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ASSESSMENT, DEVELOPMENT, AND VALIDATION

One Common Factor, Four Resources, Both, or Neither: A Network Model of Career Adaptability Resources

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ABSTRACT
Career adaptability is better described as interconnected resources than as manifestations of a common factor. Using a sample of 1053 responses to the Career Adapt-Abilities Scale, we compared traditional confirmatory factor analysis models (unidimensional, bifactor, hierarchical) with a confirmatory network model, which is found to outperform the others.

KEYWORDS
Career adaptability; career success; network model; job satisfaction; mutualism; psychometrics

In a context of rapid change, one's ability to promptly and effectively modify their career trajectory, an attribute generally referred to as career adaptability, is central to career success. More specifically, career adaptability refers to a set of abilities or resources that enable people to cope with the many challenges of career management. Scholars postulate that these resources are conditionally independent but linked by a common cause, that is, career adaptability (Savickas, 2005). In this paper, we challenge this assumption based on theoretical arguments and empirical observations. Instead, we propose a network model of career adaptability in which career adaptability describes a set of interconnected and mutually beneficial resources.

The Construct of Career Adaptability

Various theories have been advanced to describe how an individual's career is developed. A popular framework for it is career construction theory (Savickas, 2005, p. 43), which "asserts that individuals construct their careers by imposing meaning on their vocational behavior and occupational experiences." In other words, according to career construction theory, one's career is constructed through adapting to the social environment, by finding meaning in work roles, interaction with others, etc., not through unfolding or maturing a preexisting path. Career construction theory states three main components of career development: a) vocational personality – which is made of dispositional attributes that can be likened to personality traits [e.g., Holland's (1997) RIASEC model of vocational interests]; b) life themes, which consist of an individual's concept of oneself, which they will often try to express through their vocational behaviors and occupations; and c) career adaptability, one's resources (skills, attitudes, and behaviors) that can be mobilized to fit without difficulty to the environment and its circumstances (Savickas, 1997, 2005). Career adaptability is an important and distinguishable aspect of career construction theory, as it formulates clearly that managing one's career is a highly dynamic process that requires adaptation rather than a passive process of following a preexisting career path defined by society for individuals.

Career adaptability is seen as an essential attribute, both in career construction theory and in career development (Rudolph et al., 2017; Savickas, 2005), because it allows individuals to

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solve new problems and adapt to new situations and environments throughout their careers. As comprehensively described in a recent meta-analysis (Rudolph et al., 2017), career adaptability was predictive of several occupational and vocational outcomes, such as lower job stress and lower turnover intentions, as well as high career satisfaction, job satisfaction, career planning, career exploration, promotability, occupational self-efficacy, and career decision-making self-efficacy. Beyond vocational or occupational traits, high career adaptability was also related to more general individual characteristics, such as lower negative affect, higher positive affect, hope, optimism, and life satisfaction.

Antecedents of career adaptability have been discussed using several approaches. Notably, personality traits that are generally considered adaptive, such as self-esteem, pro-active personality, conscientiousness, extraversion, openness and emotional stability have been found to be related to high career adaptability (Rudolph et al., 2017; Zacher, 2016). In addition, variability in expressing personality traits (within-person trait variability) was also found to predict career adaptability, over and beyond traits themselves (Storme et al., 2020). Further, job environment factors, like supervisory career monitoring, job demands and job autonomy have been found to be predictive of higher career adaptability (Zacher, 2016).

Measuring Career Adaptability

As Savickas and Porfeli (2012, p. 663) noted, "increasing a client's career adaptability resources or career adapt-abilities is a central goal in career education and counseling." Indeed, high career adaptability is both central in career construction theory and predictive of several positive outcomes, occupational or not (Kara et al., 2020). As a logical consequence, career adaptability is an attribute, or rather a set of attributes (Savickas, 1997), relevant to measure, not only for researchers interested in the understanding of career development and occupational well-being, but also for professionals (e.g., career counseling/vocational psychologists, managers) involved in vocational guidance. Notably, counselors may use career adaptability measures to continually assess a client's readiness to explore new career possibilities and opportunities, in order to better assist them in their self-development (see Kara et al., 2020 for a discussion of interventions based on career adaptability dimensions).

Based on career construction theory, Savickas and Porfeli (2012) developed the Career Adapt-Abilities Scale (CAAS). The CAAS was developed with a four-factor structure, with a second order (general) factor. Among the four first-order factors, *concern* refers to one's ability to anticipate changes in the social and work environment, *control* refers to one's ability to change to adjust themselves and the environment, *curiosity* refers to one's ability to consider oneself in various roles and settings, and *confidence* refers to one's certitude that they can solve problems and overcome obstacles. Each of the dimensions of the CAAS is measured by six items, with a five-point Likert-type response scale. Items correspond to specific abilities or resources facilitating the process of career adaptation (e.g. "Thinking about what my future will be like") and participants report how strongly they evaluate that they have developed the ability. In spite of the scales of the CAAS showing satisfactory internal reliability (based on Cronbach's α) in its different translations, as well as metric invariance across the countries investigated, confirmatory fit analyses (using a second-order factor model) appeared borderline acceptable (comparative fit index in the .85-.94 range). A shortened version, the Career Adapt-Abilities Scale–Short Form (CAAS–SF; Maggiori et al., 2017) was recently proposed that, in addition to shortening the instrument (12 items per scale), showed better evidence of structural validity through its fit indices.

Using Reflective Measurement Models to Study Career Adaptability

As is common practice in counseling and psychological research, investigations of the structure of the CAAS (and the CAAS–SF) have largely relied on factor analytic models (Maggiori et al., 2017; Savickas & Porfeli, 2012). In other words, it has been implicitly assumed, through the use of such models, that the items are manifestations caused by one or several latent quantitative variables (i.e., factors). This common cause (or set of common causes) explains why item scores are correlated, and, as a consequence, are assumed to not be correlated beyond the common causes (which is often referred to as the assumption of conditional or local independence). In general, this approach of measurement is broadly discussed as the assumption of a *reflective* measurement model (Bollen & Diamantopoulos, 2017; Markus & Borsboom, 2013; Schmittmann et al., 2013; van Bork et al., 2017).

In the context of career adaptability, using a reflective measurement model means that the self-reported resources obtained through the CAAS are conceptualized as manifestations of an underlying structure of latent traits (namely, the 4 factors that are concern, control, curiosity and confidence and/or possibly a general factor representing career adaptability). In particular, it is notable that career adaptability is generally discussed as set of resources (Maggiori et al., 2017; Savickas & Porfeli, 2012), and the original authors of the CAAS admitted that they did "presume that resources reflect adaptability" (Savickas & Porfeli, 2012, p. 3), and, as a consequence proposed that the CAAS should have a hierarchical or multidimensional structure. Further, it was also recently proposed (Matijaš & Seršić, 2021) that a bifactor model could better describe the structure of the CAAS. In the bifactor model (Reise, 2012), each item or specific resource facilitating career adaptation is caused simultaneously by a general factor and a specific factor (in this context, by one of the 4 factors earlier described). All models that were advanced used common latent explanatory variables as explanations for the item scores and their relations. We argue that this original *presumption*, which is so far undiscussed, deserves discussion and empirical investigation.

Questioning Reflective Measurement Models

In several contexts, reflective measurement models were pointed out as an assumption that is not always theoretically substantiated (e.g., Borsboom et al., 2019; Borsboom & Cramer, 2013). The most famous example is perhaps the general factor of intelligence *g*, which for a long time was proposed as common cause underlying scores to various cognitive ability tests. Alternative theories have been proposed to explain the observed correlations between such tests without them having a common cause, such as the mutualism model (Kan et al., 2019; Van der Maas et al., 2014), according to which, throughout development, initially uncorrelated cognitive processes are involved in mutually beneficial interactions that lead to a positive manifold situation (i.e., many positively correlated abilities). In a recent empirical comparison between the mutualism model (represented statistically by a network model) and the *g* factor model, the mutualism model outperformed the *g* factor model in various intelligence test battery datasets (Kan et al., 2019).

Another famous example was coined the "disease model" (Borsboom & Cramer, 2013, p. 92) of psychopathology, according to which relative sets of behaviors (i.e. the "symptoms") are thought to be caused by a single or small number of latent variables (i.e., the "disorder"). Alternative theories have proposed that psychological disorders may be better characterized as complex systems or networks of interacting symptoms, where for example, some symptoms facilitate others, such as fatigue and concentration issues for depressive behaviors (Borsboom & Cramer, 2013; Epskamp et al., 2017). In clinical psychology, psychometric networks have been very successful because they allow for a better description of the constructs and for the refinement of theoretical models connecting several constructs (Borsboom & Cramer, 2013; Epskamp et al., 2017). Indeed, the information contained at the level of the building blocks of the construct (e.g., specific symptoms, specific behaviors) makes it possible to investigate in a much more detailed way the links between different constructs by revealing the underlying mechanisms that remain invisible with aggregate scores.

Regarding career adaptability, should we assume that a (set of) latent attribute(s) causes the specific resources captured in the items? Let us consider two items of the CAAS as example: "planning how to achieve my goals" (an item of the concern subscale) and "observing different ways of doing things" (an item of the curiosity subscale). A reflective measurement model (e.g., hierarchical, multifactorial, or bifactor), would assume that the resources presented here are conditionally independent, meaning that their relation is only explained by one or several common latent factor(s). In this example, because the two items belong in two different subscales, the only common factor would be a general career adaptability factor. It can in fact be argued that the two abilities are related directly and, therefore, not conditionally independent, because one could imagine that the ability to "observe different ways of doing things" could require the ability to "plan how to achieve my goals." In some sense, the former could be considered as a step in achieving the latter. As another example, "realizing that today's choices shape my future" (an item of concern) could be thought as a direct prerequisite to "taking responsibility for my actions" (an item of control).

A Network Model of Career Adaptability Resources

As an alternative to the reflective measurement models discussed for the construct (Matijaš & Seršić, 2021; Savickas & Porfeli, 2012), we propose a *network theory of career adaptability resources,* according to which career adaptability is best described as a set of abilities or resources that engage in interactions with one another, and according to which these interactions are the cause for the relations observed between them. Similar to the mutualist approach to the structure of intelligence (Kan et al., 2019), and based on previous findings that suggest overall positive correlations between career adaptability resources (Maggiori et al., 2017; Matijaš & Seršić, 2021; Savickas & Porfeli, 2012), we propose that most of these resources are mutually beneficial, leading to overall positive relations among them. In contrast with the reflective models previously advanced for career adaptability resources, this model does not assume the presence of latent causal variables, and does assume direct relations between observations (i.e., it assumes local dependencies). In Figure 1, we represent conceptually the distinction between the reflective models discussed previously and a network model. Importantly, a network model, if supported, makes implications that are different from a reflective model. In the case of career adaptability, a network model suggests that using general or subscale scores would be reductionist (Borsboom et al., 2019), and, if empirically supported, it would encourage counselors to use career adaptability measures at the item-level instead, with a particular focus on items that are central and/or have a strong influence on the rest of the network.

The Aim of This Study

Because we argue that career adaptability resources are best described as a network of mutually beneficial resources rather than as caused by one (or four) factors, we here propose to use a procedure recently developed (Kan et al., 2020) that allows model fit comparisons between (confirmatory) network models and factor models. The rationale for such a comparison is to examine the plausibility of conceptualizing career adaptability as a set of mutually reinforced abilities, rather than caused by one or a few general traits, as well as to support this mutualist model as an evidence-based framework for counseling and interventions focusing on the domain of career adaptability.

The procedure consists of a) splitting a dataset of CAAS responses in two sets (a training and a testing set); b) training an exploratory Gaussian graphical model (GGM) in the first (training) set (from this phase, only a set of relations between items are retained); and then c) comparing, in the second (testing) set, the fit measures of the (now confirmatory) GGM with competing confirmatory factor (reflective) models. To explore the space of previously considered models (Maggiori et al., 2017; Matijaš & Seršić, 2021; Savickas & Porfeli, 2012) we chose as

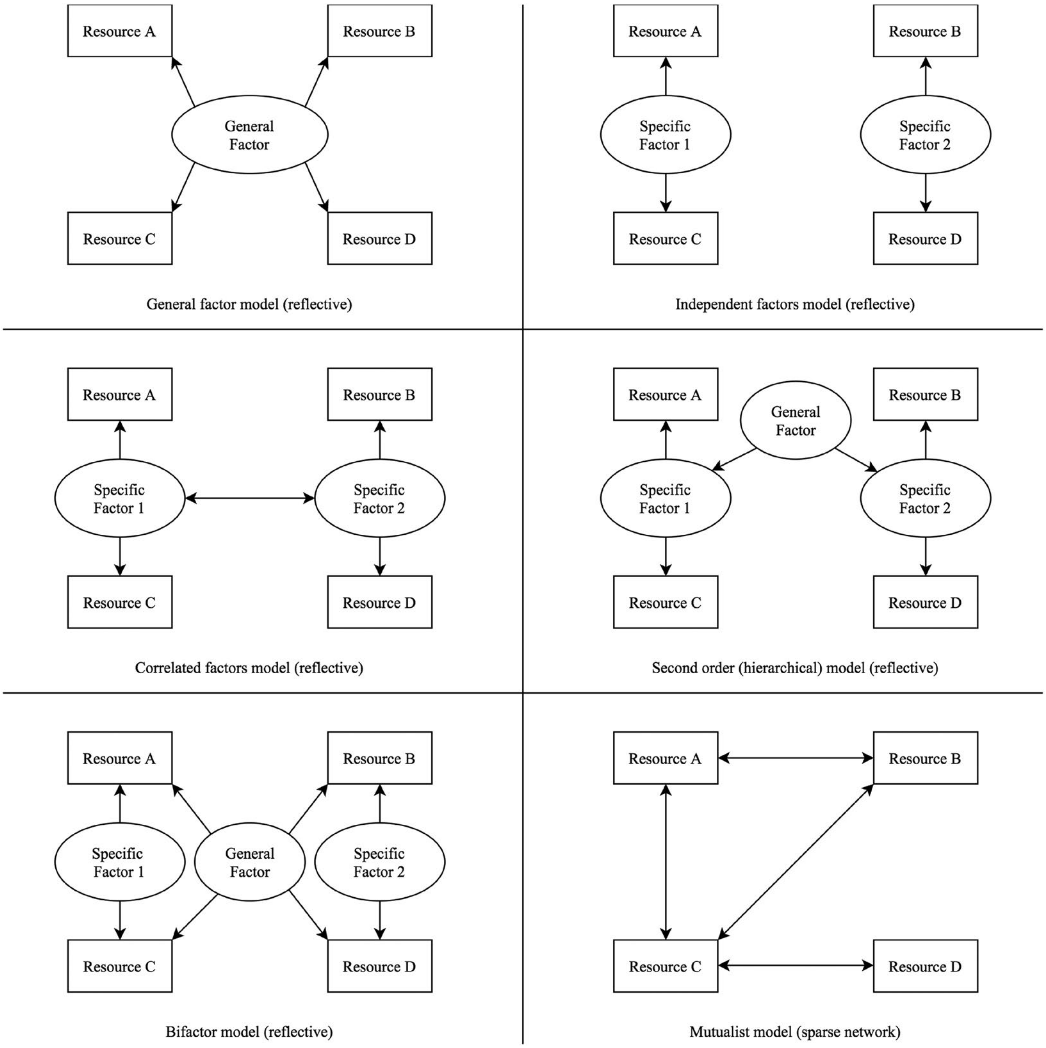

Figure 1. Conceptual representations of the various discussed models.

competing models here the 4-factor model, the hierarchical (second order) model and the bifactor model. We hypothesized that the network model (GGM) will adequately fit the testing sample and will outperform all the factor models tested, thereby supporting the network theory of career adaptability resources. Although we did not suspect any specific measurement invariance issue, we later studied measurement invariance based on the network model, across the variables of gender, age and seniority.

Methods

Participants

This study used existing data from respondents registered on a French e-assessment application that was primarily used for continuing education, vocational guidance and recruitment. Participation was voluntary and not rewarded. Because the study was retrospective non-interventional and participation was anonymous, ethics board approval was not required for data collection. The final sample was composed of 1,053 French employees. The sample consisted of 688 females and 365 males, with ages ranging between 16 and 88 years ($M = 42.4$,

$SD = 12.1$). As per French law, race/ethnicity demographic data was not collected. Regarding education, most participants had a master's (48.8%), bachelor (24.2%), high school level (14.1%), or doctoral level education (8.5%). The respondents reported an average of 8.9 years of seniority ($SD = 9.01$) in their current occupation. Most participants reported their current primary occupation as executive (45.5%), craftsperson/merchant or business owner (19.0%), worker (28.5%) or clerk (17.9%).

Procedure

Instrument

The participants responded to the French version of the CAAS international form 2.0 (Johnston et al., 2013; Rossier et al., 2012). The CAAS is self-report questionnaire comprised of 24 items, divided into four subscales. Each subscale corresponds to a set of resources representing concern, control, curiosity and confidence. The CAAS has demonstrated satisfactory scale score reliability for all subscales in its French translation (Johnston et al., 2013; Rossier et al., 2012; Storme et al., 2019). However, confirmatory factor analyses of the CAAS international form in French resulted in mixed results. Based on a hierarchical model, a study indicated borderline acceptable fit, unless item parceling was used (Johnston et al., 2013). In another study (Rossier et al., 2012), it showed insufficient fit, unless item covariances were added post hoc (based on modification indices).

Data Splitting and Comparison Between Sets

Network models are generally built through exploring the relations between variables and discarding the relations that are deemed superfluous. This creates an identified structural model (which we will refer to later as the confirmatory network model, or CNM) whose fit can be evaluated using typical fit measures used in structural equation modeling. However, since the CNM is already created from the exploration on the dataset, another dataset is needed to investigate its fit. Consequently, we randomly split the original sample into two sets. To do so, we used the R package "caret" (Kuhn, 2008), which is largely used in predictive modeling in R, and which allowed us to randomly (but evenly) assign cases within each quintile of the distribution of CAAS total scores. This ensures that the two sets had equivalent CAAS distributions (Myszkowski & Storme, 2017). We later refer to the two datasets created as the training set and the testing set.

As expected from the splitting method, the two sets did not significantly differ in CAAS total scores: $t(1051) = -0.11$, $p = .912$, $d < 0.01$. The data sets also did not significantly differ in any of the subscale scores (all $p > .1$, all $|d| < .1$). They also did not significantly differ in gender distribution, $\chi^2(1) = 0.19$, $p = .667$, $V = .01$; in education level, $\chi^2(1) = 0.04$, $p = .835$, $V = .00$; in socio-professional category, $\chi^2(1) = 0.36$, $p = .546$, $V = .00$; or in age, $t(1051) = 1.50$, $p = .133$, $d = 0.09$. We therefore concluded that the splitting method was successful in creating equivalent sets for all variables relevant to the study.

Estimating an Exploratory Network Model in the Training Sample

A network model, the Gaussian graphical model (GGM), was first estimated in the training sample. The GGM consists of a network of partial correlations between all items. It is initially saturated, meaning that all items have non-zero (partial) correlations with one another. Several algorithms exist that allow reducing the number of these partial correlations, leading to parsimonious (and thus reproducible) and identifiable (and thus testable) models.

To reduce the number of partial correlations, we used the graphical least absolute shrinkage and selection operator for estimation, with the extended Bayesian information criterion for tuning (EBICglasso; Golino & Epskamp, 2017). Because it is not the point of this study to discuss exploratory graph algorithms and because there are many of them, we direct the reader to the original paper that describes the EBICglasso procedure and offers a tutorial along with the "bootnet" package (Epskamp et al., 2018). The EBICglasso method uses the graphical least absolute shrinkage and selection operator, which penalizes the sum of absolute model parameter values in order to shrink (and discard) parameters. As the magnitude of penalty increases, some parameters eventually shrink to 0, which creates sparsity in the partial correlation matrix, thereby reducing the number of edges in the network. The amount of penalization is controlled by a hyper-parameter, which is tuned by minimizing the extended Bayesian information criterion. Once the network model was built in the training sample with the EBICglasso method, we extracted its adjacency matrix (i.e., a matrix indicating which pairwise partial correlations were non-zero in the model), to later be used for confirmatory analyses in the testing sample. Because it is then used for confirmation in a separate sample, we later refer to this newly specified model as the confirmatory network model (CNM).

Confirmatory Analyses in the Testing Sample

All confirmatory models (network and reflective measurement models) were estimated with the new package for R "psychonetrics" (Epskamp, 2021), which assesses the fit of both types of models (see Kan et al., 2020 for an example and explanation of the procedure). Because "psychonetrics" is very recent and in active development, as a measure of caution, we cross-validated the fit of all reflective measurement models using the package "lavaan" (Rosseel, 2012), and found no discrepancy between the results.

The confirmatory network model (CNM) was specified as a sparse Gaussian graphical model (GGM) that only included the edges that were selected from the EBICglasso procedure used previously in the training sample. The competing reflective measurement models included models previously proposed for the CAAS: a general factor model (Johnston et al., 2013; Rossier et al., 2012), a four-factor model (Matijaš & Seršić, 2021) with correlated and with independent factors, a second-order model with 4 factors explained by one second-order factor (Johnston et al., 2013; Maggiori et al., 2017; Rossier et al., 2012), and a bifactor model where each item is simultaneously predicted by one of four specific factors (corresponding to the subscales) and a general factor (Matijaš & Seršić, 2021). To the best of our knowledge, this set of models represents both the typical confirmatory models tested on theoretically multidimensional/hierarchical instruments like the CAAS and the models previously considered for this instrument (Maggiori et al., 2017; Matijaš & Seršić, 2021; Savickas & Porfeli, 2012).

As suggested by a reviewer, based on the training sample, we also augmented one of the CFA models (the four-correlated factors model) by adding new parameters in a stepwise fashion, based on the largest modification index, until we reached the same complexity (same degrees of freedom) as the network model. We later refer to this model as the data-trained CFA model. Although more exploratory than confirmatory, and not meant to be conceptually meaningful, the purpose of fitting this model is to compare a reflective model and a network model that are of equal complexity and both specified from the data of the training sample. The bifactor model had been originally chosen as starting point because of its better fit, but adding parameters quickly led to convergence errors, so we used the second-best fitting CFA model in this case, which was the four-correlated factors model.

The fit of all models was investigated using the fit measures and thresholds generally recommended in structural equation modeling (Hu & Bentler, 1999), including the χ^2 test (where a significant test indicates a significantly imperfect fit), the confirmatory fit index (*CFI*) and Tucker-Lewis index (*TLI*), for which a higher value indicates better fit – we used threshold values of .95 for excellent fit and .90 for acceptable fit – and the root mean squared error of approximation (*RMSEA*), for which smaller values indicate better fit – we used a threshold of .05 for excellent fit and .08 for acceptable fit. Finally, because most of the models were non-nested and therefore cannot be compared with χ^2 tests, we used the Akaike information criterion (*AIC*) and Bayesian information criterion (*BIC*) to compare models, with smaller values indicating better fit.

Results

Creating a Sparse Network Model from the Training Set

With the EBICglasso method, we were able to successfully build a model with good confirmatory fit in the training set: $\chi^2(133) = 196.8$, p<.001, *CFI* = .989, *TLI* = .978, *RMSEA* = .030. This excellent fit is of course to be expected because the model was built from the same sample.

Comparing Reflective Models and the Network Model in the Testing Set

As hypothesized, in the testing set, we found that the network model had excellent fit: χ^2 (133) = 199.85, p<.001, *CFI* = .988, *TLI* = .975, *RMSEA* = .031, *AIC* = 24215.5, BIC = 25030.1. This was in contrast with all of the reflective models tested, apart from the data-trained CFA model. We present a full table with the fit indices of all the models in Table 1. This was still largely outperformed by the network model when considering all fit indices. These results suggest that the network model presents a more accurate account of the statistical relations between the items of the CAAS, and therefore support our network theory of career adaptability resources over a reflective measurement account.

Additional Analyses: Further Interpreting the Network Model

While the main point of this study was to examine the possibility of a confirmatory network model outperforming reflective models, we also investigated the network model itself to describe its main characteristics. Because at this point the case for the network model is made from the previous comparisons in the cross-validation sample, it is more appropriate to now study its characteristics in the entire sample, so as to use more stable parameter estimates in interpretation. As can be expected from how well it fit the data in each subsample, the confirmatory network model had excellent fit in the full dataset: $\chi^2(133) = 217.2$, p<.001, *CFI* = .993, *TLI* = .985, *RMSEA* = .025, *AIC* = 48065.9, *BIC* = 49013.1. For reference, the fit indices of all models in the full sample are reported in Table 1.

Do the Items Cluster According to the Original Facets?

As a first step in interpreting the network model, we used the R package "qgraph" (Epskamp et al., 2012) to plot it, as reported in Figure 2. Dashed lines are used to represent negative edges (negative relations), and the width of the edges represent the magnitude of the relations. As would

Table 1. Model Fit Indices (Testing Sample and Full Sample).

	χ^2	*df*	*p*	*AIC*	*BIC*	*RMSEA*	*CFI*	*TLI*
Testing sample								
Unidimensional	2,329.64	252	<.001	26,107.2	26,414.3	0.125	0.633	0.598
Independent factors	1,790.24	252	<.001	25,567.8	25,874.9	0.108	0.728	0.702
Correlated factors	1,134.12	246	<.001	24,923.7	25,256.4	0.083	0.843	0.824
Second order	1,159.45	248	<.001	24,945.1	25,269.2	0.084	0.839	0.821
Bifactor	934.28	228	<.001	24,759.9	25,169.3	0.077	0.875	0.849
Data-trained CFA model	327.52	133	<.001	24,295.1	25,007.4	0.024	0.966	0.929
Mutualist (GGM)	199.85	133	<.001	24,215.5	25,030.1	0.031	0.988	0.975
Full sample								
Unidimensional	4,204.95	252	<.001	51,815.7	52,172.7	0.122	0.654	0.621
4 independent factors	3,138.83	252	<.001	50,749.6	51,106.6	0.104	0.747	0.723
4 correlated factors	1,799.07	246	<.001	49,421.8	49,808.6	0.077	0.864	0.847
Second order	1,819.15	248	<.001	49,437.9	49,814.8	0.078	0.862	0.847
Bifactor	1,389.93	228	<.001	49,048.7	49,524.8	0.070	0.898	0.877
Data-trained CFA model	216.14	133	<.001	48,016.9	48,845.1	0.024	0.993	0.985
Mutualist (GGM)	217.17	133	<.001	48,065.9	49,013.1	0.025	0.993	0.985

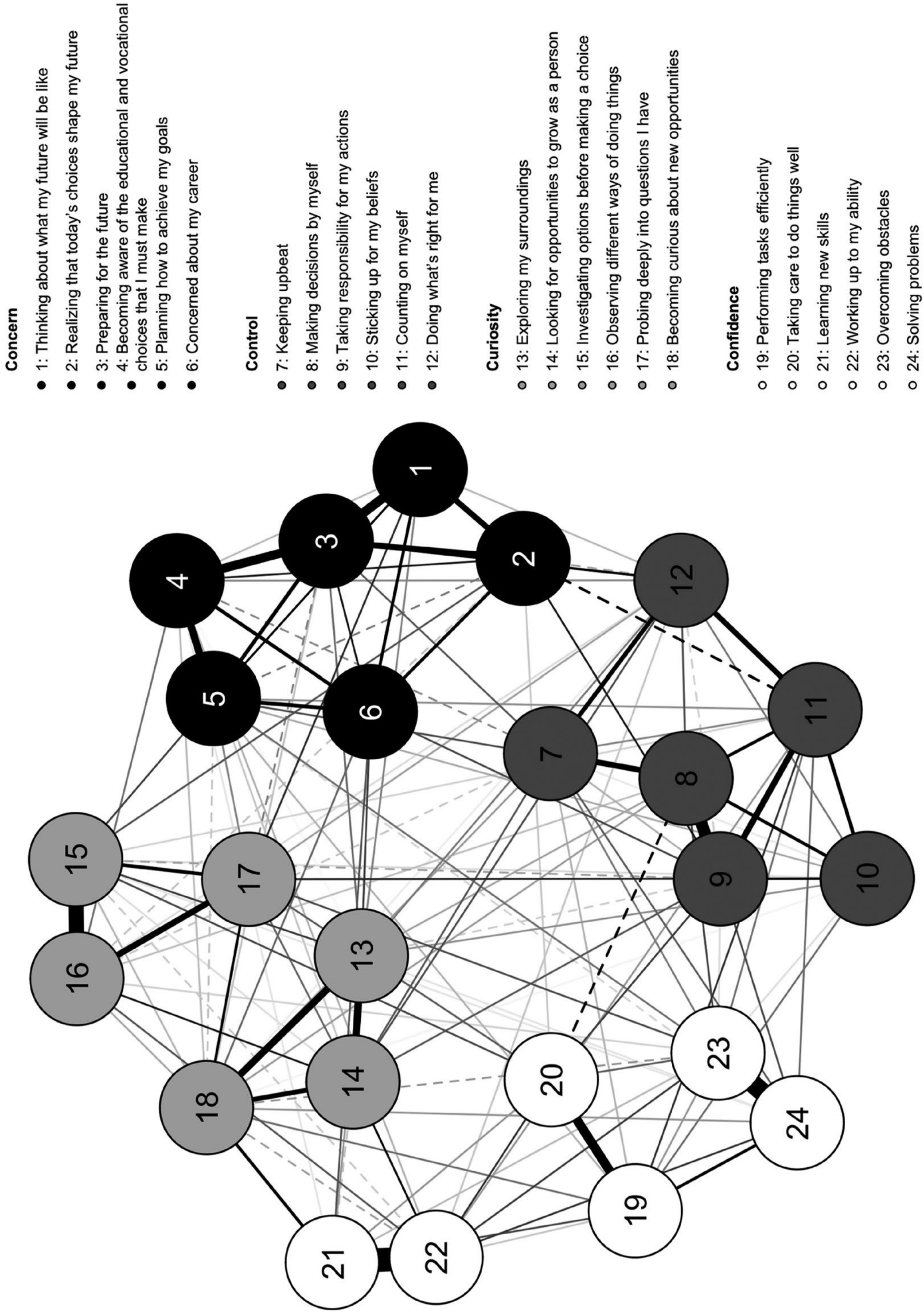

Figure 2. Sparse Gaussian graphical model (full sample).

be expected from mutually beneficial resources, a large majority of (non-zero) edges were positive (over 89.4%). Further, as can be expected, all edges within the items of a subscale were positive. Although the subscales are not specified in the network model itself, in the plot we labeled the variables to match items to their original facets because we think it is useful to see whether the network model provides a different clustering of items from the originally conceptualized facets.

Here, the network approach appears to confirm the original clustering of items. Because this interpretation is partly based on eyeballing the graph, we used the Walktrap and Louvain algorithms (Golino & Epskamp, 2017), two of the most popular algorithms for automatic cluster detection in networks, implemented in the R package "EGAnet" (Golino et al., 2020; Golino & Epskamp, 2017). Both algorithms detected four clusters in the network, which matched the original subscales. The results therefore indicate that, in spite of the multidimensional reflective models presenting insufficient fit, in the network model, the items still form four clusters corresponding to the original facets of the scale.

Which Items Are Central?

The centrality of a node is generally used as a measure of its importance in the network, and several measures of node (i.e., item) centrality have been developed and used in psychometric contexts (see Epskamp et al., 2018 for an overview). Using the R packages "qgraph" (Epskamp et al., 2012) and "NetworkToolbox" (Christensen, 2018b), we computed the most commonly reported centrality measures. They are presented on a standard scale in a graph in Figure 3.

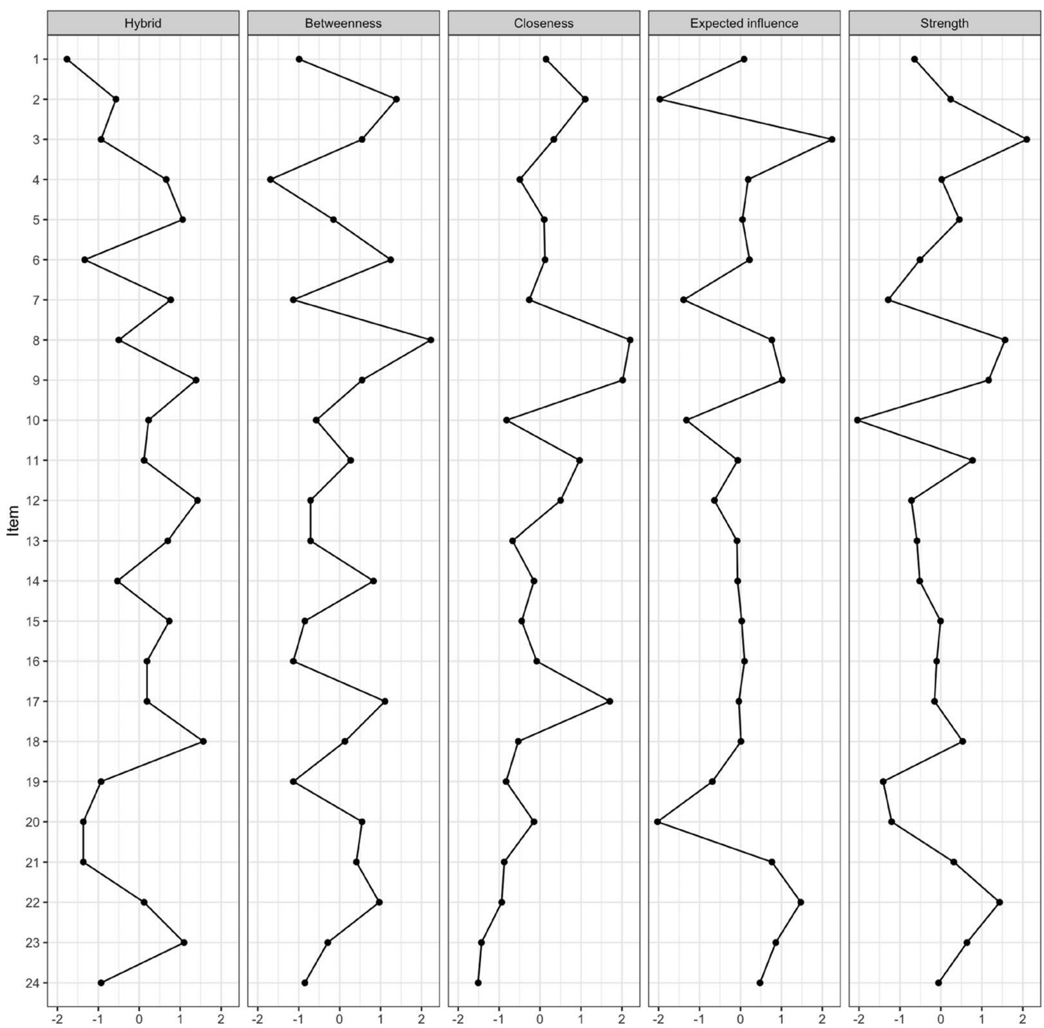

Figure 3. Centrality measures (standardized) of the items.

For interpretation, we chose to use the hybrid centrality measure (Pozzi et al., 2013), which combines multiple measures of centrality and therefore produces results that are less dependent on which centrality measure is chosen (Christensen et al., 2018). The results indicate that the items “Becoming curious about new opportunities,” “Doing what’s right for me,” “Taking responsibility for my actions,” and “Overcoming obstacles” (in that order) were the most central items.

Assessing Measurement Invariance

There is evidence for the measurement invariance of the CAAS, but this evidence is only based on reflective models, and focused on invariance between countries (Johnston et al., 2013; Rossier et al., 2012). Here, we used the network model to test measurement invariance across gender, age (which we dichotomized with a median split) and seniority (also dichotomized using a median split). Age was dichotomized using a median split, resulting in a mean age of 32.9 (SD = 7.35) in the lower age group and a mean age of 52.3 (SD = 7.12) in the higher age group. Seniority was also dichotomized using a median split, resulting in a mean seniority of 2.33 (*SD* = 1.85) in the lower seniority group and a mean age of 16.0 (*SD* = 8.25) in the higher seniority group. For each of these variables, we compared four models: a) a model where the network is estimated freely in the groups (referred to as the configural invariance model); b) the same model but with the edges being constrained equal across groups (metric invariance); c) then constraining the means (scalar invariance); and finally d) constraining the residual variances (strict invariance). Likelihood ratio tests were performed at each step, and the fit of all models is reported in Table 2. Adequate fit was observed for all models when looking at *CFI*, *TLI* and *RMSEA*. Although the likelihood ratio tests were all significant, and the *AIC* tended to favor metric invariance models, while the BICs tended to favor the scalar invariance model for age and the strict invariance model for the other two variables, the excellent fit of the strict invariance models suggests measurement invariance for all three variables considered.

Discussion

Understanding one’s career adaptability as a set of resources has been an important advance in the understanding of what allows individuals to thrive in a rapidly changing work environment. Yet, we argue that reflective measurement models, which have been the only models tested so far on career adaptability measures, and have not yet been questioned empirically or statistically, make incorrect assumptions about these resources. Namely, reflective models assume that there

Table 2. Measurement Invariance Comparisons Based on the Best Fitting Model (Sparse Gaussian Graphical Model) in the Full Sample.

Group Variable	Model	χ^2	$\Delta\chi^2$	*df*	Δdf	*p*	*AIC*	*BIC*	*RMSEA*	*CFI*	*TLI*
Gender	Configural	354.69	–	266	–	–	48,106.7	50,001.2	0.025	0.992	0.984
	Metric	575.27	220.58	409	143	<.001	48,041.3	49,226.5	0.028	0.986	0.980
	Scalar	628.52	53.24	433	24	.001	48,046.5	49,112.8	0.029	0.983	0.978
	Strict	695.91	67.40	457	24	<.001	48,065.9	49,013.1	0.032	0.979	0.975
Age	Configural	396.67	–	266	–	–	47,965.0	49,859.5	0.031	0.989	0.976
	Metric	613.55	216.88	409	143	<.001	47,895.9	49,081.2	0.031	0.982	0.976
	Scalar	690.13	76.58	433	24	<.001	47,924.5	48,990.8	0.034	0.978	0.971
	Strict	879.52	189.39	457	24	<.001	48,065.9	49,013.1	0.042	0.963	0.956
Seniority	Configural	411.92	–	266	–	–	48,057.1	49,951.6	0.032	0.987	0.974
	Metric	595.53	183.61	409	143	.012	47,954.7	49,140.0	0.029	0.984	0.978
	Scalar	662.30	66.76	433	24	<.001	47,973.5	49,039.7	0.032	0.98	0.975
	Strict	802.73	140.44	457	24	<.001	48,065.9	49,013.1	0.038	0.97	0.964

Note. $\Delta\chi^2$, Δdf and *p* refer to likelihood ratio tests of the model, in comparison with the previous model (row above). Age and seniority were used as group variables after being dichotomized by median split.

is a small set of traits and/or one general trait of adaptability which explains the resources probed by the items, while these resources are locally independent. To the contrary, we argue that career adaptability is instead organized as a network, comprised of a set of interconnected (i.e., locally dependent) mutually beneficial resources that are not caused by a single or small set of underlying latent traits.

Using a set of 1,053 responses to the CAAS, a widely used measure of career adaptability resources, we compared a comprehensive set of reflective models used on previous studies of the CAAS (Matijaš & Seršić, 2021; Savickas & Porfeli, 2012) with a network modeling approach. The network model was created through an exploratory graph analysis in a first half of the sample, and all models were compared in the second half. The network model had excellent fit, largely outperforming all the reflective models, which had insufficient fit. This result supports a network approach of career adaptability as a more accurate representation of the organization of career adaptability than reflective models. Further research may seek to analyze the reproducibility of this result in other versions of the CAAS (different languages other than French, contexts of use, and instrument lengths, for example).

The graphical representation of the network suggests that, although the multifactorial reflective models had insufficient fit, the original facets are still present in the network in the form of clusters. Since the clusters observed corresponded to the four subscales, this suggests that the lower fit of the reflective measurement models compared with the network model is probably not due to their structure being incorrect. In other words, this suggests that the network model outperformed the most relevant of the reflective models in the present dataset.

Theoretical, Methodological and Practical Implications

In line with the findings of prior research on intelligence (Kan et al., 2020) or disease models (Borsboom & Cramer, 2013; Epskamp et al., 2017), our findings suggest that the network approach to career adaptability better describes the construct than the classical factorial approach. In other words, we should not think of career adaptability resources as manifestations of a common (set of) latent career adaptability construct(s) but rather as a system of resources that are interconnected and mutually beneficial. This has important theoretical, methodological, and practical implications.

From a theoretical viewpoint, the network approach to career adaptability could lead to many re-analyses of the empirical studies conducted to date on the antecedents and consequences of career adaptability. Indeed, studies aggregating the various resources of career adaptability into a single score do not allow for the detailed investigation of the processes linking career adaptability to its antecedents or consequences. For example, personality traits may have a direct impact on only some resources rather than all resources at once. Without calling into question the relevance of the empirical studies conducted to date, the network approach could generate new hypotheses that would make it possible to achieve a much greater level of precision regarding the understanding of career adaptation processes.

From a methodological viewpoint, an interesting feature of reflective measurement models is their practicality in providing measurements for persons, through the form of factor scores (if using factor analysis or item-response theory models) or, more simply (by implicitly making stricter assumptions) through sum/average scores. However, computing person estimates is also possible consistent with network models, by, for example, using the centrality of the items as weights in computing a weighted average score (Christensen, 2018a). Thus, the network approach to career adaptability does not indicate that reducing item scores to a smaller subset of scores is impossible, nor irrelevant. It simply provides a more accurate description of the construct and a more appropriate way of deriving a score of career adaptability from the items. Further research is needed to confirm that scores derived from network models have a better predictive value than factor scores derived from reflective models.

From a practical viewpoint, the network model of career adaptability could provide an alternative approach to interventions aimed at developing career adaptability by allowing career counselors to target specific resources that could trigger cascading effects on other resources. Indeed, a network model of career adaptability could set the stage for new training programs, as career counselors could use network-based interventions that focus on developing central abilities that may effectively "activate" and develop, in turn, other aspects of career adaptability. Perhaps these targeted interventions may present more tangible and long-lasting benefits compared to training programs that focus on developing all attributes of career adaptability at once. More research is needed to investigate the long-term success and developmental consequences of training programs based on network models that target central abilities compared to more holistic programs. Network models could also help practitioners to design tailored development paths for their clients. The network can indeed be considered as a representation of the career adaptability development process, especially if it is a directed network. Based on the item scores of the participants, practitioners could target the abilities that are most likely to be influenced according to the stage of development the client is at. This could increase the efficiency of interventions by avoiding focusing efforts on abilities that are not in the client's optimal zone of development. Finally, it was recently proposed that network models could be used to derive network loadings for each item (which represent the importance of the item in the network), which could then also be used to derive factor scores, where items are weighted by network loadings (Christensen & Golino, 2021; Golino et al., 2021). If a network model is considered more appropriate for the CAAS, such scoring procedures may be considered as a replacement for sum scores or CFA factor scores.

Limitations and Future Research

Our goal was to propose a new approach to the construct of career adaptability. As with any pioneering work, our work has many limitations, and thus many avenues to explore for future research. First, our focus was on comparing models, more than on interpreting the network model. Future research may investigate the reproducibility of the network in other contexts. Further, one could also study how different item features (especially centrality) in this network model are more or less related to external criteria (e.g., job success, life satisfaction, personality traits, etc.). We could speculate that the most central resources could be the ones that are most strongly predictive of other variables, because they would also benefit other resources.

Further, a limitation of this study concerns the modeling procedure used in this study. Notably, the network model was specified through an exploratory procedure, while the reflective models (apart from the data-trained model) were specified a priori, based on previous studies with the same instrument. Therefore, it may be that the difference in fit observed is due to simply allowing and exploring for a more complex model, not to the conceptual differences between network models and latent variable models. Related to this, the data-trained CFA model, which was, like the network model, specified from the training set, appeared to fit as well as the network model in the testing sample. Consequently, it may be that the network model outperformed the other CFA models in fit because it had been specified from the training data, and not only because it is a network model. In other words, there may be a bias in favor of the network model when comparing it to a CFA, which would be due to the network model being specified from training data, as opposed to being specified from a measurement theory alone. It should also be noted that the network model specified from the training sample resulted in a model that had many more parameters than the CFA models (apart from the data-trained CFA model, which was built to have the same number of parameters as the network model), and such model complexity may also be an "unfair" advantage of the exploratory network approach over CFA specified a priori.

When giving the same advantage to a CFA model, both this data-trained CFA model and the network model had similar fit. In the independent testing sample, for the same degrees of freedom, the GGM fit better when considering the χ^2, AIC, CFI and TLI, while the CFA model fit better when considering the BIC and RMSEA. Ultimately, it may be more important to consider the (radical) differences in the data generation mechanisms that these two types of models assume (Christensen et al., 2020; van Bork et al., 2021), more than their differences in fit. On one hand, the excellent fit of the data-trained CFA model implies that the reflective approach is correct, but that the measurement models typically used with the CAAS may be mispecified; on the other hand, the excellent fit of the network model suggests that these usually tested CFA models were not appropriate, and that career adaptability is better described as a composite of mutually influenced behaviors.

Another important limitation of our study is that it was entirely cross-sectional and did not investigate the structure of career adaptability dynamically (i.e., within individuals). Future studies may investigate whether, for example, the network structure observed at the between-person level is also found at the within-person level, an assumption often referred to as network ergodicity. It may be, for example, that the resources that are central in differentiating between individuals are not the resources that across time have the strongest impact. Purely speculatively, it could be that "Becoming curious about new opportunities," although very central in this study to distinguish between individuals, is not a resource that leads to the development of other resources.

Finally, and more generally, we believe that the network approach could be successfully applied to other constructs of career counseling and vocational psychology. We encourage more research in this direction because the network approach has many benefits. First, it allows researchers to get closer to the structure of constructs and thus to propose theoretical models that are potentially more meaningful. Second, it allows studying the dynamics of constructs in a more detailed way, notably by disentangling the central elements of a construct from its peripheral elements, without excluding the possibility of aggregating the different elements by calculating scores. Finally, it allows envisaging new fruitful practices for vocational counselors. We hope that our work will encourage researchers to adopt a network approach to vocational constructs.

Disclosure Statement

No potential conflict of interest was reported by the authors.

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