predicting distress becomes a model predicting the quality of interactions within the couples, or at least suggesting its important connectivity. Far from telling the subjective importance of one or another for each informal caregiver, it however shifts the consideration that distress should be the main final end of our predictive models (Marino et al., 2017). Because of their central role, distress and dyadic adjustment are not simply consequences but active components of the caregiver's experience that dynamically influence their experience (Riley et al., 2018; Wawrziczny et al., 2016). As exploratory methods, psychological networks serve the purpose of providing novel inputs to our current models and opening new avenues in research to further explore and better understand informal care. In that fashion, they are one of the reflections of processual modeling that can be performed in the clinical setting, highlighting how different processes interact in maintaining a balance or psychopathological state (Hayes et al., 2020).

The inclusion of Bayesian Network displayed as a Directed Acyclic Graph (DAGs) are part of that approach to understanding how that influence spreads. Such method offers an exploration of causality through directed arrows and conditional independence (Pearl, 2016). The present model considers distress—the impact of being a caregiver on health– as the endpoint of the causal model, while showing causal paths of how the included variables influenced it. By doing so, it highlights the complex influence of depression on quality of interactions, which in turns influences the perceived impact of caregiving on health. This result shows that a distress indicator influences a dyadic component that in turns influence another individual distress indicator. By doing so, DAGs highlight here the dynamic influence variables can have. Such result is particularly striking since DAGs have the assumption of acyclicity, which therefore excludes the possibility of retroacting arrows (Epskamp, Waldorp, et al., 2018). In a real world where acyclicity is rarely present (McNally, 2016), using multiple indicators of variables could therefore be a way to partially circumvent that limitation. Additionally, and because of the nature of conditional causality, the arrows included in the bootstrapped DAG are the result of a probabilistic approach, drawing conclusions based on their frequency of occurrences across resamplings. The inclusion of additional or different variables in the network could also alter the arrows by modifying conditional causality (Epskamp, Borsboom, et al., 2018), as not all causes of all measured variables can realistically be included (problem of causal sufficiency, see Briganti et al., 2022). Finally, psychological networks based on the use of intensive longitudinal methods could also provide complementary information by exploring temporal dynamics (Bringmann et al., 2017).

The present study must however be regarded with its limitations. First, the sample size was not ideal for the use of such analyses which are particularly demanding in light of the number of parameters to estimate (Golino & Epskamp, 2017). The present study relied on bootstrap, *glasso,* and regularized models, which helped to account for the sample size, but larger sample size would allow for greater exploitation of the variety of uses that network analysis provides. Second, the number of included variables was limited. This decision was necessary based on the sample size but may have hindered the range of conclusions that could have been drawn, the DAGs in particular as the assumptions of causal sufficiency central. In addition, a node reduction analysis could have been performed (e.g. *goldbricker* from Jones, 2020) but because the present study already explored only a limited number of variables, the community analysis was preferred, which serves a comparable purpose of showing how variables interact together with the additional feature of exploring bridges between communities.

Conclusion

The present study was the first to use network analysis in the context of informal dementia care. Network analysis highlighted the necessity to take a different stance when considering the interconnectivity of the variables included in our models, notably by showing how central dyadic adjustment was. This interdependency supports the assumption that caregivers face risk and resources in matters of network of interconnected factors, which is closer to their daily reality. Such interconnection raises perspectives in terms of equilibrium to understand how an imbalance in one area of their lives can lead to a disruption of their own balance and lead to deleterious outcomes or lower well-being.

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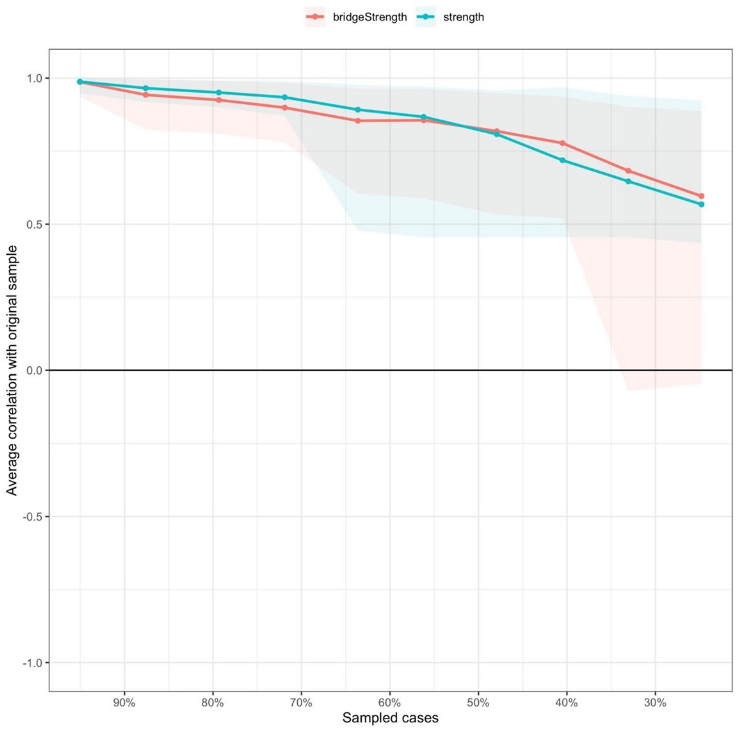
Appendix



Appendix 1. Case-dropping bootstrap of node strength for the network