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Applying the Psychological Network Approach to Understanding Employee Well-Being

ORIGINAL ARTICLE

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ABSTRACT

Traditional research on employee well-being often uses regression-based models that assume unidirectional effects between job demands or resources and well-being outcomes, potentially oversimplifying their complex interrelationships. We conceptualize well-being states, job demands, and resources as an interconnected network that may change over time. To illustrate the interplay among well-being states and well-being factors (i.e., job demands, job resources, personal resources), we first employ the psychological network approach (PNA) to provide a comprehensive understanding of these interrelationships, considering all relationships simultaneously. Second, we use the PNA to explore how this network of relationships changes over time, specifically in a coaching context designed to foster proactive personal and professional development. A sample of 332 Dutch physicians completed online questionnaires before (T1) and after (T2) the coaching period. At T1, personal resources were strongly connected to well-being states, particularly work engagement and stress. At T2, resources showed more negative connections with cynicism compared to T1. These findings showcase the PNA's value for capturing the complexity of overall well-being and exploring how relationships evolve over time.

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Work and organizational psychology research provides several models of employee well-being, including the Job Demand-Control model (JDC; Karasek, 1979), the Demand-Induced Strain Compensation model (DISC; De Jonge & Dormann, 2003), and the Job Demands-Resources model (JD-R; Bakker & Demerouti, 2007). These models generally propose that high demands combined with insufficient resources impair well-being, whereas job and personal resources promote it. The JD-R model further recognizes reciprocal relationships: Poor well-being may deplete resources and increase demands through maladaptive strategies, whereas optimal well-being may facilitate motivation and resource accumulation (Bakker, Demerouti & Sanz-Vergel, 2023; Demerouti, Bakker & Bulters, 2004).

Expanding on this reciprocal perspective, we propose that well-being states (e.g., stress, work engagement, exhaustion) and well-being factors (e.g., job demands, personal resources) emerge concurrently and reinforce one another in an ongoing interactive process, collectively shaping an individual's experience of overall well-being. Traditional regression and path analyses may not fully capture this complexity. By modeling unidirectional relationships, they overlook how well-being constituents covary and reciprocally influence each other, resulting in a fragmented understanding of the overall system (Epskamp & Fried, 2018). This limitation obscures the intricate interplay between well-being factors like job demands, job and personal resources, and well-being states (Schaufeli & Taris, 2014). Acknowledging this complexity is essential for advancing a comprehensive understanding of work-related well-being. Hence, to complement traditional approaches, we conceptualize overall well-being as a network of interrelated well-being states and factors that co-emerge and influence one another, and apply the psychological network approach (PNA; Borsboom et al., 2021; Borsboom et al., 2022) to examine their interconnectedness. The PNA is a data-driven research approach that does not rely on a priori assumptions about unidirectional relationships between variables (Costantini et al., 2015). This approach allows us to complement traditional unidirectional cause-and-effect frameworks, providing insights into the intricate interplay between factors shaping well-being at work.

This study has two primary aims. First, we apply the PNA to examine the interconnectedness of well-being states and factors. Second, we explore how this network changes over time by comparing its structure and connections before and after coaching. Rather than focusing only on changes in variable *levels*, we examine changes in *relationships* between variables. This approach may provide a more nuanced understanding of employee well-being, identify potential intervention targets, and advance research and practice in work and organizational psychology.

THE PSYCHOLOGICAL NETWORK APPROACH (PNA)

The PNA conceptualizes a phenomenon as a network of interrelated components that emerge and evolve together (Borsboom et al., 2022). Rather than attributing a phenomenon to a single cause, it examines how components interrelate within a network (Borsboom et al., 2022). Although individual factors may provide useful insights, examining the entire network of interconnected factors offers a more comprehensive account of complex psychological phenomena.

Network components are represented as variables (i.e., *nodes*) connected by statistical relationships (i.e., *edges*). Edges vary in magnitude and may be positive or negative (Dalege et al., 2017). A positive edge indicates that two nodes covary in the same direction, whereas a negative edge indicates that they covary inversely (Jones, Ma & McNally, 2021). Nodes may also be organized into theoretically defined *communities* (e.g., job demands; Jones et al., 2021). *Centrality indices* describe the importance of nodes within the network (Opsahl, Agneessens & Skvoretz, 2010): *Node strength* is the sum of the absolute values of all edges connected to a node and thus indicates its overall connectedness (Van den Berg et al., 2022), whereas *bridge strength* is the sum of the absolute values of edges connecting a node to nodes in other communities, controlling for connections within its own community (Wang et al., 2020).

Applied to work-related well-being research, the PNA can be used to model job and personal factors as interconnected rather than independently operating elements. Partial correlations indicate which connections remain after accounting for all other variables in the network. Furthermore, comparing networks across time points can reveal whether their structure or connection strengths change over time. The PNA can therefore complement regression and path analyses by providing an account of how components of employee well-being interrelate and evolve.

NETWORK OF EMPLOYEE WELL-BEING

Extant theorizing implies that job demands, job and personal resources, and well-being states may be complexly interconnected. For example, the JD-R model proposes not only direct but also interactive and reciprocal relationships among demands, resources, and well-being (Bakker & Demerouti, 2007). For instance, poor well-being may deplete resources and generate additional demands, whereas optimal well-being may encourage individuals to build resources and adjust demands, creating cycles of well-being (Bakker, Demerouti & Sanz-Vergel, 2023; Demerouti, Bakker & Bulters, 2004). Building on these complex interrelationships, we conceptualize

employee well-being as a system of interconnected well-being states (e.g., stress, exhaustion, work engagement) and well-being factors (e.g., job demands, job resources, personal resources) that can be empirically mapped as a psychological network.

Similar to work-related well-being models, we define job demands as aspects of work that require sustained effort and may concern one's current or future work situation or the interplay between work and private life (Bakker & Demerouti, 2007; De Jonge & Dormann, 2003; Karasek, 1979). Job resources are aspects of work that provide energy and foster personal growth and achievement (Bakker & Demerouti, 2007; De Jonge & Dormann, 2003), whereas personal resources are aspects of the self that enhance perceived control over work and private life (Xanthopoulou et al., 2007).

Previous PNA studies have examined how individual well-being states, including work engagement, stress, and burnout, relate to job demands and resources (e.g., Bereznowski et al., 2023; Ji et al., 2024; Li et al., 2025). We extend this work by simultaneously examining the interplay of many well-being states (i.e., stress, exhaustion, cynicism, recovery, work engagement), job demands (i.e., workload, work-home conflict, job insecurity), job resources (colleague support, manager support, autonomy, psychological safety), and personal resources (i.e., hope, optimism, resilience, self-efficacy, self-compassion, psychological flexibility). This encompassing network may reveal important components and relationships that could inform future intervention and prevention programs.

NETWORK CHANGES OVER TIME

The PNA can reveal not only the structure of relationships among network components at one time point but also differences in network structure across time or conditions. To explore such changes in a meaningful applied context, we examine professional coaching as an external contextual factor that may be associated with shifts in the relationships among well-being states and factors over time. Coaching is a 'collaborative, result-oriented, and systematic process in which the coach facilitates the enhancement of life experience and goal-attainment in the personal and/or professional life of [...] non-clinical clients' (Grant, 2003, p. 254). Previous research has demonstrated beneficial effects of coaching on the *levels* of well-being states, including lower burnout symptoms and greater resilience (e.g., Boet et al., 2023; Jones, Woods & Guillaume, 2016; McGonagle et al., 2020; Solms et al., 2021; Wang et al., 2021).

Beyond changing the levels of well-being components, coaching may also influence how these components relate to one another. Specifically, coaching may enhance the way coachees perceive, manage, or utilize resources by teaching them to develop action plans, create strategies to overcome challenges, and reshape their relationships with the work environment (Fontes & Dello Russo, 2021). Importantly, such changes may not always be reflected in the quantity of demands or resources, but rather in the structure of *relationships* among well-being states and factors. From a network perspective, coaching may therefore be particularly likely to induce structural changes in the well-being network. Therefore, to address our second aim, we compare networks estimated before and after coaching, examining changes in their structure and in the strength of connections among job demands, job and personal resources, and well-being states.

METHOD

PARTICIPANTS AND PROCEDURE

To examine both the work-related well-being network and explore changes within it, we spaced our study along a coaching intervention. Physicians from 16 Dutch hospitals signed up for a coaching program. They were invited to fill out a questionnaire before starting the coaching (T1) and approximately 14 days after completing it (T2). The program comprised six sessions with a professional coach, typically delivered over 10 months. Physicians selected their own coaching goals and discussion topics. The institutional Ethics Review Board of the University of Amsterdam approved the study (IRB no. 2019-WOP-11566).

In total, 603 physicians completed the T1 questionnaire, of whom 332 also completed the T2 questionnaire. To accurately compare T1 and T2 networks, we included in the analyses only the 332 participants who completed both questionnaires.[1] Of these participants, 274 completed six coaching sessions, 54 completed five, and 4 completed four. A logistic regression in which all T1 variables predicted T2 participation provided no evidence that the dropout was related to the studied variables, $\chi^2(19) = 14.50$, $p = .754$. Participants enrolled in staggered waves, with T1 data collected between November 2019 and October 2022, and T2 data collected between August 2020 and February 2024. At T1, participants were aged 24–66 years ($M = 37.02$; $SD = 8.19$), and 74.10% were women. The sample included medical residents (54.52%) and medical specialists (41.27%). Most participants (92.58%) had held their current position for up to 15 years ($M = 5.30$; $SD = 5.54$). The most frequently represented specialties were pediatrics (21.99%), gynecology (13.80%), neurology (10.24%), and internal medicine (9.94%).

MEASURES

Based on the JD-R and DISC models (Bakker & Demerouti, 2007; De Jonge & Dormann, 2003), we assessed 18 well-being states and factors using validated scales administered in Dutch. Table 1 lists references,

COMMUNITIES AND NODES	REFERENCE	DESCRIPTION	SAMPLE ITEM
Job Demands			
Workload (6)[a]	Spector & Jex (1998)	The perceived amount of work and work pace	How often does your job require you to work very fast?
Work-home conflict (4)[b]	Netemeyer, Boles & McMurrian (1996)	Extent to which the job interferes with performing family-related responsibilities	Due to my work, I have to adjust my plans in my private life.
Job insecurity (3)[b]	De Witte (2000)	Extent to which the job and its future are perceived as uncertain	I feel insecure about the future of my job.
Job Resources			
Colleague support (3)[c]	Vinokur, Schul & Caplan (1987)	Experienced psychological and work support from colleagues	My colleagues support me if I have problems at work.
Manager support (3)[c]	Vinokur, Schul & Caplan (1987)	Experienced psychological and work support from the supervisor	My supervisor says things that increase my confidence.
Autonomy (5)[c]	Morgeson & Humphrey (2006)	Extent to which a job allows freedom in work scheduling, decision making, and work methods	In my job, I can take a lot of decisions on my own.
Psychological safety (8)[c]	Edmondson (1999)	The feeling of being safe to make mistakes, take risks, and ask for help	It is safe to take a risk.
Personal Resources			
Hope (3)[c]	Luthans, Youssef & Avolio (2007)	Persevering toward goals and, when necessary, redirecting paths to goals to succeed	Right now, I am energetically pursuing my work goals.
Optimism (3)[c]	Luthans, Youssef & Avolio (2007)	Making a positive attribution about succeeding now and in the future	I always look on the bright side of things regarding my job.
Resilience (3)[c]	Luthans, Youssef & Avolio (2007)	When beset by problems and adversity, sustaining and bouncing back, and even beyond to attain success	When I have a setback at work, I have trouble recovering from it, moving on. (reverse-coded item)
Self-efficacy (3)[c]	Luthans, Youssef & Avolio (2007)	Having confidence to take on and put in the necessary effort to succeed at challenging tasks	When encountering difficult problems in my work, I know how to solve them.
Self-compassion (6)[d]	Neff & Vonk (2009)	Treating oneself with kindness and recognizing one's shared humanity	I try to see my failings as part of the human condition.
Psychological flexibility (7)[d]	Bond et al. (2013)	Ability to flexibly take actions toward achieving goals even when facing challenges	I can work effectively, even when I doubt myself.
Well-Being Outcomes			
Stress (6)[e]	Cohen, Kamarck & Mermelstein (1983)	Degree to which situations in one's life are appraised as stressful	How often did you feel nervous and stressed out?
Exhaustion (5)[c]	Schaufeli & Van Dierendonck (2000)	The draining of emotional resources	I feel mentally exhausted by my work.
Cynicism (4)[c]	Schaufeli & Van Dierendonck (2000)	Negative, cynical attitudes toward one's recipients	I noticed that I have got too much distance from my work.
Recovery (5)[c]	Sonnentag & Fritz (2007)	Indication of how much individuals unwind and recuperate from work	After my work is done, I use time to relax.
Work engagement (9)[e]	Schaufeli et al. (2002)	The vigor, dedication, and absorption with one's work	When I am working, I forget everything around me.

Table 1 References, descriptions, number of items, response scales, and sample items for all measures.

Note. The number of items is indicated in the first column between brackets. Response scales: [a]1 (never) to 5 (always), [b]1 (not at all applicable) to 7 (very applicable), [c]1 (totally disagree) to 7 (totally agree), [d]1 (rarely) to 5 (almost always), [e]1 (never) to 7 (very often).

descriptions, number of items, response scales, and sample items. Coefficient alphas are presented in Table 2.

NETWORK ANALYSIS

First, we estimated the T1 network and examined its interrelations. Second, we estimated the T2 network and compared the two networks. We describe below the identical estimation procedures used at both time points.

Network estimation method

We estimated partial-correlation networks for T1 and T2 data using the *estimateNetwork* function from the *bootnet* package (Epskamp, Borsboom & Fried, 2018, v1.6). We applied the *EBICglasso* method, which produces sparse, interpretable networks by shrinking weak edges to zero (Foygel & Drton, 2010). Because this study was exploratory, we set the tuning parameter to 0.5, which

COMMUNITIES AND THEIR NODES	LIKERT SCALE	MEANS		*SD*		PAIRED *t*-TEST FOR T2-T1 (*t*)	PREDICT-ABILITY (R^2)		SKEWNESS		KURTOSIS		COEFFICIENT α	
		T1	T2	T1	T2		T1	T2	T1	T2	T1	T2	T1	T2
Job Demands														
Workload	1 to 5	3.27	3.23	0.80	0.79	−1.203	40%	36%	−0.04	0.06	−0.50	−0.44	0.86	0.85
Work-home conflict	1 to 7	4.41	4.17	1.35	1.41	−3.104*	33%	34%	−0.35	−0.25	−0.30	−0.73	0.89	0.90
Job insecurity	1 to 7	3.43	3.14	1.82	1.75	−3.697**	33%	19%	0.31	0.39	−1.08	−0.89	0.92	0.91
Job Resources														
Colleague support	1 to 7	5.43	5.64	0.94	0.97	3.954**	24%	28%	−0.54	−1.10	0.37	2.34	0.85	0.89
Manager support	1 to 7	4.66	4.80	1.43	1.47	1.700	20%	19%	−0.47	−0.62	−0.42	−0.16	0.92	0.94
Autonomy	1 to 7	4.18	4.51	1.18	1.17	5.947**	29%	21%	0.26	−0.19	−0.62	−0.37	0.86	0.86
Psychological safety	1 to 7	4.56	4.73	0.64	0.62	5.304**	20%	27%	−0.40	−0.44	0.03	0.24	0.62	0.63
Personal Resources														
Hope	1 to 7	4.42	5.04	0.99	0.96	11.135**	45%	58%	−0.27	−0.41	−0.24	0.58	0.81	0.85
Optimism	1 to 7	4.75	5.05	1.10	0.99	5.834**	60%	56%	−0.45	−0.53	−0.14	0.04	0.80	0.80
Resilience	1 to 7	4.95	5.18	0.93	0.91	4.803**	44%	51%	−0.33	−0.48	−0.31	0.37	0.69	0.64
Self-efficacy	1 to 7	4.95	5.27	0.86	0.81	7.447**	43%	58%	−0.55	−0.61	0.84	0.70	0.74	0.78
Self-compassion	1 to 5	3.23	3.33	0.65	0.62	3.198*	43%	35%	−0.09	−0.26	−0.20	−0.22	0.68	0.66
Psychological flexibility	1 to 5	3.56	3.75	0.65	0.57	5.778**	29%	27%	−0.43	−0.24	−0.04	0.32	0.82	0.78
Well-Being Outcomes														
Stress	1 to 7	3.86	3.44	0.85	0.82	−9.393**	61%	54%	0.04	0.11	0.11	−0.10	0.73	0.75
Exhaustion	1 to 7	2.72	2.51	1.18	1.14	−4.095**	58%	65%	0.86	0.99	0.46	0.82	0.87	0.89
Cynicism	1 to 7	2.56	2.18	1.17	1.02	−6.226**	42%	58%	0.82	0.89	0.32	0.29	0.81	0.81
Recovery	1 to 7	4.04	4.31	1.02	1.07	5.413**	29%	36%	0.01	0.02	−0.30	−0.24	0.80	0.84
Work engagement	1 to 7	4.91	5.06	0.82	0.83	4.155**	55%	62%	−0.60	−0.51	0.17	0.31	0.91	0.91

Table 2 Means, standard deviations (SDs), paired sample t-tests, predictabilities, skewness, kurtosis, and coefficient alphas for all nodes.

Note. Due to incidental missing values, N varies between 331 and 332 at T1, and between 311 and 331 at T2. T1 = Time 1 measure; T2 = Time 2 measure. Differences in means between T1 and T2 measures are indicated by the following significance values: *$p < .05$, two-tailed; **$p < .01$, two-tailed.

eliminated many false-positive edges while retaining enough edges to facilitate our exploratory approach (Epskamp & Fried, 2018). Missing responses were handled using pairwise deletion. Networks were visualized with the *qgraph* package (Epskamp et al., 2012, v1.9.8) using its colorblind theme. To facilitate comparison, we used a fixed layout obtained by averaging the two network layouts with the *averageLayout* function.

Node strength, bridge strength, and predictability

To describe and analyze our networks, we computed node and bridge strength indices. The node strength index was calculated using the *centralityPlot* function in *qgraph* (Epskamp et al., 2012, v1.9.8). The bridge strength index was calculated using the *bridge* function in the *networktools* package in R (Jones, 2017, v1.5.2). Because node strength does not indicate how much variance is explained by its connections, we also calculated nodewise predictabilities after listwise deletion of missing data (Haslbeck & Waldorp, 2018). Predictability estimates (R^2) were visualized as rings around nodes using the *mgm* package (v1.2–14).

Network stability and accuracy

To assess and visualize the uncertainty around the estimated network parameters (Burger et al., 2023), we performed two checks: network stability, which evaluates how reliably the network structure holds across subsets of the data, and network accuracy, which examines the precision of the estimated edge weights. These checks help ensure that the conclusions drawn from the network are robust and not driven by sampling variability. More information about these analyses can be found in Supplement A.

Network changes over time

The T1 and T2 networks were compared using the *Network Comparison Test* (NCT; Van Borkulo et al., 2023, v2.2.2). This test enabled us to examine differences in node strengths, bridge strengths, and edge weights between the two networks. A significantly different node strength suggests that the total of all edge weights connected to this node significantly changed between the two networks. A significantly different bridge strength indicates that the sum of all edges

connecting this node and nodes outside its community significantly changed between the two networks. Lastly, a significantly different edge suggests that the partial correlation between two variables significantly changed between the two networks. To evaluate global and local differences in edges between networks, we conducted three tests within the NCT (α = .05; Van Borkulo et al., 2023).

First, the invariant global strength test assesses whether the overall connectivity level differs significantly between two networks. This connectivity is calculated as the absolute sum of all edge weights in each network (Opsahl, Agneessens & Skvoretz, 2010). However, interpreting this test requires careful examination of the two networks since its nonsignificance does not imply that there is no difference between them. Even if the total sum of all edge weights remains the same, the sign of each individual edge or the nodes they connect could change (Van Borkulo et al., 2023). Second, the invariant network structure test serves as an omnibus test comparing all edges in a network as a whole. Thus, when comparing two networks, this test is statistically significant if at least one edge differs significantly between them. If the omnibus test is significant, we would subsequently conduct the invariant edge strength test to identify which specific edges differ. That is, because our approach is exploratory and does not involve testing predefined hypotheses, we would examine individual edge differences only if the omnibus test indicates an overall structural difference (Van Borkulo et al., 2023). Because these analyses were exploratory in nature and did not involve predefined hypotheses regarding specific network differences, we reported unadjusted *p*-values, consistent with recommendations that routine multiple-testing correction may not always be necessary in exploratory or hypothesis-generating analyses (Rothman, 1990; Wason, Stecher & Mander, 2014). Accordingly, local network differences were interpreted cautiously, given the increased risk of Type I error associated with multiple comparisons. All analyses were performed using *R* (v4.2.1).

RESULTS

Table 2 displays means, standard deviations (*SDs*), paired *t*-tests, predictabilities, skewness, and kurtosis for all nodes for the T1 and T2 data. The paired *t*-tests show that most job demands and negative well-being states significantly decreased from T1 to T2, while most job and personal resources and positive well-being states significantly increased from T1 to T2.

T1 NETWORK

The T1 network (see Figure 1a) had a moderate density, with 58 non-zero edges (i.e., partial correlations), corresponding to 38% of 153 possible edges. The exploration of this network revealed that the edge weights (i.e., partial correlation coefficients) ranged from −.258 (work engagement and cynicism) to .316 (cynicism and exhaustion).

Node strength, bridge strength, and predictability

Figure 2 shows node and bridge strength indices for all included variables. The most strongly connected node was stress, as it had, in total, the strongest relationships both when other variables from its community (i.e., well-being states) were considered (i.e., highest node

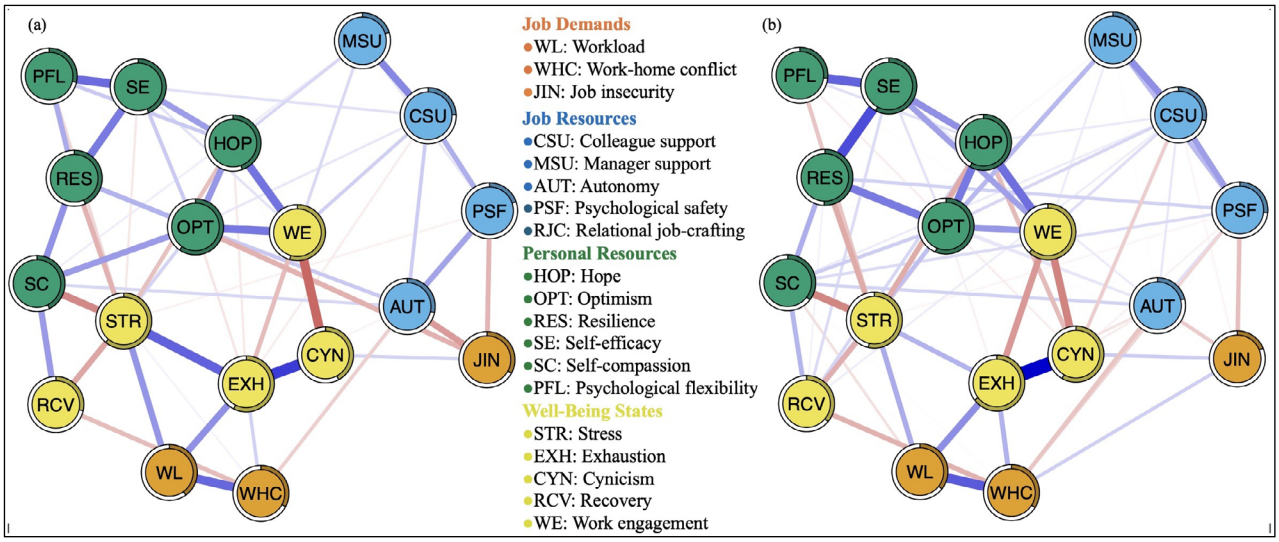


Figure 1 The **(a)** Time 1 and **(b)** Time 2 networks.
Note. Regularized partial correlation networks (tuning-parameter gamma = 0.5) for the T1 and T2 measures. Due to incidental missing values, N varies between 331 and 332 at T1, and between 311 and 331 at T2. Blue edges represent positive and red edges represent negative regularized partial correlations. The maximum value was set to the highest edge weight in both networks (max = .417). The rings around the nodes show the percentage of explained variance.

strength) or excluded (i.e., highest bridge strength). Predictability values (Table 2) showed that the explained variance for all variables ranged between 20% (for psychological safety) and 61% (for stress). This indicates that the included variables explained the most variance in stress, whereas in psychological safety, the included variables explained the least variance.

Network stability and accuracy

The stability analysis showed that the node strength estimates had sufficient stability when estimated on our sample size, indicating that there was sufficient power to estimate centrality indices. Regarding the network accuracy, the stronger the edge, the more confidence we can have in its estimate, while the weaker edges need to be interpreted with caution. See Supplement A for more information about these results.

Network of employee well-being

To explore the complex relationships between well-being states and factors when all their relationships are accounted for simultaneously, we examined connections within and between the communities. First, regarding the connections *within* communities, all nodes representing job demands were positively interconnected. Additionally, all nodes representing personal resources were positively interconnected, and the same pattern was observed for job resources. This suggests that these demands and resources are not independent but rather mutually dependent and tend to covary within the network. Furthermore, all relationships among negative well-being states (i.e., stress, exhaustion, and cynicism) were positive, while all relationships between positive and negative well-being states (e.g., work engagement and stress) were negative. This indicates that negative well-being states tend to cluster together, whereas positive and negative well-being states are negatively associated.

Second, regarding the connections *between* communities, the nodes representing job demands were negatively connected to both job and personal resources, suggesting that higher job demands were associated with fewer available resources. Furthermore, all the connections between job and personal resources were positive, implying that these types of resources often co-occur and may reinforce one another. Finally, stress, exhaustion, and cynicism had positive relationships with job demands and negative relationships with both personal and job resources. Contrarily, work engagement and recovery had positive relationships with personal and job resources and negative relationships

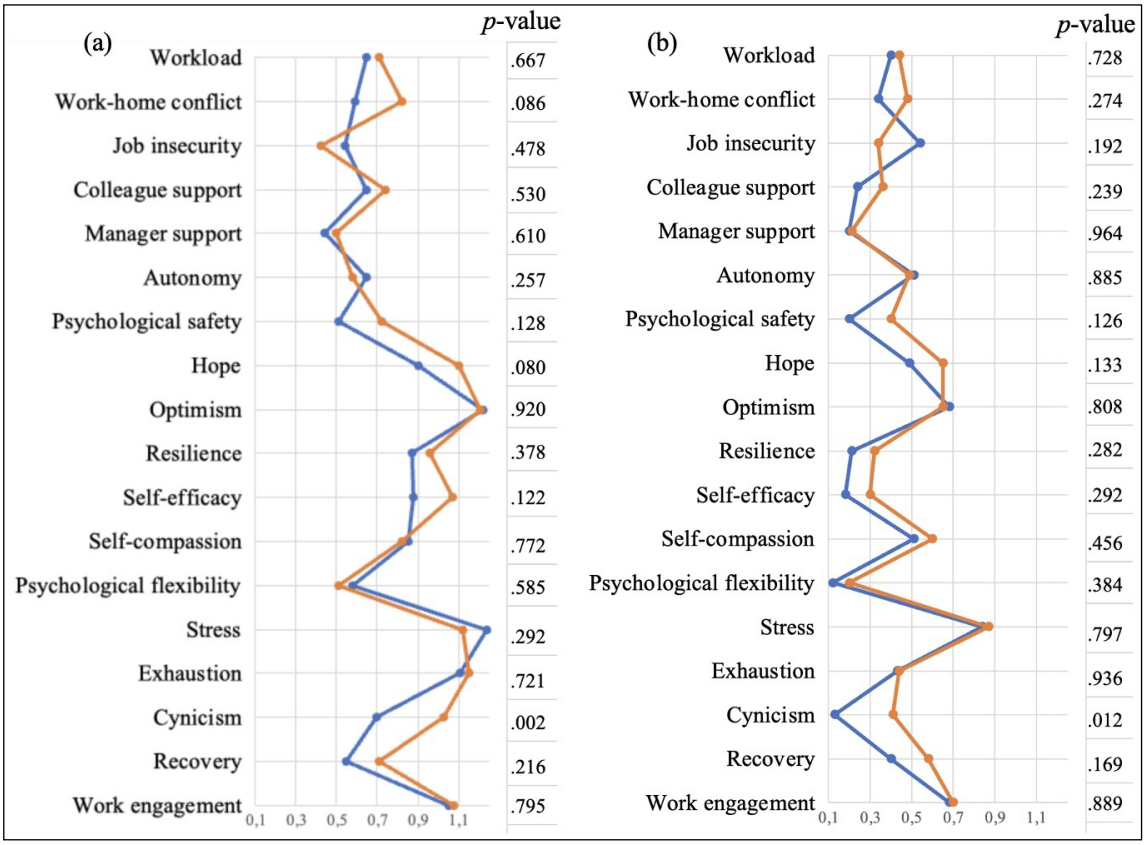


Figure 2 Bootstrapped **(a)** Node strengths and **(b)** Bridge strengths in the Time 1 and Time 2 networks, and the exact *p*-values for their differences.

Note. (a) Blue dots represent the node strengths estimated on the T1 network. Orange dots represent the node strengths estimated on the T2 network. (b) Blue dots represent the bridge strengths estimated on the T1 network. Orange dots represent the bridge strengths estimated on the T2 network. For each variable in these graphs, we tested how significant the differences were between the T1 and T2 (a) node and (b) bridge strengths.

with job demands. Moreover, taking into account all interrelationships between the included variables, well-being states were more closely related to all personal resources (i.e., hope, optimism, resilience, self-efficacy, self-compassion, and psychological flexibility) and job demands (i.e., workload, work-home conflict, and job insecurity), while having somewhat more distant relationships with some job resources (i.e., colleague support and manager support).

T2 NETWORK

The T2 network (see Figure 1b) also had a moderate density, with 74 non-zero edges (i.e., partial correlations), corresponding to 48% of 153 possible edges. Edge weights ranged from –.209 (work engagement and cynicism) to .417 (exhaustion and cynicism).

Node strength, bridge strength, and predictability

Figure 2 shows node and bridge strength indices for all variables. The most strongly connected node (i.e., the highest node strength) was optimism, as it had, in total, the strongest relationships with other variables. However, excluding other variables from their communities (i.e., the highest bridge strength), the most strongly connected node was stress. Predictability values (Table 2) showed that the explained variance ranged between 19% (for manager support) and 65% (for exhaustion). This indicates that the included variables explained the largest portion of variance in exhaustion, whereas in manager support, the included variables explained the lowest proportion of variance.

Network stability and accuracy

As with the T1 network, the stability analysis of the T2 network showed that there was sufficient power to estimate centrality indices. Additionally, regarding the network accuracy, we can have more confidence in estimates of the stronger edges, while the weaker edges need to be interpreted with caution (see Supplement A for more information).

NETWORK CHANGES OVER TIME

To explore if and how the relationships between various well-being states and factors changed over time, we used the three NCT tests to explore differences between the T1 and T2 networks. Firstly, the invariant global strength test was nonsignificant (S = 0.59, p = .190), indicating no difference in the total strength of all edges, despite the larger number of non-zero edges at T2 than at T1. However, although the difference in the total edge weights between networks was not significant, the comparison of node and bridge strengths showed that the edges connected different nodes within each network. For example, cynicism showed significantly larger node strength (p = .002) and bridge strength (p = .012) at T2 (Figure 2). Hence, after coaching, cynicism became more strongly and predominantly negatively connected to other variables, regardless of whether other well-being states were included. Secondly, the invariant network structure test was also nonsignificant (M = .13, p = .878), indicating that the two networks did not contain edges that were significantly different. Because the omnibus test was nonsignificant and we had no predefined hypotheses about specific edges, we did not conduct the invariant edge strength test.

DISCUSSION

Traditional research often examines employee well-being through unidirectional models. To complement these research approaches, we conceptualize well-being as an interplay between various well-being states (e.g., stress, work engagement, burnout) and factors (i.e., job demands, job resources, personal resources), and applied the PNA to examine the interconnectedness between these well-being states and factors. As a first contribution, we extend previous work by analyzing the interrelations between well-being states and factors while accounting for all their connections simultaneously. As a second contribution, we explore how these network interrelations change over time within a coaching context.

NETWORK OF EMPLOYEE WELL-BEING

The network analysis revealed that all included variables within and between communities (i.e., job demands, job resources, and personal resources) are interrelated—specifically, well-being states and factors clustered within their respective communities. Across communities, higher job demands were associated with fewer job and personal resources, whereas job and personal resources often co-occurred. These findings extend prior theorizing and research, as the interconnectedness among and between demands and resources is typically not captured in traditional models, which often assume more independent and unidirectional relationships (Schaufeli & Taris, 2014).

Moreover, our findings suggest that personal resources may function as key factors in employees' well-being networks, complementing existing models of employee well-being and functioning at work (e.g., Bakker & Demerouti, 2007; De Jonge & Dormann, 2003; Karasek, 1979). At baseline, hope and optimism had the strongest connections with work engagement, even when job demands and resources were considered. This extends meta-analytic evidence that personal resources are more strongly associated with work engagement than job resources when examined separately (Mazzetti et al., 2023). These findings suggest a potentially greater importance of personal resources for workplace well-being than emphasized in the traditional JD-R model

(Bakker & Demerouti, 2007). Similarly, resilience and self-compassion remained strongly negatively associated with stress after accounting for job demands and job resources, extending previous evidence linking these personal resources to lower perceived stress (Luo et al., 2019; Smith et al., 2010). These results suggest that even when employees simultaneously face job demands, such as workload, and have access to job resources, like manager and colleague support, their work-related well-being remains strongly linked to their personal resources.

Practically, these findings suggest that structural efforts to reduce job demands and strengthen job resources could be complemented by interventions that foster personal resources. That is, enhancing employees' capacity to adapt and rebound from adversity, as well as fostering positive attitudes and self-compassion, could promote and sustain work engagement and reduce stress levels, beyond improving job demands and job resources.

NETWORK PATTERNS OVER TIME

We proposed professional coaching as a theoretically meaningful context in which changes in the structure of well-being networks may occur, beyond changes in the levels of well-being states and factors. Our findings provide some support for this perspective.

While the overall network structure and global connectivity did not differ significantly between T1 and T2, cynicism became more strongly connected in the T2 network: Both its node strength and bridge strength significantly increased. Although some studies found that coaching did not significantly reduce cynicism (Solms et al., 2021), our results indicate that cynicism decreased at the mean level while becoming more strongly and negatively connected to job and personal resources such as colleague support and hope. Although the overall network structure and connectivity remained stable across time, this pattern highlights the collective association of resources with lower cynicism, complementing traditional analyses that focus on mean-level changes alone. This may be especially relevant for employees facing high workloads and emotional demands, such as healthcare professionals, for whom job and personal resources are crucial in buffering against burnout (Chen et al., 2024; Pérez-Marqués et al., 2023; Solms et al., 2019).

From a theoretical perspective, these changes in cynicism's connectedness could be explained by core coaching mechanisms, including cognitive reframing, increased resource awareness, and deliberate activation of personal and contextual supports (Fontes & Dello Russo, 2021; Grant, 2014). Through coaching, individuals may learn to interpret demanding situations differently and mobilize available resources more effectively, altering the way well-being components relate to one another even when levels of job demands remain stable. Our findings, therefore, underscore the importance of extending existing models of employee well-being (e.g., Bakker & Demerouti, 2007; De Jonge & Dormann, 2003; Karasek, 1979) by incorporating the interconnections among and between well-being states and factors to better reflect the complexity of employees' experiences.

Practically, these findings suggest that interventions targeting multiple resources may strengthen employees' capacity to manage challenges and sustain well-being. Importantly, the network approach allows practitioners and organizations to identify strongly connected nodes, such as cynicism, and guide targeted coaching or support strategies that may have broader effects on overall well-being.

STRENGTHS, LIMITATIONS, AND FUTURE RESEARCH DIRECTIONS

This study conceptualized well-being as an interplay between various well-being states and factors, and applied the PNA to empirically map how these factors and states are interconnected. Rather than focusing solely on a few predictors, we analyzed the interrelationships among numerous well-being states and factors and explored network changes over time in a coaching context. Understanding these complex patterns through network modeling offers valuable insights into psychological processes affecting employees' well-being and functioning (e.g., harnessing personal resources).

Our study offers insight into the well-being networks of a sizable cohort of physicians from various Dutch hospitals. This is particularly important given the high demands and unique stressors faced by medical professionals (McKenna, 2025). However, caution is needed when generalizing these findings to the broader working population, as the specific occupational context may have influenced the observed patterns. Future research is needed to explore whether similar network structures and dynamics emerge in other professional groups and sectors.

Because we did not aim to evaluate coaching effectiveness, we did not include a control group or test for causal effects. As we estimated two cross-sectional networks, directional relationships within networks could not be examined. Nevertheless, future research employing cross-lagged panel network analysis (Wysocki et al., 2022) with multiple measurement points could explore directional relationships over time. Moreover, to assess the effects of coaching interventions on well-being networks, future studies could include a control group, use different samples, and apply additional measurement points and alternative network models to address more intricate research questions. For instance, designs with a control group could utilize moderated network models (Haslbeck, Borsboom & Waldorp, 2021) to investigate intervention effects on relationships between variables. Additionally, studies with a control group and more measurement points could employ network intervention analysis (Blanken et al., 2019) to explore changes in intervention effects over time. Finally,

future studies could build on our exploratory analyses by using independent samples or longitudinal data to perform confirmatory analyses with multiple-testing correction (Chalmers, Cervin & Medvedev, 2025).

CONCLUSION

We conceptualized overall work-related well-being as an interplay between various well-being states and factors, and applied the PNA to map their relationships and examine how they evolved over time within a coaching context. Our analyses revealed that higher job demands were linked to fewer available resources, whereas job and personal resources tended to occur together. Additionally, personal resources maintained strong associations with well-being states, even when accounting for job demands and job resources. These findings suggest that, alongside existing job resources like autonomy or managerial support, organizations should consider offering interventions, such as coaching, to strengthen personal resources. Paired sample *t*-tests also indicated improvements in the levels of well-being states and factors between T1 and T2. Beyond these level changes, the network comparison revealed more negative connections between different resources and cynicism at T2 compared to T1. This suggests that the coaching period was associated with both improvements in individual resources and well-being states and changes in their interrelationships. These results support further research using network models to examine well-being concepts as interconnected systems and evaluate how interventions alter these complex systems.

NOTE

1 Anonymized data and the complete *R* code may be accessed via the following hyperlink: https://osf.io/5s49z/?view_only=29b541d6c4834388aab387bc926b40fb.

DATA ACCESSIBILITY STATEMENT

Anonymized data may be accessed via the following hyperlink: https://osf.io/5s49z/?view_only= 29b541d6c4834388aab387bc926b40fb.

ADDITIONAL FILE

The additional file for this article can be found as follows:

- **Supplement A.** Node strength difference tests and bootstrap analyses of centrality stability and edge-weight accuracy for the T1 and T2 networks. DOI: https://doi.org/10.16993/sjwop.424.s1

COMPETING INTERESTS

The authors have no competing interests to declare.

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