Investigating the broad domains of intrinsic capacity, functional ability and environment: An exploratory graph analysis approach for improving analytical methodologies for measuring healthy aging

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ABSTRACT

The current paper compared the empirical structure of 280 variables from the 2016 wave of the *Health and Retirement Study* (N = 16,327) estimated using exploratory graph analysis with a theoretical structure based on 20 broad domains of intrinsic capacity, functional ability and environment, identified in the *International Classification of Functioning, Disability and Health* compendium. The results showed that a structure with 21 first-order factors had the best fit to the data (i.e., lowest total entropy fit value) for both the training and validation sample. A second-order exploratory graph analysis was applied on the interfactor correlation matrix and identified five second-order factors. The five-factor structure presented a better fit than the theoretical three-factor structure (approximately) representing intrinsic capacity, functional ability and environment. A close inspection of the network structure generated by analyzing the rotated network loadings of the 21 first-order factors revealed an interplay between cognition, mobility, need for help with daily activities, walking capacity, physical capacity, liver functioning, positive affect and perceived mastery, low perceived control, and depression/negative mood. Combined, our results can help guide future research by providing a framework for estimating the structure of multi-domain aging research as well as generating questions that can be addressed in future research.

Introduction

As the human population gets older around the world, the need to address aging issues increases. The study of aging processes have been conducted in the past decades with a strong emphasis on health deficits (e.g., diseases, disabilities, limitations). The logic behind this focus is straightforward: the socio-economic cost of a population living longer with multimorbidity and disabilities is high[1]. Despite the relevance of studying health deficits, aging processes should be investigated more broadly. In this line, the World Health Organization proposed a comprehensive response to population aging as the promotion of healthy aging across the life-course[2].

The first WHO's Action Plan on Ageing and Health[3] called for a fundamental transformation in policies and institutions to enable individuals in the second half of life to achieve their needs and aspirations, embracing diversity and narrowing health inequities. A second action plan on aging and health termed '*A Decade of Healthy Ageing: From 2020 to 2030*' will address relevant questions related to aging such as the quantification of the baseline indicators of healthy aging in countries, the projections of Member State-endorsed outcome and impact indicators through 2030, and the use of evidence-informed interventions as a way to improve older adults' intrinsic capacities and functional ability[2].

To address the topics of the WHO's action plan on aging and health, it is necessary to operationalize and measure healthy aging in a meaningful, valid, and reliable way. Michel and Sadana[4] recently reviewed publications in the area of healthy aging and summarized the types of assessments and measures used by the researchers. The authors

verified that the studies use eight general categories of variables: (1) education, (2) diet, (3) physiological/physical health, (4) mental health, (5) daily functioning, (6) personal perception (e.g., engagement, goals, satisfaction, quality of life), (7) social life, and (8) environmental characteristics. Each study assessed different domains (or combinations of domains) with different elements in each domain demonstrating the lack of a reference criterion or integrative theoretical model for assessing healthy aging[4].

Such an integrative theoretical model is a necessary step to construct measures of healthy aging and guide the analysis and interpretation of existing aging-related datasets that employ multiple scales, tests, and questionnaires. An integrative theoretical model of healthy aging was developed using the WHO's definition of healthy aging[2, 3] that combined elements from three concepts: intrinsic capacity (**IC**), functional ability (**FA**), and environment (**EN**). Beard et al.[3] defines *intrinsic capacity* as a combination of physical and mental capacities of an individual, *functional ability* as the health related attributes that enable people to be and do what they value, and *environment* as a combination of factors in the extrinsic world (understood in the broadest sense and including physical, social and policy environments) that form the context of an individual's life[5]. The combination of IC, FA, and EN forms the general definition of healthy aging adopted by the WHO[6]: the process of developing and maintaining functional ability that enables well-being in older age, with functional ability determined by the intrinsic capacity of the individual, the environments they inhabit, and their interactions.

The three broad concepts of healthy aging (IC, FA, EN) are informed by the WHO's *International Classification of Functioning, Disability and Health* (**ICF**) compendium[3]. ICF is a normative classification system of health that can be used as a starting point for the development of an integrative theoretical model to inform the operationalization of healthy aging concepts, development of new measures, and interpretation of results from existing aging research data[5]. Figure 1 presents general domains of IC, FA, and EN as factors of the ICF compendium, which were grouped by global experts[2]. IC combines several domains of mental and body functioning: (1) sensory, (2) mental, (3) neuromusculoskeletal, (4) voice and speech, (5) cardiovascular, (6) haematological, (7) immune, (8) respiratory, (9) endocrine, (10) genitourinary, (11) reproductive, (12) integumentary and (13) metabolic. FA is comprised of the following broad domains: (1) basic needs, (2) learn, grow and make decisions, (3) mobility, (4) build and maintain relationships, (5) contribute to community/society. Finally, environment includes five broad domains: (1) products and technology, (2) natural and human-made environment, (3) support and relationship, (4) attitudes and (5) service, systems and policies.
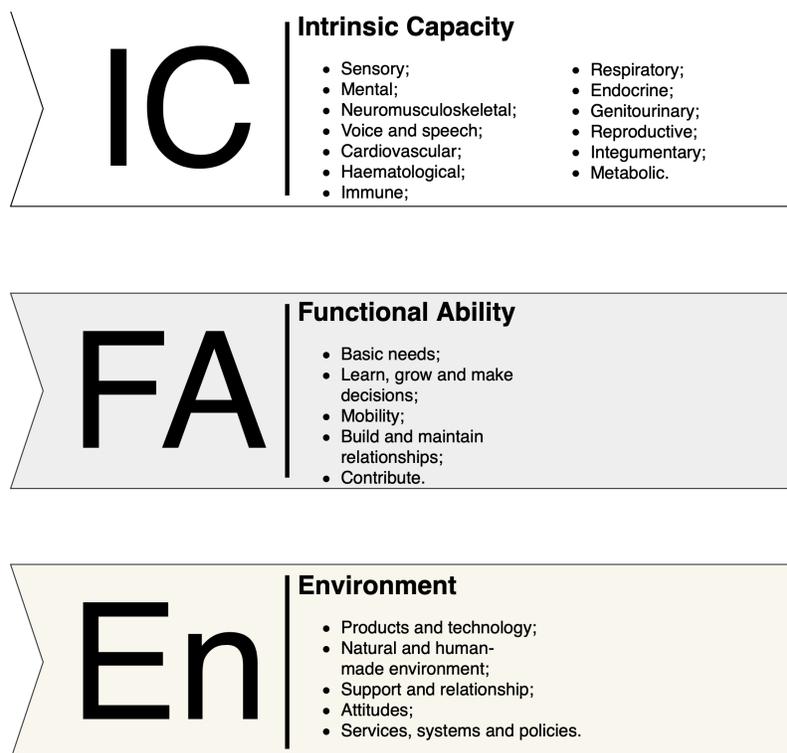
Figure 1. Broad domains of intrinsic capacity, functional ability, and environment.

The broad domains of IC are consistent with the ICF's body functions and structures, while the broad domains of FA and EN draw on the ICF classifications for activities, participation, and environments. The names of the broad domains of IC, FA and EN are slightly different from the original ICF framework—these changes were necessary to fit the target population, definitions, and framework of healthy aging.

The use of the ICF framework to conceptualize broad domains of healthy aging was pioneered by Cesari et al.[5] with the goal to pave the way for its operationalization and measurement. However, they focused on IC only and did not check the suitability of their theoretical model with empirical data. The current paper seeks to investigate the structural validity of the IC, FA, and EN broad domains (Figure 1) using data from the 2016 wave of the Health and Retirement Study (HRS), a large-scale study on aging. The structural validity of the healthy aging domains will be investigated using an innovative approach for dimensionality assessment termed Exploratory Graph Analysis (**EGA**[7,8]). The fit of the theoretical structure (23 broad domains of IC, FA and EN; Figure 1) will be compared to the fit of data-driven structures estimated using EGA, using the total entropy fit index[9]. After estimating the structural organization of the broad domains (first-order factors), we will estimate the structure of the second-order factors (i.e., IC, FA, and EN).

A secondary goal of the current paper is to work as a detailed guide for how to examine the dimensionality of healthy-aging data in two levels of analysis (first-order and second-order factors), introducing new techniques and strategies that are part of the EGA framework. Therefore, in the Methods section we briefly introduce the EGA approach, describe a new fit index for dimensionality assessment termed *total entropy fit index* (**TEFI**)[9], and present a strategy to optimize the estimation of the dimensionality structure via EGA using the TEFI index. In this section, we also introduce *network loadings*, a network metric roughly equivalent to factor loadings[10], and how it can be used to estimate the structure of second-order factors. A brief proof-of-concept simulation for second-order EGA is also presented in the Methods section.

Results

For each sample (training, N = 9,796; validation, N = 6,531), the EGA technique was employed using two network techniques, i.e. the Gaussian graphical model (GGM[11]) and the triangulated maximally filtered graph (TMFG[?,8,12]), varying the number of steps in the Walktraph algorithm, and computing the total entropy fit index to detect the optimal dimensionality structure.

Table 1 shows the *TEFI* per EGA technique and number of steps used in the Walktrap algorithm as well as the number of dimensions estimated. Since *TEFI* is a relative measure of fit, to check the best fitting structure is necessary to compare two or more dimensionality solutions (number of factors and placement of items per factor). The lower the value of *TEFI*, the better the fit of the structure to the data. EGA with the *GGM* estimation presented the lowest *TEFI* when the Walktrap algorithm was implemented with 10 steps, estimating a structure with 30 factors (*TEFI* = -641.84). EGA with the *TMFG* method presented the lowest *TEFI* when the number of steps was four, estimating 21 factors (*TEFI* = -706.89). The best fitting EGA structure was obtained by the *TMFG* method.

Table 1. Total entropy fit index per number of steps of the Walktrap algorithm and network technique.

	TEFI (Dimensions)	
Walktrap Steps	EGA GGM	EGA TMFG
3	-639.10 (31)	-621.24 (18)
4	-602.57 (24)	-706.89 (21)
5	-622.93 (26)	-682.86 (20)
6	-630.04 (27)	-659.42 (19)
7	-538.10 (21)	-667.32 (19)
8	-532.72 (21)	-670.31 (20)
9	-530.58 (21)	-582.07 (16)
10	-641.84 (30)	-582.08 (16)

Note. Grey boxes indicate the lowest TEFI for each EGA method.

Table 2 shows the total entropy fit index per sample (training and validation), EGA technique and also for the theoretical structure. The result is consistent across samples with *EGA TMFG* presenting the lowest *TEFI* and the theoretical structure (20 factors) the highest. The network loadings of the variables and their description is presented in a supplementary Table (see Additional Information at the end of the manuscript). The network loadings are ordered by magnitude of the loadings and factor number. Focusing on the variables with the moderate or high loadings per factor (i.e., network loadings equal to or higher than 0.25), the factors can be interpreted as follows.

Table 2. Total entropy fit index per structure in the training and validation samples

Data	Structure	TEFI	Dimensions
Training	EGA GGM	-641.84	30
Training	EGA TMFG	-706.89	21
Training	Theoretical	-543.45	20
Validation	EGA GGM	-577.88	30
Validation	EGA TMFG	-627.11	21
Validation	Theoretical	-531.65	20

Factor one (*cognition*) is composed by items involving subtraction, date orientation (year, date, day of the week), delayed recall, and number series. The second factor, *close relationships*, has items related to support and criticism offered by close family members and friends as well as communication with them. Factor three (*physical capacity*) is composed by items related to grip strength, eye intraocular pressure (measured via the *puff test*), and balance. The fourth factor (*negative affect*) involved items related to negative emotions such as feeling nervous, sad, afraid, frustrated, and scared (see Supplementary Table, link at the Additional Information section at the end of the paper). Factor five (*positive affect/perceived mastery*), on the other hand, presents variables related to positive emotions such as perceived mastery and relationship with the spouse/partner. Factor six combines variables related to one's ability to drive and biomarkers of genitourinary functioning. Factor seven is composed by items related to cognition, especially from the number series test, while factor eight is a combination of items related to agreeableness, extroversion and reliance on friends, which we labeled as a *people-oriented* trait. Factor nine, by its turn, is related to depression and negative mood, factor ten is a factor related to cognition (but involving number series items with moderate difficulty) and mobility. Factor eleven is composed by mobility indicators (walking test – time) and the need of specialized equipment (bed and walk equipment) and factor twelve by variables related to the need of help with instrumental activities of daily life.

Factor thirteen is composed by variables that indicate a creative and curious mind, with an active intellect that seeks learning new things, while factor fourteen is composed by indicators of communication and interpersonal interactions with family members, friends and children, and one item related to incontinence. Factor 15 contains biomarkers of basic metabolic functioning (cholesterol and triglycerides), factor 16 contains biomarkers of liver functioning (alanine, aspartate aminotransferase, ferritin, and alkaline phosphatase), and factor 17 is composed by biomarkers of genitourinary functioning (chloride, sodium, bicarbonate). Factor 18 has items related to volunteering activities and other activities (attending non-religious organizations and writing letters, stories or journal entries), while factor 19 has items related to low perceived control. Factor 20 contains items related to the (negative) quality of the close environment (neighbourhood) and factor 21 has indicators of blood pressure.
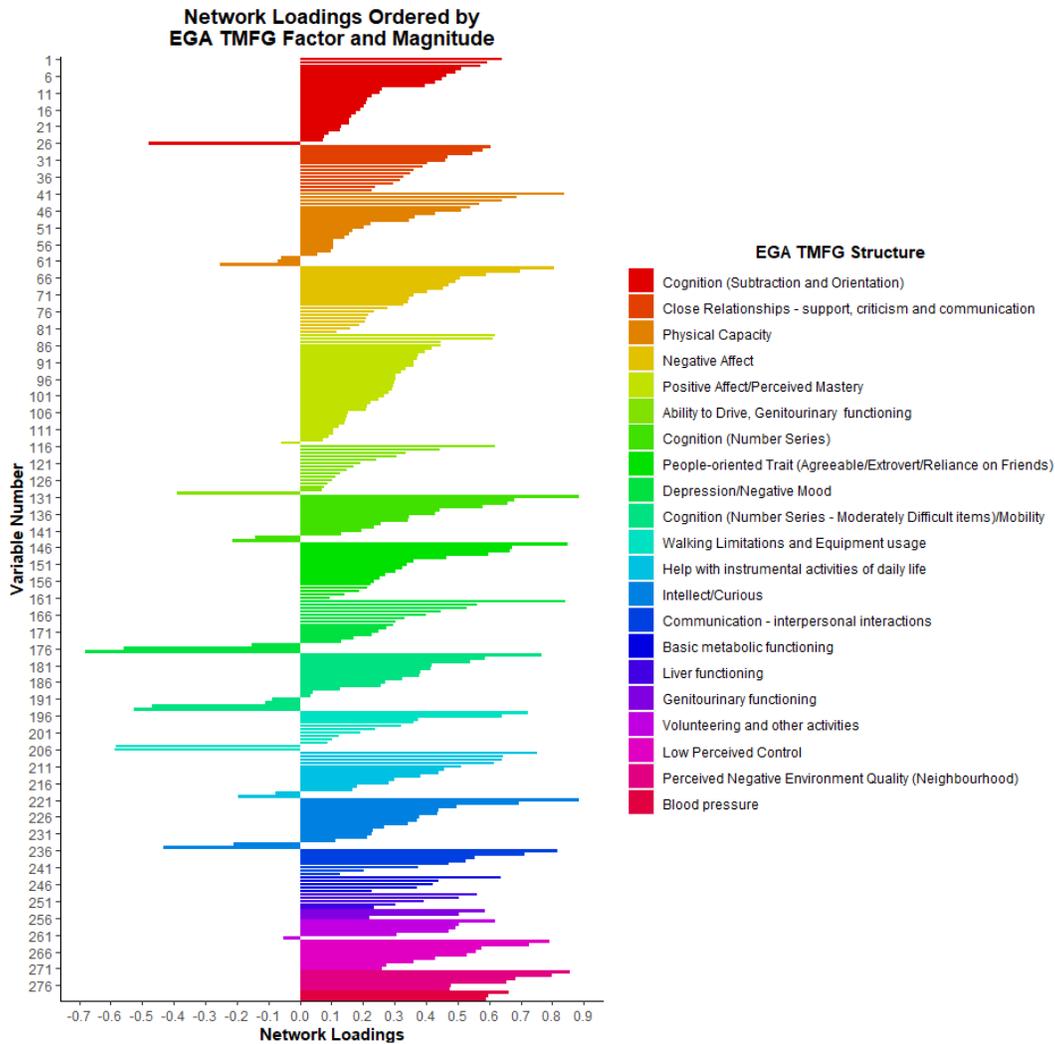
Figure 2. Network loadings ordered by magnitude within each EGA TMFG factor. Variable number represents each item as a number that corresponds with the item labels and descriptions found in the Supplementary Table. Effect sizes follow standard factor loading conventions: .40 (small), .55 (moderate), and .70 (large; Comrey, 2013).

Figure 2 depicts the magnitude of network loadings within each factor defined by EGA TMFG. The variable numbers correspond to the items found in the Supplementary Table. Figure 3 shows the structure estimated using *EGA TMFG*. Nodes (variables) are represented by colored circles, where each color represents a factor. The node size represents the magnitude of the network loadings. Since plotting hundreds of items and 21 factors is a challenge for interpretation, Figures 4 and 5 shows the same network structure as Figure 3, but each factor is now being represented separately to improve interpretability.
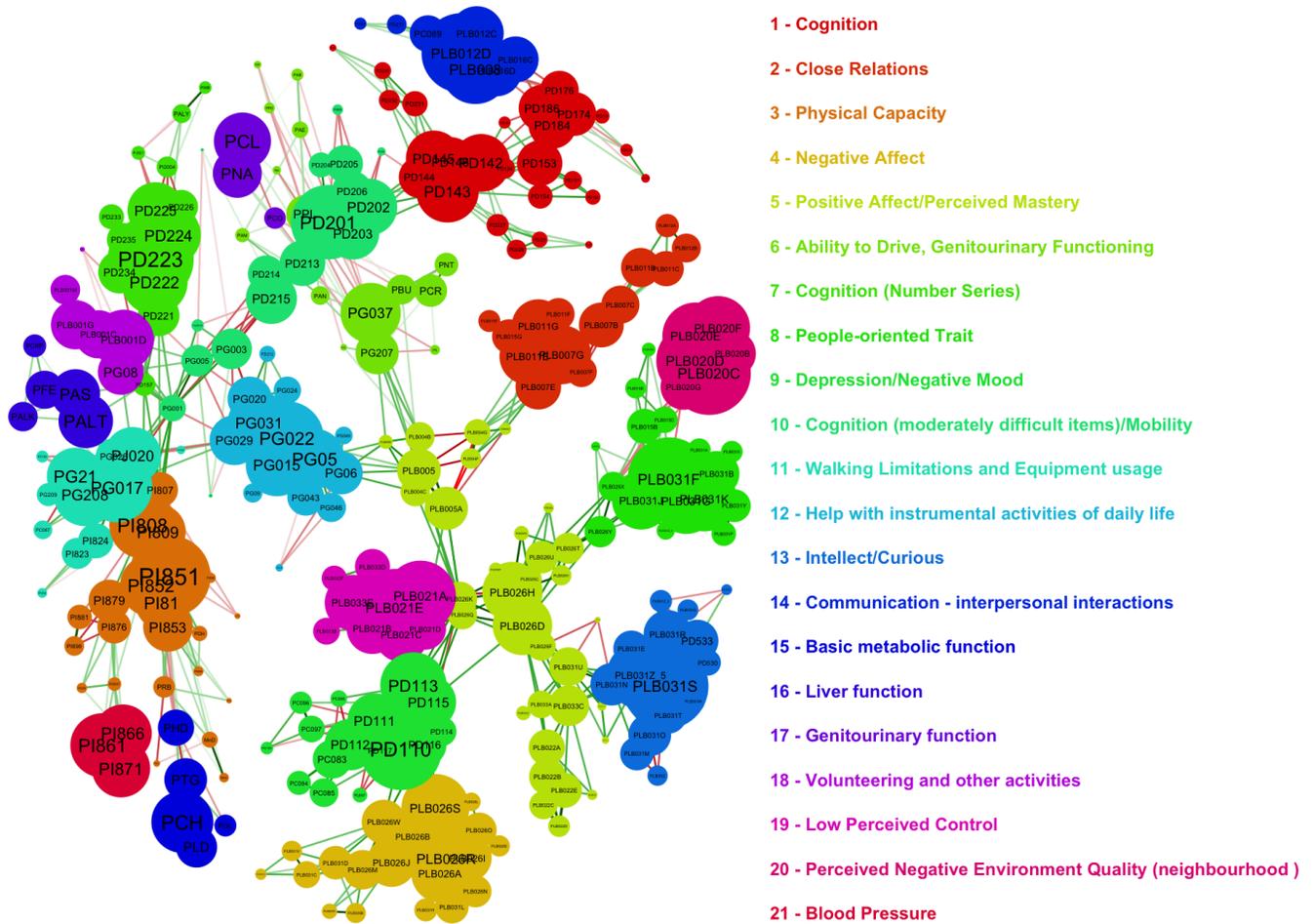
Figure 3. The EGA TMFG network structure colored coded by factors. The size of th node corresponds to the magnitude of the network loading for each item on their dominant factor.

1 - Cognition

2 - Close Relations

3 - Physical Capacity

4 - Negative Affect

5 - Positive Affect/Perceived Mastery

6 - Ability to Drive, Genitourinary Functioning

7 - Cognition (Number Series)

8 - People-oriented Trait

9 - Depression/Negative Mood

10 - Cognition (moderately difficult items)/Mobility

11 - Walking Limitations and Equipment usage

12 - Help with instrumental activities of daily life

13 - Intellect/Curious

14 - Communication - interpersonal interactions

15 - Basic metabolic function

16 - Liver function

17 - Genitourinary function

18 - Volunteering and other activities

19 - Low Perceived Control

20 - Perceived Negative Environment Quality (neighbourhood)

21 - Blood Pressure

Figure 4. EGA TMFG factor structure depicted with each factor's (factors 1–12) location in the network. The colored nodes represent items in the factor.
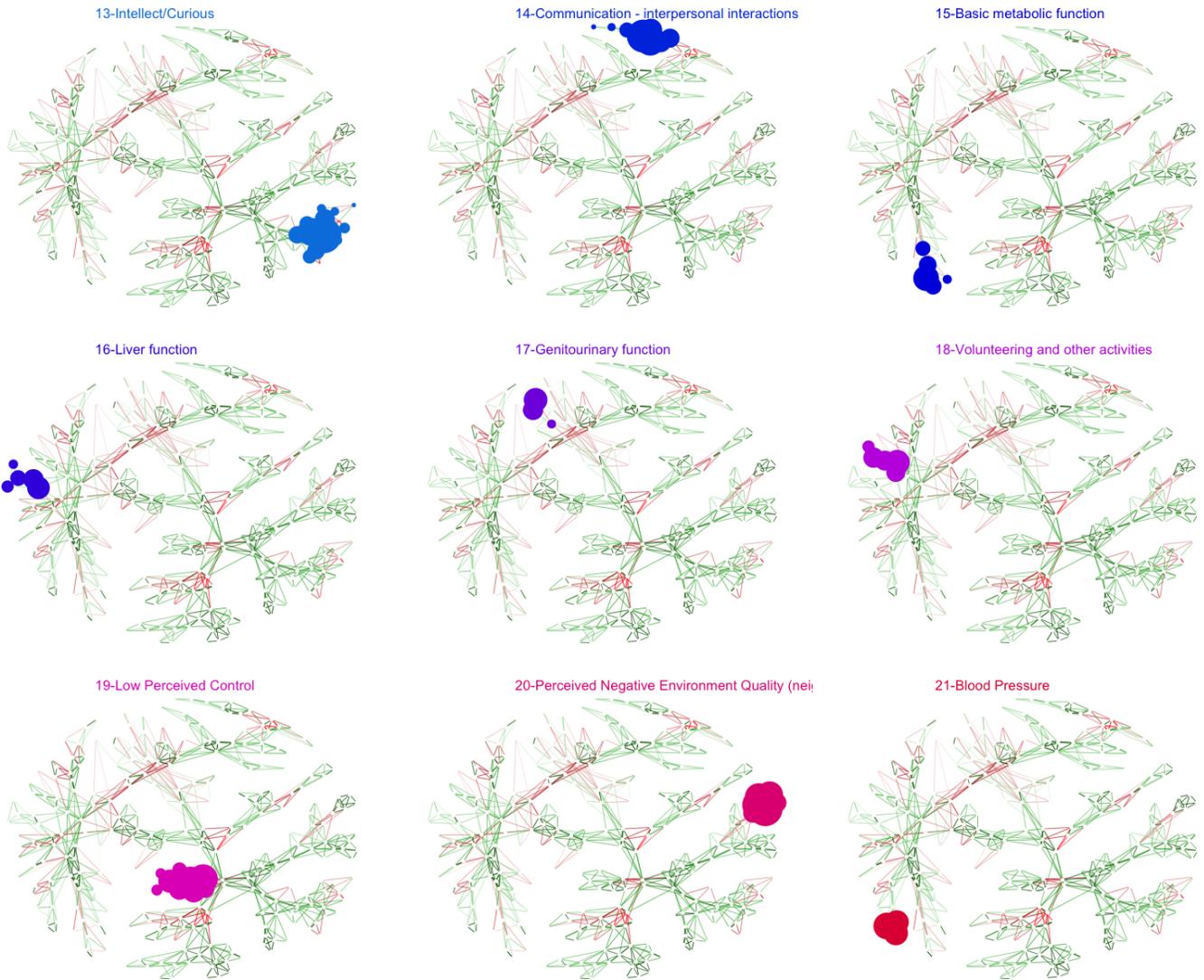
Figure 5. EGA TMFG factor structure depicted with each factor's (factors 13–21) location in the network. The colored nodes represent items in the factor.

The second-order structure of the 21 factors described above was estimated by rotating the network loadings using the *GeominQ* rotation via the *GPArotation* package[13]. The resulting interfactor correlation matrix was analyzed using EGA. Factor 15 (*basic metabolic function*) was estimated as a single-node cluster, and was removed from the second-order analysis. Figure 5 shows the second-order structure with five factors. The first second-order factor (red nodes) was composed of the following first-order factors: (1) Factor 1: Cognition, (2) Factor 10: Cognition (moderately difficult items)/mobility, (3) Factor 11: Walking Limitations and Equipment usage, (4) Factor 12: Help with instrumental activities of daily life, (5) Factor 14: Communication - interpersonal interactions, and (6) Factor 18: Volunteering and other activities. Second-order factor two had the following first-order factors: (1) Factor 2: Close Relations, (2) Factor 5: Positive Affect/Perceived Mastery, (3) Factor 6: Ability to Drive, Genitourinary Functioning, (4) Factor 13: Intellect/curious, (5) Factor 17: Genitourinary function, and (6) Factor 19: Low Perceived Control. The third second-order factor had the following composition: (1) Factor 3: Physical Capacity, (2) Factor 7: Cognition (Number Series), (3) Factor 16: Liver function, and (4) Factor 21: Blood Pressure. The fourth second-order factor was composed of factors 8 (People-oriented Trait) and 20 (Perceived Negative Environment Quality - neighbourhood), while second-order factor five by the factors 4 (Negative Affect) and 9 (Depression/Negative Mood). The *TEFI* of this five second-order factors—Physical and Mental Capacity, Social Mobility, Cardiovascular Capacity, Environment, and Negative Affect, respectively—was -12.55, which was lower than the *TEFI* of a three-factor structure that combined the first-order factors into functional ability, intrinsic capacity, and environment factors (*TEFI* = -5.26).
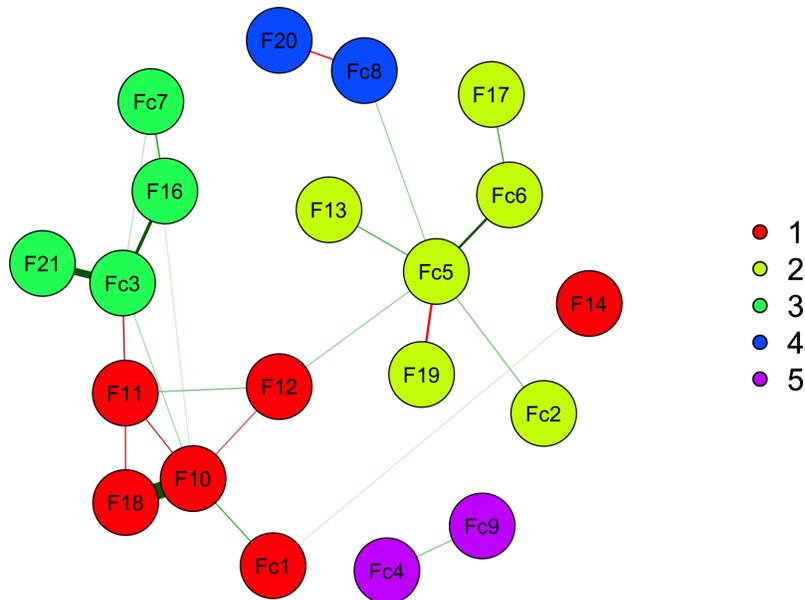
Figure 6

Discussion

The use of the *International Classification of Functioning, Disability and Health* compendium[3] framework to conceptualize broad domains of healthy aging was pioneered by Cesari et al.[5] with the goal to pave the way for its operationalization and measurement. Having an unified framework that can be used to inform the development of new metrics and in the interpretation of the results from multi-domain aging research is an important step in the field. As pointed out by Michel and Sadana[4] in a recent review, each study of healthy aging assesses different domains or combinations of domains with different variables in each domain, evidencing the lack of an integrative approach that can be used as a reference criterion to the development of an integrative theoretical model.

The most integrative theoretical model of healthy aging was developed using the WHO's definition of healthy aging[2,3]: the process of developing and maintaining functional ability that enables well-being in older age, with functional ability determined by the intrinsic capacity of the individual, the environments they inhabit, and their interactions. Twenty-one general domains from the ICF compendium were identified as possible indicators of IC, FA and EN by global experts[2]. In this theoretical model with 20 first-order factors, intrinsic capacity is composed by

several domains of mental and body functioning, functional ability is comprised by broad domains related to basic needs, the capacity to learn, grow and make decisions, mobility, the capacity to build and maintain relationships, and to contribute to community/society. Finally, environment includes five broad domains related to products and technology, natural and human-made environment, support and relationship, attitudes and service, systems and policies.

The present research used data from the 2016 wave of the Health and Retirement Study ($N = 16{,}327$ adults and elderly from the US), which was split into two random subsamples (training set with 60% of the observations and validation set, with 40%). EGA was used to identify the structure of 280 variables from the HRS study in the training set, and the fit of the empirical structure estimated using two different network techniques (GGM and TMFG), which were compared to the fit of the theoretical structure with 20 broad dimensions from the ICF in both the training and the validation samples. The total entropy fit index[9] was used to optimize the number of steps used in the Walktrap algorithm, an important part of the estimating factors using EGA technique, and to compare the empirical and theoretical models. The result shows that the structure estimated using *EGA TMFG* presented the lowest *TEFI* values in both training and validation samples, with the following 21 first-order factors: cognition, close relationships, physical capacity, negative affect, positive affect and perceived mastery, ability to drive and biomarkers of genitourinary functioning, cognition (number series), a people-oriented trait of personality, depression and negative mood, cognition (number series items with moderate difficulty) and mobility, walking capacity and the need of specialized equipment, need of help with instrumental activities of daily life, intellect and curious mind, communication and interpersonal interactions with family members, friends and children, basic metabolic functioning, liver functioning, genitourinary functioning, volunteering and other activities, low perceived control, perceived negative quality of the close environment (neighbourhood) and blood pressure.

Next, the 21 empirical factors were analyzed using a method to estimate second-order factors from the EGA results described earlier. A brief Monte-Carlo simulation was implemented to check the efficiency of the second-order EGA technique in detecting the number high-order factors, quantified using normalized mutual information. The results of the simulation showed that a very high efficacy for first-order factors (mean NMI close to 1) and for second-order factors with sample sizes of 5,000 and 10,000. The application of the second-order EGA technique in the 21 first-order factors revealed a structure composed by five factors (Figure 6). These five second-order factors were largely congruent with the three proposed domains. Specifically, IC was related to second-order factors 1 (Physical and Mental Capacity) and 3 (Cardiovascular Capacity), FA was related to second-order factors 2 (Social Mobility) and 5 (Negative Affect), and EN was related to second-order factor 4 (Environment).

It is interesting to note that each second-order factor shown in Figure 6 has a very clear central node, and the direction of the connections (positive or negative regularized partial correlations) also reveals interesting patterns. In the first second-order factor, cognition (moderately difficult items)/mobility is the most central node, being positively linked to volunteering and other activities (factor 18) as well as to cognition (first-order factor one). However, it is negatively linked to walking limitations and equipment usage (factor 11) and to the need for help with instrumental activities of daily life (factor 12). Therefore, the greater people's reasoning and mobility capacity, the more they engage as volunteers and attend non-religious organizations. This is in line with previous studies that identified that the variety and frequency of engagement in social activities coupled with the sense of social connection, are related with less cognitive decline in old age.[14–16] James, Wilson, Barnes, and Bennett[17], for example, examined the association of social activities (including volunteer work, participation in clubs, attendance of religious services, and others) with cognitive decline in a longitudinal study with 1138 people and reported that more social activity at baseline was associated with less cognitive decline in five cognitive domains (episodic memory, semantic memory, working memory, perceptual speed and visuospatial ability). A one point increase in social activity score was associated with a reduction of 0.034 units in the rate of cognitive decline per year[17]. Lövdén, Ghisletta, and Lindenberger[18] reported that the level of social engagement, including activities that are cognitively stimulating, like attending lectures, predicted the rate of change of perceptual speed.

Engaging in social activities, such as doing volunteer work, is considered positive for older adults because being useful to others instills a sense of being needed and valued[19], but the impact on cognition depends on the type of social activity[20]. Interventions focusing on sustained engagement in productive social activities, which involves learning new things, can positively impact the cognitive capacity of older adults[20]. But the same doesn't hold for receptive social activities, such as participating in social clubs, which presents limited cognitive benefits[20].

Our results show that cognitive capacity alone (first-order factor one) is not linked to volunteering and other social activities, which may indicate that mobility can be a potential mediator between cognitive capacity and engagement

in organized social activities. Mobility is, indeed, known to modulate the level of participation of older adults in social activities, even in the absence of disability[21]. In their 21 year follow-up study with elderly Finish men and women, Katja, Timo, Taina, and Tiina-Mari[22] investigated a tangential but related question: whether mobility, cognitive functioning, and depressive symptoms were mediators of the relationship between social activity and mortality risk. The authors discovered that mobility could explain part of the association between social activity and mortality, but cognitive functioning and depression were not. Instead, Katja et al.[22] concluded that a good cognitive capacity and less depressive symptoms were prerequisites for engaging in collective social activity.

At the same time, the negative relationship between cognition and mobility (factor 10) and need for help with daily activities (factor 12) and to mobility and use of equipment (factor 11), may suggest that older adults with more intrinsic physical and mobility limitations have more difficulty with tasks demanding the use of fluid intelligence. This result is in line with a number of studies[23–25] showing that mobility is related to cognitive performance in older adults (for a recent meta-analysis see[26]).

Surprisingly, the need for help with instrumental activities of daily life was positively linked to positive affect and perceived mastery (formed by items such as *interested*, *enthusiastic*, *close with spouse/partner*, *spend enjoyable time together with the spouse/partner*, *am an active person in carrying out the plans set for myself*, *active*, *usually find a way to succeed*, *do anything I set my mind to* and *do things that I want to do*), which was the most central variable of the second-order factor two. Perceived mastery has been conceptualized as a psychological construct that might be central to the process of selective optimization with compensation[27], and operationalized in terms of "the extent to which one regards life chances as being under one's own control in contrast to being fatalistically ruled"[28] or in terms of self-efficacy, which refers to the belief that an individual has the skills or qualities necessary to control the events that happen to his/her life[29] and the belief that one has the means to achieve desired ends[30]. People with high levels of mastery can modify the meaning and consequence of their experience by using cognitive strategies and modifying their behaviors[31], which may be an important mechanism for successful adaptation to challenges of the life as well as an important predictor of the stability in activities of daily life among elders[32]. Based on the positive relationship between need for help with IADL, positive affect/perceived mastery and close relationships, we hypothesize that a sense of efficacy might be achieved when the individual, with the help of a social support, successfully adapt to a new reality, even if with loss of independence/autonomy in daily life activities.

At the same time, our results show that positive affect and perceived mastery is negatively connected to low perceived control (first-order factor 19), but positively associated with the other indicators of second-order factor two (i.e. close relations, ability to drive and genitourinary functioning, as well as intellect/curious). This result is in line with previous studies showing that low perceptions of control are strongly associated with negative emotions as sadness[33], and that control beliefs impact health and well-being[34].

The most central variable in the third second-order factor is physical capacity (first-order factor 3), which is positively connected to cognition, liver function and blood pressure. This result is also in line with previous studies showing that physical capacity is positively related to cognitive performance in older adults[35] and that higher levels of physical activity are associated with lower cognitive decline in longitudinal studies[36].

At the same time, liver functioning is known to positively impact people's cardiovascular health and physical capacity, with higher levels of alanine aminotransferase being previously associated with lower cardiovascular mortality[37] and with functional measures of physical capacity[38]. Another variable of liver functioning, aspartate aminotransferase (PAST) is an indicator of muscle disorders[39,40], so it makes sense to have factors three (physical capacity) and 16 (liver functioning) in the same second-order factor.

Another interesting result shows that the people-oriented trait (first-order factor 8—a mix of agreeableness, extraversion, and reliance on friends) is negatively associated with factor 20 (perceived negative quality of the neighbourhood). Dunkel et al.[41] found that higher scores in people-oriented traits (i.e. agreeableness and extraversion) are associated with higher scores in perceived positive neighbourhood qualities (such as safety) and lower scores in negative qualities such as neighbourhood inequality. The relationship between people-oriented traits and perceived neighbourhood quality (the higher people's person-oriented trait the lower their perceived negative qualities in neighbourhoods) may be explained by the mechanism described by Robinson, Meier, and Vargas[42]. In their experimental study, Robinson et al.[42] showed that introverts that are faster in tasks of threat categorizations are more vulnerable to experience negative affect compared to introverts that are slow in the task. At the same time, high levels of extraversion inhibitthe negative affective consequences, being sufficient to "override implicit tendencies to regard the world as somewhat threatening in nature"[42]. Together with our results, the findings described above point to the

need to use more objective indicators/measures of neighbourhood quality in aging studies, since people with higher people-oriented traits have a tendency to see their immediate environment via a more positive lens.

Finally, negative affect (factor 4) was identified in the same second-order factor as depression and negative mood (factor 9), being not connected to the other factors. This might suggest that second-order factor 5 is a unique psychopathological dimension. The lack of a second-order association between depressive symptoms and cognition (factors 1, 7 and 10) in our study is not consistent with the literature findings, however[43–45]. Our findings may suggest that cognition and the combination of depression, negative affect and negative mood are independent phenomena and their co-existence might be explained by additional common causes underlying major depression and dementia, like vascular risk factors[46], cerebrovascular lesions[47], and damage on the hypothalamic-pituitary-adrenal-stress axis[48].

It is worth noting that the relationship between the first-order factors shown in Figure 6 may be better represented by a network model instead of a factor model, since it is somehow different from the usual EGA results, where the variables are densely connected within factors[7, 8]. In any case, the results presented in the current paper can be used for both interpretations, since in the EGA framework factors are clusters of nodes in a network.

The current paper compared the empirical structure of 280 variables from the 2016 wave of the HRS study estimated using exploratory graph analysis with a theoretical structure based on 20 broad domains of intrinsic capacity, functional ability and environment, identified in the ICF compendium. The results showed that a structure with 21 first-order factors (estimated using *EGA TMFG*) has the best fit to the data (i.e., lowest total entropy fit value) for both the training and validation sample. A second-order exploratory graph analysis was applied in the interfactor correlation matrix, computed using the rotated matrix of network loadings, and identified five second-order factors. The five-factor structure presented a better fit than a three-factor structure (approximately) representing intrinsic capacity, functional ability and environment. A close inspection of the network structure generated by the second-order EGA revealed an interesting interplay between cognition, mobility, need for help with daily activities, walking capacity, physical capacity, liver functioning, positive affect and perceived mastery, low perceived control, and depression/negative mood. Combined, our results might help guide future research not only by providing a framework for the analysis of the dimensionality structure of multi-domain aging research, but also by generating questions that can be addressed in future research such as: (1) a possible mediation effect of mobility in the relationship between cognition and engagement in structured social activities, (2) expanding our understanding of the connection between liver functioning, cognition and physical capacity, (3) exploring the directionality of the relation between positive affect and perceived mastery and the need for help with daily activities. The present paper is the first investigating the structure of broad domains of intrinsic capacity, functional ability and environment. Although our findings diverge from the theoretical structure based on 20 broad domains presented in the ICF, future research could expand our analysis in two different ways: 1) by using the variables with the highest network loadings per dimension to evaluate healthy aging, and check how a reduced sample of variables from the 21 first-order factors is organized in terms of structure; 2) by using the ICF and the definition of intrinsic capacity, functional ability and environment as an integrative theoretical model to develop new measures of healthy aging. Without a clear integrative theoretical model guiding the development of instruments, the structural organization of variables collected in aging studies will possibly lack the homogeneity that is necessary to find generalizable dimensions.

Methods

Data

The current study uses data from 16,327 adults and elderly from the US that participated in the 2016 wave of the Health and Retirement Study (HRS). From all variables collected in 2016, two hundred eighty were selected as indicators of intrinsic capacity, functional ability and environment. The indicators combine variables related to 20 domains: cognition, psychological functioning, sensory capacity, cardiovascular capacity, respiratory capacity, immunological system, genitourinary system, endocrine system, haematological system, metabolic system, neuromuscular system, basic needs, capacity to learn and grow, mobility, capacity to build and maintain relationships, contribution to society/community, as well as the products and technology of the environment, nature and human modifications of the environment, support and relationships in the environment and attitudes of people. These 20 domains represent the broad domains of the IC, FA, and EN theoretical model described in the introduction.

Data Analysis

The goal of the structural analysis presented here is to estimate how the selected 280 HRS variables are organized into broad domains (i.e., first-order factors), and if these domains correspond to the 20 broad domains pointed above (i.e., the broad domains of the IC, FA, EN theoretical model). The EGA technique was used via *EGAnet* package[49] from R[50], and three structures were compared using the *TEFI* fit index (also implemented in the *EGAnet* package): (1) the structure obtained using EGA with the *GGM* network method, (2) the structure obtained using EGA with the *TMFG* estimation, and (3) the theoretical structure with 20 domains pointed above. The correlation matrix was estimated using the available pairwise information, due to missingness.

The EGA framework was used as follows. First, the data was split into two random datasets: a training set, with 60% of the observations (N = 9,796), and a validation set with the remaining 40% observations (N = 6,531). Then, EGA was applied in the training set and the optimal number of steps of the walktrap algorithm was selected using the *TEFI* index, varying the number of steps from 3 to 10, for each network model (i.e., GGM and TMFG). The optimal structure for each network model was compared to the theoretical structure (with 20 domains) also using the *TEFI* index. The fit of the empirical (i.e., estimated using EGA with GGM and with TMFG) and theoretical structure were computed using the validation set. While the training set is used for estimating the structural organization of the variables via EGA (with the optimization process for the Walktrap algorithm described before), the validation set is used to check the best fitting structure in an independent sample.

Next, the best fitting structure identified in the steps described above was used to compute the network loadings. The goal to compute network loadings here is twofold. First, it enables the identification of the *best items per dimension* and, second it can be used to estimate the second-order dimensions (see the description of the second-order EGA technique in the next section). Finally, the network loadings were rotated using GeominQ via the *GPArotation* package[13], and the resulting interfactor correlation matrix was analyzed using EGA to estimate the second-order structure.

Exploratory Graph Analysis

Network models in psychology can be traced back to the work of Guttman[51], who proposed a method termed *image structure analysis*, which is essentially the basis of contemporary node-wise regression network models[52]. The use of network models in psychology and health, however, have only gained momentum after the publication of the mutualism model of intelligence[53]. In this mutualism model, the positive manifold of intelligence tests were proposed to be a consequence of a network of reciprocal causal relations between cognitive abilities instead of the product of a single general factor (the *g* factor). The same conceptual framework was used by Borsboom[54] in the area of psychopathology. Psychopathological disorders were proposed as a network of causal relations between symptoms[54] that could be used not only to re-think the nature of psychopathology but also as an approach to interpret comorbidity[55], reproducing empirical population statistics of mental disorders[56]. From the mutualism model of intelligence and the dissemination of network methods in psychopathology[57], these types of models have also been used in clinical psychology,[58] cognitive psychology and individual differences[59,60], aging[8,9], social psychology[61], and many other areas[62].

The network perspective of psychological constructs originated a new subfield of quantitative psychology called *network psychometrics*.[62,63] From this perspective, network models are used to estimate the relationship between multiple variables (typically using the Gaussian graphical model, **GGM**[11]), where *nodes* (e.g., test items) are connected by *edges* (or links), which indicate the strength of the association between the variables.[64] In the past few years, evidence has emerged showing that network models and latent variable models are closely related and can be mathematically equated in some circumstances[62,65,66], and that it could also be used as a way to explore the dimensionality structure of measurement instruments (e.g., scales, questionnaires, tests)[7,59,67].

Golino and Epskamp[7] showed that the GGM model combined with a clustering algorithm for weighted networks (e.g., Walktrap[68]) could accurately recover the number of simulated factors, presenting a higher accuracy than traditional factor analytic based methods. Golino and Epskamp[7] termed this new method *exploratory graph analysis* (**EGA**). More recently, the accuracy of EGA was investigated in a simulation study that expanded the work of Golino and Epskamp[7] by comparing the EGA results with different types of traditional factor-analytical methods (including two types of parallel analysis)[8]. The results suggest that EGA (using the GGM network model) achieves the highest overall accuracy (87.91%) in estimating the number of simulated factors, followed by the traditional

parallel analysis with principal components of Horn[69] (83.01%), and parallel analysis using principal axis factoring proposed by Humphreys and Ilgen[70] (81.88%).

The EGA technique estimates the number of factors by combining the GGM model[11] with the Walktrap clustering algorithm[68], a common approach for estimating clusters in weighted networks. The algorithm iteratively identifies how each node is connected to neighboring nodes, using them to determine which cluster each node belongs to. First, the technique starts by estimating a network. The current approach is to estimate a GGM using the $\mathbf{K}$ (kappa) matrix or the inverse of the variance-covariance matrix, ($\mathbf{\Sigma}$), in which the elements k_{ij} (row i, column j of $\mathbf{K}$) can be standardized to yield the partial correlation between two variables y_i and y_j, given all other variables. If every nonzero element of $\mathbf{K}$ is a freely estimated parameter, the resulting matrix is the GGM—that is, a sparse model of $\mathbf{\Sigma}$.[64] There are many methods to control the level of sparsity of the GGM, but the most common approach in network psychometrics is to use the *graphical LASSO* (GLASSO[71]) technique, and to tune its hyperparameter, λ, in a way to minimize the extended Bayesian information criterion (**EBIC**[72]). This approach has been shown to accurately retrieve the true network structure in simulation studies[64,73].

Recently, a new approach to estimate psychometric networks, the *Triangulated Maximally Filtered Graph* (TMFG), was proposed[8,12,74]. The TMFG method uses zero-order correlations (as opposed to the GGM network model used in network psychometrics that is estimated as regularized partial correlations), and applies a structural constraint on the network, which restrains the network to retain a certain number of edges ($3n$-6, where n is the number of nodes)[74]. The network is comprised of triangles (3 connected nodes) and tetrahedrons (4 connected nodes), and can be associated with the inverse covariance matrix (yielding a GGM[75]). The network estimation using the TMFG approach starts by forming a tetrahedron of the four nodes that have the highest sum of correlations to all other nodes (i.e., strength centrality). In the second step the algorithm iteratively identifies and incorporates the node that maximizes its strength centrality to three of the nodes already included in the network.

Figure 7 shows a schematic simplification of the EGA approach. Data is collected and imported to R. The *EGAnet* package[49] is used to implement the EGA analysis. As pointed before, two network estimation techniques can be used: the GGM and TMFG. Both will generate networks in which the nodes represent the variables and the edges represent the association between variables. When the GGM model is used, the edges are regularized partial correlations. The resulting network (for both models) is plot as a two-dimensional image in which nodes with higher associations are placed closer to each other using the Fruchterman-Reingold algorithm[76]. Finally, the factors are automatically identified using the Walktrap algorithm. A detailed description of EGA (using GGM or TMFG) was provided by Golino et al.[8], including an explanation of how the technique can be used to identify unidimensional structures.
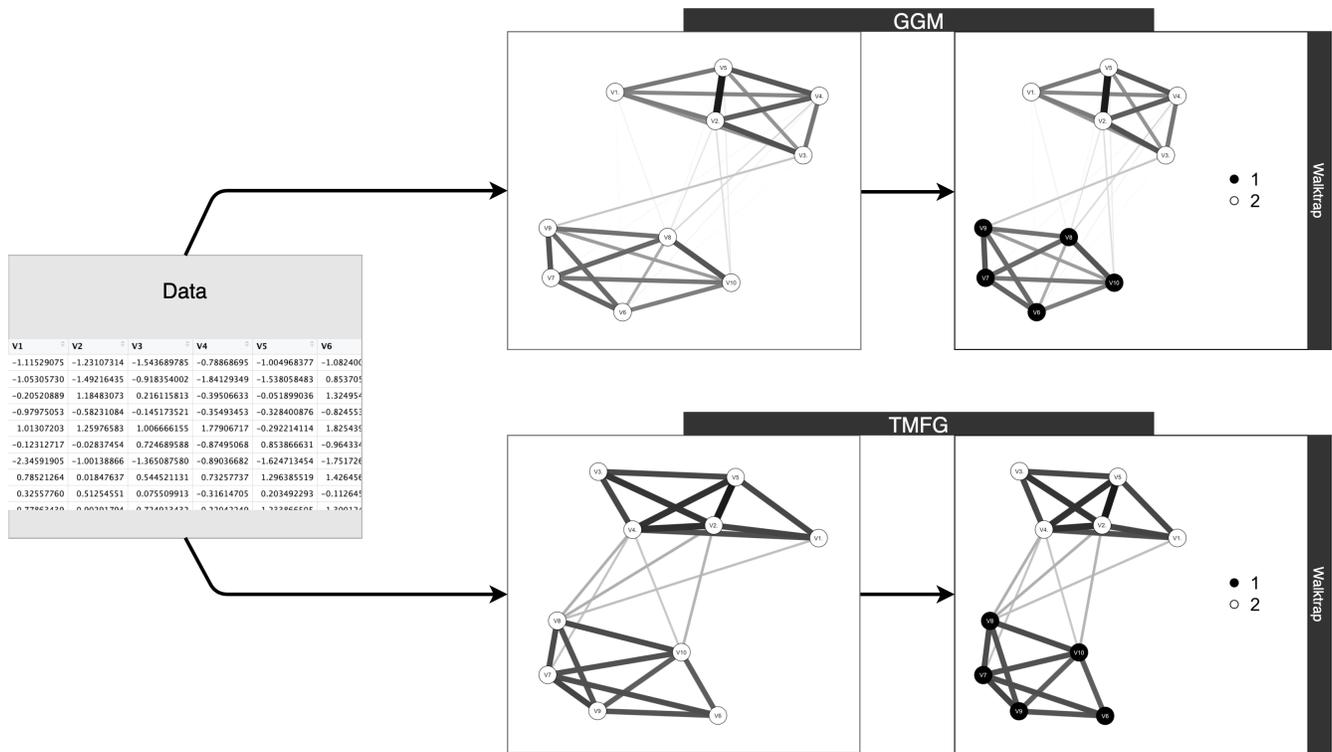
Figure 7. Exploratory graph analysis

The Walktrap algorithm plays an important role in EGA, and works as follows. First, the sum of a node's connection to its neighbors (node strength) is calculated using the square matrix of edge weights (e.g., partial correlations). A hyperparameter, *number of steps*, is set to move from one node to another randomly and uniformly using a transition matrix. The number of steps is arbitrary and defined by the user, however, simulation studies[68] and applied research have used four steps as the default value[8]. To determine the communities that the nodes belong to, the transition matrix is used to compute a distance metric (r) that measures the structural similarity between nodes[68]. This distance metric can be generalized to the distance between nodes and communities by beginning the random walk at a random node in a community, and then is further generalized to the distance between two communities.

Starting with each node as a cluster (i.e., n clusters), the Walktrap algorithm computes the distances, r, between all adjacent nodes, and iteratively chooses two clusters. These two clusters are then merged into a new cluster, updating the distances between the node(s) and cluster(s) with each merge (in each $k = n-1$ steps). Clusters are only merged if they are adjacent to one another (i.e., an edge between them), using a methods based on Ward's agglomerative clustering approach (Ward[77]), and that depend on the estimation of the squared distances between each node and its community (σ_k), for each k steps of the algorithm. Computing σ_k is computationally expensive, so Pons and Latapy[68] adopted an efficient approximation that only depends on the nodes and the communities rather than the k steps. The approximation seeks to minimize the variation of σ that would be induced if two clusters are merged into a new cluster. The resulting values can be stored in a balanced tree, and the best number of clusters is defined as the partition that maximizes an index termed modularity[78].

As pointed out earlier, the number of steps used in the walktrap algorithm is arbitrary, generally being set to four[8, 79]. Recently, a new fit metric for dimensionality analysis based on entropy was developed by Golino and colleagues[9]. This metric can be used to select the optimal number of steps in the walktrap algorithm that will lead to a best fitting dimensionality structure in the EGA estimation process.

Optmizing Model Fit using the Total Entropy Fit Index

The EGA technique presents several advantages over more traditional methods[8]. First, unlike exploratory factor analysis (EFA) methods, EGA does not require a rotation method to interpret the estimated first-order factors. Although rotations are rarely discussed in the validation literature, they have significant consequences for validation

(e.g., estimation of factor loadings[80]). Second, EGA automatically places items into factors without the researcher's direction, which contrasts with exploratory factor analysis where researchers must decipher a factor loading matrix. Third, the representation of the network allows inferences into which dimensions are more central and how items relate within and between dimensions. Thus, EGA can be used as an evaluation tool for whether the items forming into the dimensions they intended and supports a fuzzy interpretation of the dimensions where the boundaries between items and dimensions are blurred. In contrast, factor analysis (e.g., confirmatory factor analysis; CFA) models usually depict the relations across the same level (i.e., dimensions with dimensions).

After applying the EGA method in a given dataset using both the GGM and the TMFG network method, the best fitting dimensionality structure (i.e., latent factors) can be verified using the *total entropy fit index* (**TEFI**[9]). The *TEFI* fit index was developed as an alternative to traditional fit measures used in factor analysis and structural equation modeling, showing a higher accuracy in correctly identifying the number of simulated factors than the comparative fit index (**CFI**), the root mean square error of approximation (**RMSEA**), and other indices used in structural equation modeling.[9] Golino et al.[9] showed that the *TEFI* index presented a general accuracy of 92% in identifying the number of latent dimensions in a Monte-Carlo simulation, *CFI* and *RMSEA* presented an accuracy of 35% and 14% when used with the traditional cut-off criteria (respectively), and an accuracy of 74% and 78% when used as relative measures of fit (respectively).

The *TEFI* fit index is based on the Von Neumann entropy[81]—a measure developed to to quantify the amount of disorder in a system as well as the entanglement between two subsystems[82]. Golino et al.[9] showed that the Von Neumann entropy can be estimated in correlation matrices by converting the correlation matrix into a density-like matrix $\boldsymbol{\rho}$, using the number of variables as a scaling factor that will make the trace of the matrix equal to one.[83]A The density-like matrix (i.e. scaled correlation matrix) $\boldsymbol{\rho}$ will, then, have the following properties: (1) it is symmetric, (2) positive semi-definite, and (3) has trace equal to one.

Given a density matrix $\boldsymbol{\rho}$ with eigenvalues $\lambda_1, \lambda_2, ..., \lambda_m \geq 0$, Von Neumann entropy can be estimated as follows:

$$\mathcal{S}(\boldsymbol{\rho}) = -tr(\boldsymbol{\rho} \times log(\boldsymbol{\rho})), \tag{1}$$

The TEFI index is calculated as:

$$TEFI_{VN} = \left[\frac{\sum_{i=1}^{N_F} \mathcal{S}(\boldsymbol{\rho}_i)}{N_F} - \mathcal{S}(\boldsymbol{\rho}) \right] + \left[\left(\mathcal{S}(\boldsymbol{\rho}) - \sum_{i=1}^{N_F} \mathcal{S}(\boldsymbol{\rho}_i) \right) \times \sqrt{N_F} \right]. \tag{2}$$

where N_F is the number of factors, $\mathcal{S}(\boldsymbol{\rho_i})$ is a Von Neumann entropy of each factor, and $\mathcal{S}(\boldsymbol{\rho})$ is the total entropy of the (density-like) matrix $\boldsymbol{\rho}$. It should be noted that the $TEFI$ fit index estimates the Von Neumann entropy in a slightly different way, rather than calculating the logarithm of the matrix, the logarithm of the each element in the matrix is obtained, resulting in an entropy-like metric.

The TEFI index is a relative measure of fit that can be used to compare two or more dimensionality structures. For example, the structure estimated via EGA using the GGM network estimation can be compared to the structure estimated using the TMFG network method (hereafter termed *EGA GGM* and *EGA TMFG*, respectively). The structure presenting the lowest TEFI value fits the data best[9]. It can also be used to a way to select the optimal number of steps in the Walktrap algorithm in the EGA estimation process. To optimize model fit, EGA is estimated using the *GGM* or the *TMFG* method, and the number of steps is set as a vector of values (e.g., from 3 to 10). The fit of the resulting structure can be checked using the TEFI index, and the optimal number of steps is the one leading to the lowest TEFI value.

Network Loadings

A key component for understanding the items that comprise these dimensions is to quantify their relations within and between dimensions of the network. In traditional methods, this is done using factor loadings. For psychometric networks, there are different measures called *centrality*, which are used to quantify a node's relative position in the

network. The most commonly used centrality measure in the literature is *node strength*, which is the sum of a node's connections to other nodes.

A recent simulation study demonstrated that node strength was directly related to and redundant with CFA factor loadings[84]. A notable finding from this study was that node strength was a blend of connections within and between dimensions, suggesting that each node's strength should be assessed within each dimension rather than as a singular measure. When standardizing this measure, it becomes roughly equivalent to an EFA factor loading matrix[10], which is the most commonly used metric for item assessment in the psychometric literature[85, 86]. Christensen and Golino[10] formally expressed how this can be derived.

We start with node strength which can be defined as:

$$S_i = \sum_{j=1}^{n} |w_{ij}|,$$

$$L_{if} = \sum_{j \in f}^{F} |w_{ij}|,$$

where $|w_{ij}|$ is the absolute weight (e.g., partial correlation) between node i and j, S_i is the sum of the edge weights connected to node i across all nodes (n; i.e., node strength for node i), L_{if} is the sum of edge weights in factor f that are connected to node i (i.e., node i's loading for factor f), and F is the number of factors (in the network). This measure can be standardized using the following formula:

$$z_{L_{if}} = \frac{L_{if}}{\sqrt{\sum L_{\cdot f}}},$$

where the denominator is equal to the square root of the sum of all the weights for nodes in factor f. It's important emphasize that these values are represented by the type of correlation used in the network—that is, regularized partial correlations (using GGM) and zero-order correlations (using TMFG).

Network loadings can substantively be interpreted as the node's contribution to the coherence of each dimension in the network[87]. In contrast, factor loadings are substantively interpreted as how well an item represents or measures the latent factor. These interpretations, however, are statistically and epistemologically connected: the more one node contributes to a dimension's coherence, the more the item represents the underlying dimension. One key difference between an EFA factor loading matrix and a network loading matrix is that the network loading matrix will have zeros because some items are conditionally independent from (or not connected to) other nodes[10]. Since factor loadings and network loadings have different scales, their magnitudes are also interpreted differently. For factor loadings, the typical guidelines corresponding to small, moderate, and large are .40, .55, and .70, respectively[88]. Christensen and Golino[10] identified effect size guidelines for (partial correlation) network loadings that correspond with traditional factor loading guidelines: small (0.15), moderate (0.25), and large (0.35).

A strategy to estimate second order dimensions using EGA

Despite the advantages of EGA pointed before, the usual application of this technique is limited to the estimation of first-order factors. However, first-order factors may present substantial correlations that might be accounted for by hypothesized higher-order dimensions, making second-order models potentially applicable[89]. Studies using EGA focused solely on first-order factors for two main reasons. First, there is a strong body of evidences showing that network psychometric methods can be used as tools for dimensionality assessment and reduction when used directly in observed data, being suited for uncovering first-order factors[7–9]. Second, only recently has evidence emerged showing that network centrality metrics are directly related to and redundant with CFA factor loadings,[84] opening space to the develop *network loadings* (as shown in the previous section).

Considering that network loadings are statistically and epistemologically connected to factor loadings, they can be used to estimate higher-order factors in a two-step approach. First, the dimensionality structure of the observed variables is estimated using EGA. Then, the standardized network loadings are computed using the equations presented in the previous section. Once the matrix of network loadings is generated, it can be rotated using an oblique method to obtain a rotated network loadings matrix and the interfactor correlation matrix. Finally, EGA can be applied to the matrix of interfactor correlation to estimate second-order dimensions.

To provide a computational proof-of-concept to the two-step approach described above, a brief Monte Carlo simulation was implemented in this section. Two between-subject data factors were systematically manipulated: sample size (1000, 5000, and 10000) and proportion of missing data (2.5%, 5% and 10%) following a missing-at-random mechanism. The following data factors were held constant: number of second-order factors (2), number of first-order factors (6), number of variables in each first-order factors (12), factor loadings (0.8 for both first and second-order factors) and number of response categories (4).

The decision to simulate data with very high factor loadings and a significant number of variables per first-order factors was to investigate how well EGA performs in the estimation of second-order factors in optimal conditions. The distribution of the variables per topic can be checked using *normalized mutual information* (NMI[90]). NMI is a metric used to compare the similarity between two vectors (of discrete variables) and assigns a value of zero where the two vectors are totally dissimilar, and a value of one where they are identical in an information theoretic perspective. The two vectors used to compute NMI are the vector of the *assigned variables per factor* (ground truth) and the vector containing the *estimated* variables per factor.

Sample data matrices of variables were generated according to a hierarchical factor model procedure that works as follows. First, the correlation matrix of the first-order factors was computed:

$$\mathbf{\Phi} = \mathbf{\Gamma}\mathbf{\Gamma}', \tag{3}$$

where $\mathbf{\Phi}$ is the correlation matrix of the first-order factors (interfactor correlations) and *gamma* ($\mathbf{\Gamma}$) is a $k \times f$ matrix of the loadings of k first-order factors on f second-order factors.

Then, the reproduced population correlation matrix ($\mathbf{R_R}$) was obtained

$$\mathbf{R_R} = \mathbf{\Lambda}\mathbf{\Phi}\mathbf{\Lambda}', \tag{4}$$

where *lambda* ($\mathbf{\Lambda}$) is a $l \times r$ factor loading matrix for l variables and r factors. The population correlation matrix $\mathbf{R_P}$ was obtained raising the matrix to full rank (i.e. inserting unities in the diagonal of $\mathbf{R_R}$). Next, a Cholesky decomposition of $\mathbf{R_P}$ was computed. If $\mathbf{R_P}$ was not semi-positive definite the matrix was replaced and a new $\mathbf{R_P}$ matrix was computed following the same procedure. Subsequently, the sample data matrix of continuous variables was computed as:

$$\mathbf{X} = \mathbf{Z}\mathbf{U}, \tag{5}$$

where $\mathbf{Z}$ is a matrix of random standard normal deviates with rows equal to the sample size and columns equal to the number of variables.

Then, 10 of the 12 resulting continuous variables were categorized by applying a set of thresholds following Garrido, Abad, and Ponsoda[8, 91]. By following this procedure, we transformed most of the items into polytomous items with four response categories, while leaving two items as continuous, generating a mixed item-type data matrix. In the last step, missing values were generated (i.e., the complete dataset was 'amputated') for half of the items, following a missing-at-random mechanism using the *mice* package[92]. The proportion of missingness were set as 0.1, 0.05 and 0.025, leading to 20%, 10% and 5% of missing data. Since only half of the items were used to generate the missing data pattern, the final proportion of missingness was 10%, 5% and 2.5%.

Following previous simulation studies[8,91] the generation of the main loadings was implemented drawing random values from a uniform distribution that has a range of $\pm.10$ from the specified value. Therefore, since the specified value of the loadings was 0.8, the actual values of the loadings can vary between 0.70 and 0.90. For each of condition tested in the simulation, multiple sample data matrices were generated and 450 were randomly selected to compute the mean normalized mutual information and it's 95% confidence interval. This strategy was necessary to deal with non-convergence of the estimates (EGA with GGM presented a convergence rate of 85.86% and EGA with TMFG a convergence rate of 63.15%).

Exploratory graph analysis was applied using the *EGAnet* package[49], and the network construction methods used were *GGM* and *TMFG*. Figure 8 shows the normalized mutual information for each condition tested.
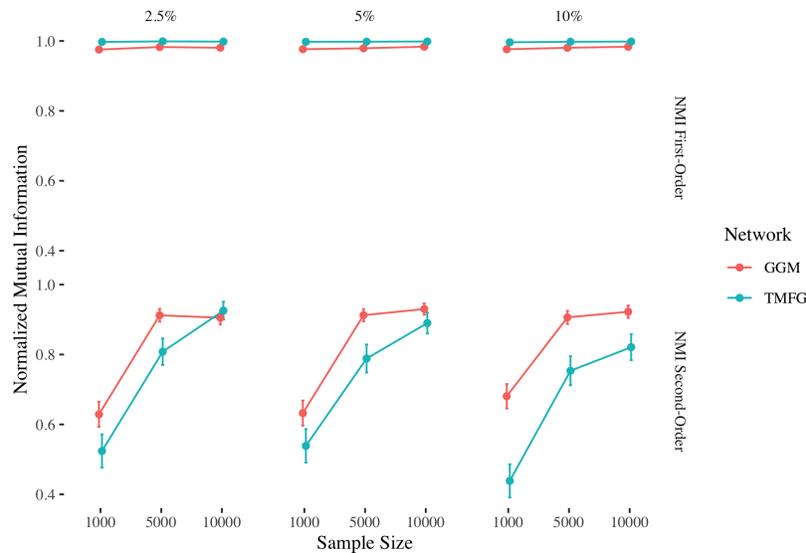
Figure 8. Normalized mutual information for first-order and second-order dimensionality solutions provided by EGA GGM and EGA TMFG

As Figure 8 shows, EGA using both the GGM and the TMFG network methods presented a very high mean normalized mutual information for the first-order factors (0.98 and 1, respectively). The mean NMI for the second-order factors were not as high as the first-order factors (*EGA GGM* = 0.84, *EGA TMFG* = 0.72), except when the sample size was very large. When the sample size was 5,000, *EGA GGM* presented a mean NMI of 0.91 (95% C.I. = 0.90,0.92) and *EGA TMFG* presented a mean NMI of 0.78 (95% C.I. = 0.76,0.81). For a sample size of 10,000, *EGA GGM* presented a mean NMI of 0.92 (95% C.I. = 0.91,0.93) and *EGA TMFG* presented a mean NMI of 0.88 (95% C.I. = 0.86,0.90).

References

1. Caballero, F. F. *et al.* Advanced analytical methodologies for measuring healthy ageing and its determinants, using factor analysis and machine learning techniques: the athlos project. *Sci. reports* **7**, 43955 (2017).

2. Sadana, R. *et al.* Metrics and evidence for healthy ageing. *Bull. World Heal. Organ.* DOI: http://dx.doi.org/10.2471/BLT.19.246801 (2019).

3. Beard, J. R. *et al.* The world report on ageing and health: a policy framework for healthy ageing. *The Lancet* **387**, 2145–2154 (2016).

4. Michel, J.-P. & Sadana, R. "healthy aging" concepts and measures. *J. Am. Med. Dir. Assoc.* **18**, 460–464 (2017).

5. Cesari, M. *et al.* Evidence for the domains supporting the construct of intrinsic capacity. *The Journals Gerontol. Ser. A* **73**, 1653–1660 (2018).

6. Beard, J. R., de Carvalho, I. A., Sumi, Y., Officer, A. & Thiyagarajan, J. A. Healthy ageing: moving forward. *Bull. World Heal. Organ.* **95**, 730 (2017).

7. Golino, H. & Epskamp, S. Exploratory Graph Analysis: A new approach for estimating the number of dimensions in psychological research. *PloS ONE* **12**, e0174035, DOI: 10.1371/journal.pone.0174035 (2017).

8. Golino, H. *et al.* Investigating the performance of exploratory graph analysis and traditional techniques to identify the number of latent factors: A simulation and tutorial. *Psychol. Methods* (in press).

9. Golino, H. *et al.* Entropy fit index: A new fit measure for assessing the structure and dimensionality of multiple latent variables. *PsyArXiv* DOI: 10.31234/osf.io/mtka2 (2019).

10. Christensen, A. P. & Golino, H. On the equivalency of factor and network loadings. *PsyArXiv* DOI: 10.31234/osf.io/xakez (2020).

11. Lauritzen, S. L. *Graphical Models* (Clarendon Press, Oxford, UK, 1996).

12. Christensen, A. P., Kenett, Y. N., Aste, T., Silvia, P. J. & Kwapil, T. R. Network structure of the Wisconsin Schizotypy Scales–Short Forms: Examining psychometric network filtering approaches. *Behav. Res. Methods* **50**, 2531–2550, DOI: 10.3758/s13428-018-1032-9 (2018).

13. Bernaards, C. A. & Jennrich, R. I. Gradient projection algorithms and software for arbitrary rotation criteria in factor analysis. *Educ. Psychol. Meas.* **65**, 676–696, DOI: 10.1177/0013164404272507 (2005).

14. Gupta, S. Impact of volunteering on cognitive decline of the elderly. *The J. Econ. Ageing* **12**, 46–60 (2018).

15. Hughes, T. F., Flatt, J. D., Fu, B., Chang, C.-C. H. & Ganguli, M. Engagement in social activities and progression from mild to severe cognitive impairment: the MYHAT study. *Int. psychogeriatrics* **25**, 587–595 (2013).

16. Zunzunegui, M.-V., Alvarado, B. E., Del Ser, T. & Otero, A. Social networks, social integration, and social engagement determine cognitive decline in community-dwelling spanish older adults. *The Journals Gerontol. Ser. B: Psychol. Sci. Soc. Sci.* **58**, S93–S100 (2003).

17. James, B. D., Wilson, R. S., Barnes, L. L. & Bennett, D. A. Late-life social activity and cognitive decline in old age. *J. Int. Neuropsychol. Soc. JINS* **17**, 998 (2011).

18. Lövdén, M., Ghisletta, P. & Lindenberger, U. Social participation attenuates decline in perceptual speed in old and very old age. *Psychol. aging* **20**, 423 (2005).

19. Gottlieb, B. H. & Gillespie, A. A. Volunteerism, health, and civic engagement among older adults. *Can. J. on Aging/La Revue canadienne du vieillissement* **27**, 399–406 (2008).

20. Park, D. C. *et al.* The impact of sustained engagement on cognitive function in older adults: the synapse project. *Psychol. science* **25**, 103–112 (2014).

21. Rosso, A. L., Taylor, J. A., Tabb, L. P. & Michael, Y. L. Mobility, disability, and social engagement in older adults. *J. aging health* **25**, 617–637 (2013).

22. Katja, P., Timo, T., Taina, R. & Tiina-Mari, L. Do mobility, cognitive functioning, and depressive symptoms mediate the association between social activity and mortality risk among older men and women? *Eur. journal ageing* **11**, 121–130 (2014).

23. Curcio, C.-L. *et al.* Life-space assessment scale to assess mobility: validation in latin american older women and men. *Aging clinical experimental research* **25**, 553–560 (2013).

24. Peel, C. *et al.* Assessing mobility in older adults: the uab study of aging life-space assessment. *Phys. therapy* **85**, 1008–1019 (2005).

25. Wang, C.-Y., Hu, M.-H., Chen, H.-Y. & Li, R.-H. Self-reported mobility and instrumental activities of daily living: test–retest reliability and criterion validity. *J. aging physical activity* **20**, 186–197 (2012).

26. Demnitz, N. *et al.* A systematic review and meta-analysis of cross-sectional studies examining the relationship between mobility and cognition in healthy older adults. *Gait & posture* **50**, 164–174 (2016).

27. Baltes, P. B. & Baltes, M. M. *Successful aging: Perspectives from the behavioral sciences*, vol. 4 (Cambridge University Press, 1993).

28. Pearlin, L. I. & Schooler, C. The structure of coping. *J. health social behavior* 2–21 (1978).

29. Bandura, A. Self-efficacy: toward a unifying theory of behavioral change. *Psychol. review* **84**, 191 (1977).

30. Chapman, M., Skinner, E. A. & Baltes, P. B. Interpreting correlations between children's perceived control and cognitive performance: Control, agency, or means€ nds beliefs? *Dev. Psychol.* **26**, 246 (1990).

31. Rodin, J., Schooler, C. & Schaie, K. W. *Self directedness: Cause and effects throughout the life course* (Psychology Press, 2013).

32. Femia, E. E., Zarit, S. H. & Johansson, B. Predicting change in activities of daily living: A longitudinal study of the oldest old in sweden. *The Journals Gerontol. Ser. B: Psychol. Sci. Soc. Sci.* **52**, P294–P302 (1997).

33. Wrosch, C., Barlow, M. A. & Kunzmann, U. Age-related changes in older adults' anger and sadness: The role of perceived control. *Psychol. aging* **33**, 350 (2018).

34. Robinson, S. A. & Lachman, M. E. Perceived control and aging: A mini-review and directions for future research. *Gerontology* **63**, 435–442 (2017).

35. de Camargo Smolarek, A. *et al.* The effects of strength training on cognitive performance in elderly women. *Clin. interventions aging* **11**, 749 (2016).

36. Yaffe, K., Barnes, D., Nevitt, M., Lui, L.-Y. & Covinsky, K. A prospective study of physical activity and cognitive decline in elderly women: women who walk. *Arch. internal medicine* **161**, 1703–1708 (2001).

37. Vespasiani-Gentilucci, U. *et al.* Low alanine aminotransferase levels in the elderly population: frailty, disability, sarcopenia, and reduced survival. *The Journals Gerontol. Ser. A* **73**, 925–930 (2018).

38. Gringauz, I., Weismann, J., Justo, D., Adunsky, A. & Segal, G. Alanine aminotransferase blood levels and rehabilitation outcome in older adults following hip fracture surgery. *Int. J. Rehabil. Res.* **41**, 41–46 (2018).

39. Hilton-Jones, D. *Principles and Practice of Geriatric Medicine*, vol. 2, chap. Muscle Disorders, 935–947 (Wiley, 2006), 4th edn.

40. Ohlendieck, K. Proteomic identification of biomarkers of skeletal muscle disorders. *Biomarkers medicine* **7**, 169–186 (2013).

41. Dunkel, C. S. *et al.* The association of perceived neighborhood safety and inequality with personality. *Evol. Psychol. Sci.* (2020).

42. Robinson, M. D., Meier, B. P. & Vargas, P. T. Extraversion, threat categorizations, and negative affect: A reaction time approach to avoidance motivation. *J. Pers.* **73**, 1397–1436 (2005).

43. Oi, K. Inter-connected trends in cognitive aging and depression: Evidence from the health and retirement study. *Intelligence* **63**, 56–65 (2017).

44. Bielak, A. A., Gerstorf, D., Kiely, K. M., Anstey, K. J. & Luszcz, M. Depressive symptoms predict decline in perceptual speed in older adulthood. *Psychol. Aging* **26**, 576 (2011).

45. Gale, C., Allerhand, M. & Deary, I. Is there a bidirectional relationship between depressive symptoms and cognitive ability in older people? a prospective study using the english longitudinal study of ageing. *Psychol. medicine* **42**, 2057–2069 (2012).

46. Butters, M. A. *et al.* Pathways linking late-life depression to persistent cognitive impairment and dementia. *Dialogues clinical neuroscience* **10**, 345 (2008).

47. Alexopoulos, G. S. Depression in the elderly. *The lancet* **365**, 1961–1970 (2005).

48. Lupien, S. J. *et al.* Cortisol levels during human aging predict hippocampal atrophy and memory deficits. *Nat. neuroscience* **1**, 69–73 (1998).

49. Golino, H. & Christensen, A. P. *EGAnet: Exploratory Graph Analysis: A Framework for Estimating the Number of Dimensions in Multivariate Data Using Network Psychometrics* (2019). R package version 0.4.

50. R Core Team. *R: A Language and Environment for Statistical Computing.* R Foundation for Statistical Computing, Vienna, Austria (2020).

51. Guttman, L. Image theory for the structure of quantitative variates. *Psychometrika* **18**, 277–296 (1953).

52. Haslbeck, J. M. B. & Waldorp, L. J. mgm: Structure estimation for time-varying mixed graphical models in high-dimensional data. *J. Stat. Softw.* **93**, 1–46, DOI: 10.18637/jss.v093.i08 (2020).

53. van der Maas, H. L. J. *et al.* A dynamical model of general intelligence: The positive manifold of intelligence by mutualism. *Psychol. Rev.* **113**, 842–861, DOI: 10.1037/0033-295X.113.4.842 (2006).

54. Borsboom, D. Psychometric perspectives on diagnostic systems. *J. Clin. Psychol.* **64**, 1089–1108, DOI: 10.1002/jclp.20503 (2008).

55. Cramer, A., Waldorp, L. J., Van Der Maas, H. L. & Borsboom, D. Comorbidity: A network perspective. *Behav. Brain Sci.* **33**, 137–150, DOI: 10.1017/S0140525X09991567 (2010).

56. Borsboom, D., Cramer, A. O. J., Schmittmann, V. D., Epskamp, S. & Waldorp, L. J. The small world of psychopathology. *PLoS ONE* **6**, e27407, DOI: 10.1371/journal.pone.0027407 (2011).

57. Fried, E. *et al.* Mental disorders as networks of problems: a review of recent insights. *Soc. Psychiatry Psychiatr. Epidemiol.* **52**, 1–10 (2017).

58. van Bork, R., van Borkulo, C. D., Waldorp, L. J., Cramer, A. O. & Borsboom, D. Network models for clinical psychology. *Stevens' Handb. Exp. Psychol. Cogn. Neurosci.* **5**, 1–35 (2018).

59. Golino, H. & Demetriou, A. Estimating the dimensionality of intelligence like data using Exploratory Graph Analysis. *Intelligence* **62**, 54–70, DOI: 10.1016/j.intell.2017.02.007 (2017).

60. Van Der Maas, H. L., Kan, K.-J., Marsman, M. & Stevenson, C. E. Network models for cognitive development and intelligence. *J. Intell.* **5**, 16, DOI: 10.3390/jintelligence5020016 (2017).

61. Dalege, J., Borsboom, D., Harreveld, F., Waldorp, L. J. & Maas, H. L. Network structure explains the impact of attitudes on voting decisions. *Sci. reports* **7**, 4909 (2017).

62. Epskamp, S., Rhemtulla, M. & Borsboom, D. Generalized network psychometrics: Combining network and latent variable models. *Psychometrika* **82**, 904–927, DOI: 10.1007/s11336-017-9557-x (2017).

63. Epskamp, S., Maris, G., Waldorp, L. J. & Borsboom, D. *The Wiley Handbook of Psychometric Testing: A Multidisciplinary Reference on Survey, Scale and Test Development*, chap. Network Psychometrics (Wiley, New York, 2018).

64. Epskamp, S. & Fried, E. I. A tutorial on regularized partial correlation networks. *Psychol. Methods* **23**, 617–634, DOI: 10.1037/met0000167 (2018).

65. Boker, S. M. The Reticular Action Model: A remarkably lasting achievement. In Ferrer, E., Boker, S. M. & Grimm, K. J. (eds.) *Longitudinal Multivariate Psychology*, 126–141 (Routledge, New York, NY, 2018).

66. Marsman, M. *et al.* An introduction to network psychometrics: Relating Ising network models to item response theory models. *Multivar. Behav. Res.* **53**, 15–35, DOI: 10.1080/00273171.2017.1379379 (2018).

67. Christensen, A. P., Cotter, K. N. & Silvia, P. J. Reopening openness to experience: A network analysis of four openness to experience inventories. *J. Pers. Assess.* **101**, 574–588 (2019).

68. Pons, P. & Latapy, M. Computing communities in large networks using random walks. *J. Graph Algorithms Appl.* **10**, 191–218 (2006).

69. Horn, J. L. A rationale and test for the number of factors in factor analysis. *Psychometrika* **30**, 179–185 (1965).

70. Humphreys, L. G. & Ilgen, D. R. Note on a criterion for the number of common factors. *Educ. Psychol. Meas.* **29**, 571–578 (1969).

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

72. Chen, J. & Chen, Z. Extended bayesian information criteria for model selection with large model spaces. *Biometrika* **95**, 759–771 (2008).

73. Foygel, R. & Drton, M. Extended bayesian information criteria for gaussian graphical models. In *Proceedings of the 23rd International Conference on Neural Information Processing Systems - Volume 1*, vol. 1, 604–612 (Vancouver, Canada, 2010).

74. Massara, G. P., Di Matteo, T. & Aste, T. Network filtering for big data: Triangulated Maximally Filtered Graph. *J. Complex Networks* **5**, 161–178, DOI: 10.1093/comnet/cnw015 (2016).

75. Barfuss, W., Massara, G. P., Di Matteo, T. & Aste, T. Parsimonious modeling with information filtering networks. *Phys. Rev. E* **94**, 062306, DOI: 10.1103/PhysRevE.94.062306 (2016).

76. Fruchterman, T. M. & Reingold, E. M. Graph drawing by force-directed placement. *Software: Pract. Exp.* **21**, 1129–1164, DOI: 10.1002/spe.4380211102 (1991).

77. Ward, J. H. Hierarchical clustering to optimise an objective function. *J. Am. Stat. Assoc.* **58**, 238–244 (1963).

78. Newman, M. Fast algorithm for detecting community structure in networks. *Phys. Rev. E* **69**, DOI: 10.1103/PhysRevE.69.066133 (2004).

79. Gates, K. M., Henry, T., Steinley, D. & Fair, D. A. A monte carlo evaluation of weighted community detection algorithms. *Front. Neuroinformatics* **10**, 45, DOI: 10.3389/fninf.2016.00045 (2016).

80. Sass, D. A. & Schmitt, T. A. A comparative investigation of rotation criteria within exploratory factor analysis. *Multivar. Behav. Res.* **45**, 73–103, DOI: 10.1080/00273170903504810 (2010).

81. Von Neumann, J. Wahrscheinlichkeitstheoretischer aufbau der quantenmechanik. *Nachrichten von der Gesellschaft der Wissenschaften zu Göttingen, Math. Klasse* **1927**, 245–272 (1927).

82. Preskill, J. *Quantum shannon entropy*, chap. 10, 94 (Cambridge University Press, 2018).

83. Anderson, T. W. *et al.* Asymptotic theory for principal component analysis. *Annals Math. Stat.* **34**, 122–148 (1963).

84. Hallquist, M., Wright, A. C. G. & Molenaar, P. C. M. Problems with centrality measures in psychopathology symptom networks: Why network psychometrics cannot escape psychometric theory. *Multivar. Behav. Res.* DOI: 10.1080/00273171.2019.1640103 (2019).

85. DeVellis, R. F. *Scale development: Theory and applications* (SAGE Publications, Thousand Oaks, CA, 2017), 4 edn.

86. Simms, L. J. Classical and modern methods of psychological scale construction. *Soc. Pers. Psychol. Compass* **2**, 414–433, DOI: 10.1111/j.1751-9004.2007.00044.x (2008).

87. Christensen, A. P., Golino, H. & Silvia, P. J. A psychometric network perspective on the validity and validation of personality trait questionnaires. *Eur. J. Pers.* DOI: 10.1002/per.2265 (2020).

88. Comrey, A. L. & Lee, H. B. *A first course in factor analysis* (Psychology Press, New York, NY, 2013), 2 edn.

89. Chen, F. F., West, S. G. & Sousa, K. H. A comparison of bifactor and second-order models of quality of life. *Multivar. behavioral research* **41**, 189–225 (2006).

90. Horibe, Y. Entropy and correlation. *IEEE transactions on systems, man, cybernetics* 641–642 (1985).

91. Garrido, L. E., Abad, F. J. & Ponsoda, V. Performance of Velicer's minimum average partial factor retention method with categorical variables. *Educ. Psychol. Meas.* **71**, 551–570, DOI: 10.1177/0013164410389489 (2011).

92. van Buuren, S. & Groothuis-Oudshoorn, K. mice: Multivariate imputation by chained equations in R. *J. statistical software* 1–68 (2010).

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Author contributions statement

H.G. wrote the paper, conceived, designed and performed the analysis, A.P.C wrote the paper and conceived and designed the analysis, M.T. wrote the paper, J.A.T and R.S. contributed data, S.M.B conceived the analysis. All authors reviewed the manuscript.

Additional information

Accession codes: All codes used in the current manuscript (both for the empirical analysis of the HRS data, and for the Monte-Carlo simulation of the Second-Order EGA) can be found at the following Open Science Framework Repository here: https://osf.io/7msf8/?view_only=f70118c5f4f84983af67e64900b4205d. The simulated data, and the supplementary Table mentioned in the manuscript are also available in the Open Science Framework repository.

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