A Longitudinal Investigation of Structural Empowerment Profiles among Healthcare Employees

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Declaration of competing interest
None

Acknowledgements

In addition to the authors listed, the project could be conducted thanks to the contribution and involvement of psycho-sociologists (Arnaud Lecun, Marine Robert, Thomas Sterchi), nurses (Solenn Renault, Jeremy Thureau, Annaïs Thureau) and physicians from the Occupational Medicine Department for data collection (Loïc Louisy, François Léger, Pierre-Alban Pioch, Amélie Mear, Guerric Fourneau, Mickael Humilier, Claire Gordeeff, Stéphanie Grégoire), and psychology students supervised by the coordination team (Annaël Joubert, Kiliane Chabonnel, Hugo Normand, Antoine Tastayre, Mélanie Gendron, Lucille Boulery, Arthur Peltier, Lola Garcia Dupuis).

Funding
This work was fully funded by the French Ministry of Health (Direction Générale de l'Offre de Soin) from a €498,180 scientific call for tender, within the framework of a PREPS (Programme de Recherche sur la Performance du Système de soin; grant number: PREPS-16-681). The grant attribution was peer reviewed by an independent scientific committee. The French Ministry of Health had no role in the protocol definition, study conduct, data collection, data processing and interpretation, nor in the choice of the results to be presented or the ways of valorization chosen.

Data availability
Our dataset can be made available upon reasonable request, starting three years after the completion of the study, from the corresponding author.

This is the prepublication version of the following manuscript:
Cougot, B., Gillet, N., Morin, A. J. S., Gauvin, J., Ollierou, F., Moret, L., & Tripodi, D. (in press). A longitudinal investigation of structural empowerment profiles among healthcare employees. *Journal of Nursing Scholarship*.

Abstract
Purpose. Research on structural empowerment has typically adopted a variable-centered perspective, which is not ideal to study the combined effects of structural empowerment components. This person-centered investigation aims to enhance our knowledge about the configurations, or profiles, of healthcare employees' perceptions of the structural empowerment dimensions present in their workplace (opportunity, information, support, and resources). Furthermore, this study considers the replicability and stability of these profiles over a period of two years, and their outcomes (perceived quality of care, and positive and negative affect).
Design. Participants completed the same self-reported questionnaires twice, two years apart.
Methods. A sample of 633 healthcare employees (including a majority of nurses and nursing assistants) participated. Latent transition analyses were performed.
Results. Five profiles were identified: Low Empowerment, High Information, Normative, Moderately High Empowerment, and High Empowerment. Membership into the Normative and Moderately High Empowerment profiles demonstrated a high level of stability over time (79.1% to 83.2%). Membership in the other profiles was either moderately stable (43.5% for the High Empowerment profile) or relatively unstable (19.7% to 20.4% for the Low Empowerment and High Information profiles) over time. More desirable outcomes (i.e., higher positive affect and quality of care, and lower negative affect) were observed in the High Empowerment profile.
Conclusions. These results highlight the benefits of high structural empowerment, in line with prior studies suggesting that structural empowerment can act as a strong organizational resource capable of enhancing the functioning of healthcare professionals. These findings additionally demonstrate that profiles characterized by the highest or lowest levels of structural empowerment were less stable over time than those characterized by more moderate levels.
Clinical Relevance. From an intervention perspective, organizations and managers should pay special attention to employees perceiving low levels of structural empowerment, as they experience the worst outcomes. In addition, they should try to maintain high levels of structural empowerment within the High Empowerment profile, as this profile is associated with the most desirable consequences. Such attention should be fruitful, considering the instability of the High Empowerment and Low Empowerment profiles over time.

Registration: NCT04010773 on ClinicalTrials.gov (04 July, 2019)

Keywords: Structural empowerment; latent transition analyses; well-being; positive and negative affect; quality of care

Introduction

Recent reductions in economic allocations directed at the healthcare system have resulted in increased job demands for healthcare professionals, who simultaneously need to contend with diminished resources (Gillet et al., 2020). Moreover, healthcare employees frequently face high emotional demands, thereby amplifying their likelihood of experiencing psychological health problems (Huyghebaert-Zouaghi et al., 2022). Auspiciously, structurally empowering work environments (Kanter, 1993) can help foster and bolster healthcare employees' well-being, development, quality of care, and work efficacy (García-Sierra & Fernández-Castro, 2018; Laschinger et al., 2001; Li et al., 2013). Moreover, structurally empowering interventions have been reported to be well-connected to the nature and needs of healthcare organizations (e.g., Fragkos et al., 2020; Orgambídez & Almeida, 2020).

Kanter (1993) initially defined a structurally empowering work environment as one that provides employees with resources (i.e., human resources, equipment, and supplies required to properly achieve one's work-related tasks), information (i.e., understanding the organization's values and goals, and having the opportunity to engage in decision-making processes within the organization), support (i.e., feedback and problem-solving advice from supervisors and colleagues), and opportunities to learn and grow (for a similar perspective focused more specifically on nursing, see Laschinger et al., 2001). Supporting this early conceptualization, the current consensus is that a thorough representation of structural empowerment should consider these four components (e.g., Boamah et al., 2017; Orgambídez-Ramos et al., 2017), which are uniquely related to predictors and outcomes (Dan et al., 2018; Orgambídez-Ramos et al., 2017).

So far, research looking at the role of structural empowerment has generally adopted a variable-centered approach (e.g., Li et al., 2013). Despite their relevance, variable-centered results have inherent limitations due to their focus on average relations occurring in the sample under study, which are assumed to generalize to every member of the sample. Moreover, variable-centered investigations are unable to investigate the combined effects of multiple variables, particularly when three or more interacting variables are considered (Meyer & Morin, 2016). In contrast, person-centered approaches account for the fact that all members of a sample may come from qualitatively distinct populations and are thus ideal to document the unique configurations of variable combinations to which discrete profiles of employees are exposed (Morin et al., 2018). Nonetheless, person-centered investigations have not yet investigated the nature of structural empowerment profiles while taking into consideration their stability or evolution over time. Relying on Kanter's (1993) structural empowerment theory (also see Laschinger et al, 2001), we address these considerations by documenting the structural empowerment profiles that most accurately represent a sample of healthcare employees. We also investigate the replicability of these profiles (number, nature, variability, prevalence), as well as within-person stability in profile membership (if employees retain the same profile) over a period of two years. Finally, we examine the relations between theoretically-relevant outcomes (perceived quality of care, and positive and negative affect) and these structural empowerment profiles, and test whether these associations remain stable over time. By documenting these outcomes, our results are likely to contribute to the identification of types of employees who might particularly benefit from interventions.

Theoretically underpinned by Kanter's (1993) structural empowerment theory, this research specifically aims to: (1) achieve a more refined person-centered comprehension of the characteristics and stability of the structural empowerment profiles observed in a sample of healthcare employees; and (2) investigate the relations between these profiles and theoretically-relevant outcomes to assess their construct validity. This study is guided by three questions: (a) Can we distinguish discrete structural empowerment profiles? (b) Can we identify similar profiles over time, and do participants transition from one profile to another over a period of two years? and (c) Do these profiles share differentiated associations with the outcomes?

A Person-Centered Representation of Structural Empowerment

Person-centered analyses seek to understand the combined effect of multiple components of structural empowerment and align more harmoniously with healthcare practitioners and managers inclination to view workers as belonging to distinct categories (Morin et al., 2011, 2018). Unfortunately, no previous person-centered research has ever sought to understand how perceptions of different structural empowerment components combine within healthcare employees, or among any other type of employees for that matter. Moreover, although Fisher (2014) has shown that structural empowerment could mitigate the adverse effects of role overload on organizational commitment, no variable-centered study has ever considered how perceptions of different structural empowerment components could interact with one another in prediction. Fortunately, valuable guidance can still be obtained, albeit indirectly, from research conducted on related constructs.

A first indirect form of evidence stems from past person-centered research examining the effects of perceived social support in the workplace. Caesens et al. (2020) found five social support profiles in two different samples: *Moderately Supported* (moderate to moderately high social support from colleagues, supervisor, organization), *Isolated* (very low to moderately low social support from all sources), *Supervisor Supported* (moderate to moderately high social support from colleagues and supervisor, and very low social support from the organization), *Weakly Supported* (moderately social support from all sources), and *Highly Supported* (high social support from all sources). Caesens et al. (2021) recently reported similar results. In both studies, the results showcased that the availability of more sources of support, or of higher support from these sources, was beneficial for employees.

A second indirect form of evidence stems from the study of perceived leadership behaviors (e.g., Boudrias et al., 2010; Chénard-Poirier et al., 2017, 2022; Gillet et al., 2022). Chénard-Poirier et al. (2022) identified three profiles based on employees' perceptions of exposure to destructive and constructive leadership behaviors: 1) primarily constructive, 2) primarily destructive, and 3) inconsistent. Interestingly, their results showed that exposure to an inconsistent leadership profile could be even more harmful than exposure to a purely destructive one. In another investigation of empowering leadership behaviors, Chénard-Poirier et al. (2017) identified four profiles:1) a *Moderately-Empowered Social-Focused* profile; 2) an *Optimal* profile; 3) a *Moderately-Empowered Task-Focused* profile; and 4) a *Non-Empowered* profile. Furthermore, they found that the level of empowering leadership behaviors in each of these four profiles was perfectly aligned with the levels of behavioral empowerment in each of the profiles.

A third and last form of indirect evidence stems from the study of psychological empowerment (Spreitzer, 1995). Recently, Gillet et al. (2023) identified five profiles of psychological empowerment among a sample of French healthcare workers: 1) a *Low Psychological Empowerment* profile, 2) a *Normative* profile, 3) a *Moderately High Psychological Empowerment and Impact* profile, 4) a *Moderately High Psychological Empowerment and High Meaning* profile, and 5) a *High Psychological Empowerment* profile. Interestingly, all five profiles were found to be very stable over a one-year period. The *Low Psychological Empowerment* profile displayed the worst outcomes (e.g., sleeping difficulties and depressive symptoms).

In the absence of direct person-centered guidance specific to employees' structural empowerment perceptions, the nature and number of profiles that will be detected remains an open research question. However, despite the diversity of indicators, methods, and samples used in previous studies, the preponderance of evidence suggests a minimum of three profiles, typically comprising a *Low Empowerment*, a *Moderate Empowerment*, and a *High Empowerment* profile. Additional profiles characterized by more differentiated configurations are also expected, given that previous person-centered studies of related-constructs have all identified profiles showing an unbalanced configuration across dimensions (for example, a *High Information* profile dominated by information; e.g., Caesens et al., 2021; Chénard-Poirier et al., 2017).

A Longitudinal Person-Centered Representation

This research also seeks to investigate the stability of structural empowerment profiles over a period of two years. This time lag was selected in accordance with previous research (Church et al., 2018), based on the recognition that is goes beyond short-term monthly fluctuations (Hagerman et al., 2017; Read & Laschinger, 2015) while being long enough to detect changes that take time to occur (Leiter et al., 2012). Determining the stability of profiles is crucial to justify their use to inform tailored interventions (Meyer & Morin, 2016).

More precisely, two distinct types of longitudinal stability can be considered (Gillet et al., 2019; Sandrin et al., 2020). First, within-sample stability pertains to the profiles themselves and their potential transformation over time. For instance, a change in the number (i.e., configural similarity) or structure (i.e., structural similarity) of the profiles without any systematic change or intervention could indicate that they represent transient phenomena unworthy of supporting intervention efforts (e.g., Morin et al., 2016). In contrast, changes in dispersion (the extent to which members of a specific profile are similar to one another) and distribution (the size of the profiles) would highlight their responsiveness to internal or external changes that are not sufficient to modify their fundamental nature. Second, we can consider the extent to which individual workers remain in the same profile over time as well as their likelihood of transitioning to another profile (Morin et al., 2016). This form of within-person stability can happen even in the absence of within-sample changes in the number, nature, dispersion, and distribution of the profiles, and provides complementary information on the expected rigidity or malleability of profile membership.

So far, most of the previously reviewed research able to provide indirect guidance to the present study has relied on a cross-sectional design, and thus cannot help us anticipate the stability of our results. Nevertheless, a longitudinal variable-centered investigation (Hagerman et al., 2017) found a moderately high level of stability over a one-year period (r = .73) for employees' perceptions of structural empowerment. Furthermore, Caesens et al. (2021) found evidence of configural, structural, and distributional similarity for their social support profiles over eight months, while indicating that similarity among profile members seemed to slightly increase over time (no dispersion similarity). They also found moderate to high levels of within-person stability (74.3% to 95.4%) for most profiles, although membership into their isolated profile was slightly weaker (59.4%). Based on these results, we anticipate a moderate to high levels of within-person stability and expect to find evidence of configural and structural similarity. Yet, lacking clear guidance from previous research, we leave the dispersion and distributional similarity of our profiles as an open research question. We similarly leave as an open research question whether the main within-person transitions will be lateral (toward profiles with similar levels of structural empowerment), upward (toward more empowered profiles), or downward (toward less empowered profiles).

A Person-Centered Construct Validation

Establishing the construct validity of person-centered solutions requires a thorough examination of their implications for theoretically-important outcomes (Meyer & Morin, 2016), especially when adopting a primarily inductive approach to their identification (Morin et al., 2018). Indeed, assessing the true practical implications of structural empowerment profiles is not possible in the absence of information on their outcomes, which makes it difficult to choose which profile(s) to prioritize in terms of intervention. We more specifically consider positive affect, negative affect, and perceived quality of care as outcomes in this study.

Current evidence indicates that structural empowerment is associated with higher levels of performance and well-being (Fragkos et al., 2020; García-Sierra & Fernández-Castro, 2018) and lower levels of ill-being (Orgambídez-Ramos et al., 2017). Caesens et al. (2020, 2021) showed that their *Highly Supported* profile evidenced the most desirable outcomes (i.e., job satisfaction, work performance, and affective commitment). In contrast, their *Isolated* profile displayed the highest levels of emotional exhaustion. Chénard Poirier et al. (2017) also found higher levels of behavioral empowerment in their *Optimal* profile. In contrast, Chénard-Poirier et al. (2022) found that, although exposure to a *Destructive* profile seemed harmful for employees, exposure to an *Inconsistent* profile was also quite problematic.

More generally, structural empowerment is a powerful organizational resource that improves the functioning of healthcare professionals (Kanter, 1993). For instance, when healthcare employees feel empowered, they perceive having enough resources to cope with their tasks effectively, leading them to report more positive affect and less negative affect. They also feel competent at work and develop positive work attitudes, which in turn facilitate a high quality of care (Boamah et al., 2017). Due to the absence of previous person-centered research evidence on structural empowerment profiles, it is impossible to formulate clear hypotheses on their associations with outcomes. However, past studies on related constructs enable us to expect that profiles with lower levels of structural empowerment (e.g., *Low Structural Empowerment*) should be accompanied by less positive affect and quality of care, and more negative affect, than profiles with higher levels of structural empowerment (e.g., *High Structural Empowerment*).

Method

Design and Context

All employees working in two divisions (both including medical and surgical activities) from a French hospital were asked to fill an online questionnaire two times, once in 2018 and once in 2020. At each measurement time, participants filled the same questionnaires. During the study period, there were no significant reorganizations or restructuring planned in either of the divisions. After obtaining the authorization from the hospital and division management, participants were allowed to complete our questionnaire as part of a mandatory physical health checkup conducted in the hospital's occupational health department. A clinical research nurse welcomed all participants, explained the study, and invited employees meeting the inclusion criteria to complete our online questionnaire on tablet after completing a signed informed consent form. Eligible employees included all professionals working in a healthcare unit within these two divisions, including nurses, nursing assistants, and chief medical officers. All participants were ensured that their answers would remain confidential, that their participation was voluntary, and that they could put an end to their participation at any time. No differences were found between participants who completed a single time point and those who completed two, except for slightly lower levels of negative affect and higher levels of information among those who participated twice.

Measures

Participants completed all questionnaires in French. The structural empowerment measure had not been previously validated in French. A standard translation back-translation process (conducted by independent bilingual translators and members of the research team) was thus used to adapt this measure to French.

Structural empowerment perceptions were assessed using a validated 12-item questionnaire (Laschinger et al., 2001) measuring: Opportunity (four items; e.g., "I have the chance to gain new skills and knowledge on the job"; $\alpha_{t1} = .62$; $\alpha_{t2} = .69$; ω_{t1} and $\omega_{t2} = .668$), information (four items; e.g., "I have information about the current state of the organization"; $\alpha_{t1} = .84$; $\alpha_{t2} = .86$; $\omega_{t1} = .846$; $\omega_{t2} = .872$), support (four items; e.g., "Helpful hints or problem solving advice"; $\alpha_{t1} = .76$; $\alpha_{t2} = .77$; ω_{t1} and $\omega_{t2} = .775$) and resources (four items; e.g., "I have time available to accomplish job requirements"; $\alpha_{t1} = .74$; $\alpha_{t2} = .75$; ω_{t1} and $\omega_{t2} = .779$). All items were rated on a five-point scale ("Strongly Disagree" to "Strongly Agree"). Scores on this measure were found to have acceptable reliability in the present research and criterion-related validity in past studies (e.g., Laschinger et al., 2001).

Positive and negative affect were assessed using the 12-item short form of the Job-Related Affective Well-Being Scale (Schaufeli & van Rhenen, 2006; French version: Gillet et al., 2018), which measures: Positive affect (six items; e.g., "My job made me feel enthusiastic"; α_{t1} = .87; α_{t2} = .88; ω_{t1} and ω_{t2} = .804) and negative affect (six items; e.g., "My job made me feel discouraged"; α_{t1} = .87; α_{t2} = .88; ω_{t1} and ω_{t2} = .689). All items were rated on a five-point scale ("Never" to "Very Often"). Scores on this questionnaire were found to have satisfactory reliability in the present research and criterion-related validity in prior research (e.g., Schaufeli & van Rhenen, 2006).

Quality of care was assessed with a validated single-item measure (Schmalenberg & Kramer, 2008; French version: Chevalier et al., 2017) asking employees to report their individual perception in response to: "Select a number that indicates the usual quality of care provided to patients on your unit". Answers were given on a ten-point scale ("Dangerously Low" to "Very High Quality"). This single-item measure demonstrated good criterion-related validity in prior research (e.g., Schmalenberg & Kramer, 2008).

Ethical statement

This study was approved by the Nantes University Hospital Ethics Committee (#GNEDS02122018), was conducted according to the guidelines from the Declaration of Helsinki, and is registered on ClinicalTrials.gov (#NCT04010773). This specific protocol (#NCT04010773) covers two distinct data collections, one involving a one-year follow up (published in Gillet et al., 2023), and the other one involving the two-year follow up published in the current study.

Analyses

Preliminary Measurement Models

We first assessed the psychometric properties of all multi-item measures with preliminary factor analyses. The nature and results from these analyses are presented in the online supplements (Tables S1 to S5). These results support the factor validity, measurement invariance over time and across groups of healthcare employees, composite reliability, and discriminant validity (i.e., factor correlations) of scores obtained on our measures. For our main analyses, we used factor scores obtained from these analyses (apart from quality of care which is a single-item measure; Meyer & Morin, 2016). These factor scores were estimated in standardized units (SD = 1; M = 0) from longitudinally invariant models (Millsap, 2011) to ensure comparability over time. Factor scores are partially corrected for unreliability (Skrondal & Laake, 2001).

Model Estimation

The Mplus 8.7 statistical package (Muthén & Muthén, 2021) was used in all analyses. Analyses relied on the maximum likelihood robust (MLR) estimator and on full information maximum likelihood procedures (FIML) to ensure unbiased estimation of all model parameters despite missing data. FIML allowed us to use data from all participants irrespective of whether they completed one or two time points (n = 633) rather than resorting to a problematic listwise deletion strategy (including only those who participated at both time points: n = 422). FIML is less computationally demanding but as efficient as multiple imputation (Enders, 2010). To account for the sensitivity of latent profile analyses (LPA) to initial start values (Hipp & Bauer, 2006), these analyses relied on 5000 random starts, 1000 iterations, and 200 optimizations. In longitudinal analyses, these parameters were increased to 10000, 1000, and 500.

Latent Profile Analyses (LPA)

LPA summarize the multivariate distribution of scores on a set of profile indicators by identifying a limited number of profiles representing subpopulation of workers presenting a different configuration of scores (McLachlan & Peel, 2000). These prototypical profiles are probabilistic, meaning that each worker has a likelihood of belonging to all latent profiles (which represents a statistical control for classification errors; Morin et al., 2018). First, LPA comprising one to eight latent profiles were estimated at each time point, while allowing for the free estimation of the means and variances of the four structural empowerment factor scores (Morin & Litalien, 2019).

Model Comparison and Selection

At each time point, deciding how many profiles to retain relies on the careful evaluation of their meaningfulness, theoretical alignment, and statistical adequacy (Marsh et al., 2009; Morin & Litalien, 2019). Consulting statistical indicators help inform this choice (McLachlan & Peel, 2000). A lower value on the Bayesian Information Criterion (BIC), sample-size Adjusted BIC (ABIC), Consistent AIC (CAIC), and Akaïke Information Criterion (AIC) indicate that the models have a better fit to the data. In addition, a statistically significant adjusted Lo, Mendell and Rubin's (2001) Likelihood Ratio Test (aLMR) and Bootstrap Likelihood Ratio Test (BLRT) both indicate improved fit compared to a model including fewer profiles. However, although statistical simulations (e.g., Diallo et al., 2016) have supported the utility of the BIC, CAIC, BLRT, and ABIC, they have not supported that of the aLMR and AIC as indicators of the optimal number of latent profiles. Hence, these two indicators are only disclosed for transparency and will not be involved in model comparisons. Furthermore, all of these tests have a sample-size contingency and thus sometimes fail to support a specific solution (Marsh et al., 2009). When this happens, one should rely on an elbow plot (i.e., a graphical display of the value of these indicators as a function of the number of profiles) to identify a plateau suggestive of an optimal solution (Morin et al., 2011). Lastly, the entropy (ranging from 0 to 1; Lubke & Muthén, 2007) is reported for descriptive purposes as an indicator of classification accuracy.

Longitudinal Tests of Profile Similarity

Contingent on the identification of an equal number of profiles at both time points (i.e., *configural* similarity; Morin et al., 2016; Morin & Litalien, 2017), both time-specific solutions where then combined into a single longitudinal model for longitudinal tests of profile similarity. These tests were conducted sequentially, based on the imposition of successive equality constraints to test for *structural* similarity (i.e., equality on the within-profile means), *dispersion* similarity (i.e., equality on the within-profile variances), and *distributional* similarity (i.e., equality constraints on the size of the profiles). Each model was compared to the previous one based on BIC, ABIC, and CAIC, and a decrease in the value of two of these indicators represents evidence of longitudinal similarity (Morin et al., 2016).

Latent Transition Analyses (LTA)

Within-person stability and transitions in profile membership were then examined by converting the most similar LPA solution into a LTA (Collins & Lanza, 2010). As advised by Morin and Litalien (2017), this conversion was done with the manual three-step approach (Asparouhov & Muthén, 2014). Interested readers should consult Morin and Litalien (2019) for more details about LPA and LTA.

Predictors and Outcomes of Profile Membership

Associations between profiles, predictors, and outcomes were then estimated, as well as their replicability over time (i.e., *predictive* and *explanatory* similarity). Demographic predictors (including age, sex, status, position, and job type [nurses and nursing assistants *versus* other employees]) were considered across a series of four models (Morin & Litalien, 2019; Morin et al., 2016). In these models, predictors were incorporated through a multinomial logistic regression. First, a null effects model was estimated, fixing to zero the associations between these variables and the profiles. Second, relations between the predictors and the profiles were freely estimated and allowed to vary across the two time points and T1 profile membership (to test their associations with distinct profile transitions). A third model only allowed these associations to vary across the two time points, while a last model of *predictive* similarity fixed them to equality over time.

Outcomes measured at both time points (T2 outcomes can be seen as controlled for their baseline level) were finally integrated in the final model and allowed to vary across the profiles at their corresponding time of measurement. Next, the profile-outcome associations were constrained to equality over time within a model of *explanatory* similarity. The multivariate delta method, described by Raykov and Marcoulides (2004), was used to test the statistical significance of outcome differences among profiles.

Results

Participants

A total of 633 participants (86.6% females) completed our T1 questionnaire with a participation rate of 40.6%. Of these, 422 also completed the T2 questionnaire. Participants worked in the same hospital and did not transition to a different healthcare unit between T1 and T2. Nursing assistants and nurses were the most represented in the sample (66.8%). Participants had an average tenure of 6.89 years (SD = 6.03) and an average age of 40.80 years (SD = 9.45). The majority held permanent (87.8%) full-time (67.8%) positions.

Latent Profile Analyses (LPA)

The model fit results associated with solutions including different numbers of profiles at both time points are reported in Table S6 and Figures S1 and S2, in the online supplements. At both time points, the statistical indicators were unable to identify a prevailing solution. However, a first inflexion point was visible after three profiles in the elbow plots, followed by a second smaller inflexion after five profiles. On this basis, LPA solutions ranging from two to five profiles were thoroughly inspected for their theoretical and heuristic value. This inspection revealed very similar solutions over time, consistent with their *configural* similarity. This inspection also showed that additional profiles, up to the five-profile solution, had a distinctive and meaningful configuration. However, the addition of a sixth profile led to the separation of an existing profile into smaller profiles with a comparable configuration. We thus retained the five-profile solution at T1 and T2.

The fit of the longitudinal solutions can be found in Table 1, and supported the second and third models of *structural* and *dispersion* similarity, which both resulted in a reduction in CAIC, BIC, and ABIC values. The model of *distributional* similarity, however, was not supported. The final retained model of *dispersion* similarity is illustrated in Figure 1. The parameter estimates from this model can be found in the online supplements (Tables S7 and S8). Consistent with its high entropy (.822), this model had a high classification accuracy at T1 (ranging from 80.4% to 92.7%) and T2 (from 82.2% to 92.4%).

Profile 1 (*Low Empowerment*) reported being exposed to low to very low levels of opportunity, information, support, and resources, and represented 8.10% of the sample at T1 and 3.78% at T2. Profile 2 (*High Information*) reported high levels of information coupled with average levels of opportunity, support, and resources, and represented 12.53% of the sample at T1 and 9.08% at T2. Profile 3 (*Normative*) reported moderately low levels of information coupled with average levels of opportunity, support, and resources, and represented 50.72% of the sample at T1 and 51.44% at T2. Profile 4 (*High Empowerment*) reported high levels of opportunity, information, and support coupled with moderately high levels of resources, and represented 13.55% of the sample at T1 and 7.91% at T2. Lastly, Profile 5 (*Moderately High Empowerment*) reported moderately high levels of information, support, and resources, and average levels of opportunity, and represented 15.10% of the sample at T1 and 27.78% at T2[1].

Latent Transitions Analyses (LTA)

As shown in Table 2, the most stable profiles over time were Profiles 5 (*Moderately High Empowerment*) and 3 (*Normative*), with respective stability rates of 79.1% and 83.2%. Next came Profile 4 (*High Empowerment*), which was moderately stable (43.5%). Finally, Profiles 1 (*Low Empowerment*) and 2 (*High Information*) fluctuated over time, with respective stability rates of 19.7% and 20.4%.

Participants with initially low to very low structural empowerment, when transitioning to a different profile at T2, were likely to move to a profile presenting higher structural empowerment. In fact, 70.5% of the participants from Profile 1 (*Low Empowerment*) at T1 shifted to the *Normative* profile at T2, and 9.8% shifted to the *Moderately High Empowerment* profile at T2. In relation to Profile 2 (*High Information*) at T1, the primary shift (53.2%) was to Profile 5 (*Moderately High Empowerment*) at T2. However, we also observed shifts to the *High Empowerment* (12.9%), *Normative* (12.7%), and *Low Empowerment* profiles (0.9%). For Profile 3 (*Normative*) at T1, the primary shift (7.8%) was also to Profile 5 (*Moderately High Empowerment*) at T2, while some participants shifted to the *High Information* (5.4%) and *Low Empowerment* (3.6%) profiles at T2. Likewise, the primary shift (32.0%) for members of Profile 4 (*High Empowerment*) at T1, was also to Profile 5 (*Moderately High Empowerment*), although some also shifted to Profiles 3 (*Normative*; 12.4%) and 2 (*High Information*; 12.0%) at T2. Finally, among individuals in Profile 5 at T1 (*Moderately High Empowerment*), the primary shift (14.1%) was to Profile 2 (*High Information*) at T2, although some also shifted to the *High Empowerment* (4.3%), *Low Empowerment* (1.7%) or *Normative* (0.7%) profiles at T2.

Predictors of Profile Membership

As shown in Table 1, the predictive model associated with lowest values on the information criteria was the null effects model. An examination of the parameter estimates associated with these models also revealed a lack of association between these demographic predictors and profile membership. These variables were thus excluded from further analyses.

Outcomes of Profile Membership

Table 1 also displays the fit from the models with the outcomes. The model of *explanatory* similarity is supported, in line with profile-outcome associations generalizing over time. These associations can be found in Table 3. They showed obvious differences between two of the five profiles (i.e., no significant difference was found between the *High Information*, *Normative*, and *Moderately High Empowerment* profiles). The lowest levels of quality of care and positive affect were observed in Profile 1 (*Low Empowerment*). Then, Profiles 5 (*Moderately High Empowerment*), 3 (*Normative*) and 2 (*High Information*) exhibited an equally higher level of quality of care and positive affect. Finally, the highest levels of these outcomes were displayed by Profile 4 (*High Empowerment*). Conversely, the most elevated levels of negative affect were noticed within Profile 1 (*Low Empowerment*), followed equally by Profiles 2 (*High Information*), 5 (*Moderately High Empowerment*), and 3 (*Normative*) with no significant difference between these three profiles, and finally by Profile 4 (*High Empowerment*).

Discussion

To increase our theoretical understanding of healthcare workers' structural empowerment perceptions, we sought to identify the various structural empowerment configurations perceived by these workers. We also examined the within-sample and within-person stability of these profiles to assess their generalizability and the consistency of employees' profile membership across a two-year interval. Finally, we investigated the associations between these profiles and quality of care, positive affect, and negative affect to help document their construct validity and practical relevance.

Structural Empowerment Profiles

Perceptions of structural empowerment reported in our sample were best summarized by five distinct

[1] Finally, we also estimated multi-group models to assess LPA similarity across samples of nurses and nursing assistants *versus* other healthcare employees (at both time points). The statistical indicators associated with these analyses can be found in Table 1 (middle section). At both time points, distributional similarity was supported, suggesting that the profiles were highly similar across subsamples of healthcare employees. The only difference was identified at Time 2, showing higher levels of support in the *Normative* profile among nurses and nursing assistants (M = .156) relative to other healthcare employees (M = -.724).

profiles. These profiles displayed a *Low Empowerment* (Profile 1), *High Information* (Profile 2), *Normative* (Profile 3), *High Empowerment* (Profile 4) and *Moderately High Empowerment* (Profile 5) configuration. These profiles were generally consistent with our expectations, matching findings from previous person-centered studies of employees' perceptions of slightly different work characteristics (e.g., Caesens et al., 2020, 2021; Chénard-Poirier et al., 2017, 2022; Gillet et al., 2022, 2023). Although the size of these profiles changed over time, their number, structure, and dispersion (within-profile variability) was found to generalize over time. This generalizability suggests that these profiles may capture central psychological mechanisms underlying employees' perceptions of structural empowerment, regardless of which constructs, scales, and measurement models considered in any given study. However, although many have previously mentioned the need to account for multiple, and conceptually distinct, components of structural empowerment (Boamah et al., 2017; Orgambídez-Ramos et al., 2017), our results rather underscore the limited value of distinguishing among these four components, which rather converged with one another within almost all profiles identified in this study, except for the *High Information* profile. This conclusion is aligned with earlier studies reporting strong correlations between structural empowerment components (Bawafaa et al., 2015).

However, the *High Information* profile suggests that, unlike the other dimensions of structural empowerment, some employees may have access to significantly more information than to the other three dimensions of structural empowerment. This result underscores that access to information (e.g., regarding top management goals and values) seems to play a core role in structural empowerment. Indeed, supervisors are known to play a central role in relaying information from top management to front-line employees, particularly in large bureaucratic organizations (Davids et al., 2019) as in hospitals (Lega & De Pietro, 2005). Thus, this high level of information associated with the *High Information* profile may reflect a strong alliance between employees and their supervisor. However, future research should attempt to understand why such interpersonal relationships can be strengthened by considering potential determinants of structural empowerment profiles. To achieve a comprehensive picture of employees' perceptions of structural empowerment profiles, our results also suggest that it may not be necessary to separately consider their levels of opportunity, information, support, and resources, although it does appear relevant to differentiate the information component from the other components. However, it would be necessary to systematically assess whether similar profiles would emerge in other countries and cultures (e.g., Eastern Europe, America, Asia) and when using different research designs.

Our findings indicated that membership in the *Normative* and *Moderately High Empowerment* profiles was highly stable (79.1% to 83.2%) across the two time points, whereas the other profiles displayed moderate (43.5% for the *High Empowerment* profile) to low (19.7% to 20.4% for the *Low Empowerment* and *High Information* profiles) levels of stability. These rates of stability indicate that these profiles do not represent entirely rigid psychological states, nor exclusively reflect ephemeral phenomena (Meyer & Morin, 2016), thus supporting the relevance of profile-based interventions. Interestingly, the three profiles (*Low Empowerment*, *High Information*, and *High Empowerment*) with the lowest rate of stability were also those characterized by the most extreme levels (low or high) of structural empowerment. These observations thus suggest that structural empowerment profiles displaying moderate levels of structural empowerment may be more stable over time, and that more extreme profiles may be harder to maintain over time. One the one hand, healthcare workers may lack the resources (e.g., clear information, support) they need to support high perceptions of structural empowerment over time as their social connections with their colleagues and supervisors are known to be particularly challenging relative to those of employees from other sectors (Caesens et al., 2021). On the other hand, when they feel exposed to lower than ideal levels of structural empowerment, they may come to experience a sense of frustration, dejection, or resignation, forcing them to restructure their work arrangements in order to improve their work reality (Smith et al., 2012). Given the undesirability of the *Low Empowerment* profile, it would seem important for organizations to consider implementing actions to help those employees who not feel empowered to change this undesirable profile over time. In addition, organizations should ensure that they support highly empowered workers to remain at a high level. Indeed, the low stability of these profiles suggests that such interventions are likely to be not only feasible, but also potentially able to capitalize on employees' efforts to increase their low levels or to maintain their high levels of empowerment. Such an intervention could possibly be accomplished via the consultation of employees to identify which practices seem particularly helpful (or harmful) in this regard. Such interventions may subsequently be expanded to help all employees optimize their work experiences.

Outcomes of Profile Membership

Supporting their criterion-related validity, the profiles were found to be clearly associated with all outcomes. Indeed, the *High Empowerment* profile appeared to be the most desirable, from an outcome perspective (the highest positive affect and quality of care, and the lowest negative affect), while the *Low Empowerment* profile displayed the most detrimental ones. However, beyond these two extremes, our results indicated that the three other profiles did not differ from one another, hinting that it may not be critical to distinguish different types of moderate profiles when structural empowerment is considered. Beyond calling into question the true value of differentiating between these three profiles, this result also showcases the need for further investigations designed to better document the differences (in terms of predictors, outcomes, or correlates) between these three profiles. For instance, there might not be some additional benefits to a profile with high *versus* moderate levels of information. However, these benefits might be specific to outcomes closely tied to the availability of information (e.g., patient safety, interpersonal citizenship behaviors, team cohesion), rather than to the more generic outcomes considered in this study. In line with previous research (Fragkos et al., 2020; García-Sierra & Fernández-Castro, 2018), these results invite us to consider structural empowerment as an organizational resource that could contribute to improving the well-being and performance of healthcare professionals (Kanter, 1993).

Limitations and Future Directions

There are some limitations worth considering when interpreting our results. First, since only self-report questionnaires were used, this study could not control for the biases associated with self-reports and social desirability. To control these biases, future studies could incorporate objective measures (such as absenteeism and turnover), and external sources (e.g., supervisor, coworkers, spouse). Second, our sample solely included French healthcare professionals. Additional research is required to support the generalizability of our conclusions to other work environments, cultures, countries, and languages. Third, we evaluated the stability of structural empowerment profiles over a span of two years, during which most participants did not encounter any major organizational or societal transformation. Consequently, the consideration of longer time intervals or of more meaningful transitions or interventions, such as job redesign interventions, could potentially reveal lower rates of stability. In addition, although we relied on state-of-the-art procedures to manage missing data, information on transitions could only come from participants (n = 422) who participated at both measurement occasions (*versus* the full sample of n = 633). Subsequent research could therefore seek to limit attrition to more precisely investigate the extent to which our findings are generalizable to extended timeframes, diverse transitions, interventions, and changes. Lastly, we only considered demographics (sex, age, status, position, and job) as predictors. Thus, examining how other personal characteristics (e.g., job crafting, readiness to change) relate to these profiles and to changes over time in profile membership would provide valuable insights. Similarly, additional negative (e.g., deviant behaviors, absenteeism) and positive (e.g., engagement, job satisfaction) outcomes, as well as psychological mechanisms (need satisfaction and frustration) could be considered to improve our understanding of the individual and organizational consequences of these profiles.

Practical Implications

Considering our findings, employees who feel exposed to low levels of structural empowerment should be considered as a priority target for organizations and managers. Indeed, our findings showed that these employees experienced the worst outcomes. In contrast, employees belonging to the *High Empowerment* profile exhibited far more positive outcomes. Consequently, interventions seeking to enhance structural empowerment while maintaining high levels of structural empowerment could be associated with higher well-being and better functioning. Thus, Bawafaa et al. (2015) have shown that developing resonant leadership competencies among nurses occupying a position of leadership may be valuable to create access to adequate empowering structures and well-being. Supervisors could also encourage their employees to take on new challenges while offering them sufficient support and guidance, and also sharing with them their previous experiences of facing challenging situations (Gillet et al., 2022). Supervisors could also foster employees' creativity in handling work challenges by nurturing safe climate. Supportive human resource practices could also be helpful to promote high relationship quality between supervisors and their subordinates (Caesens et al., 2020, 2021). Moreover, human resources departments could devise and implement training designed to support supervisors in learning and managing through resonant leadership practices, in order to foster a thriving workforce. In parallel, human resources departments could also directly support employees by providing them with socioemotional support and opportunities for learning and growth, considering that supervisors may sometimes lack the resources they need to build strong positive relationships with their employees (Gillet et al., 2019). These efforts could be directed towards fostering a shared understanding that supervisors can enhance collective performance by relying on social exchange to accommodate work-life balance (Caesens et al., 2021).

Clinical resources

Conditions for Work Effectiveness Questionnaire. https://www.uwo.ca/fhs/hkl/cweq.html

Data availability

Our dataset can be made available upon reasonable request, starting three years after the completion of the study, from the corresponding author.

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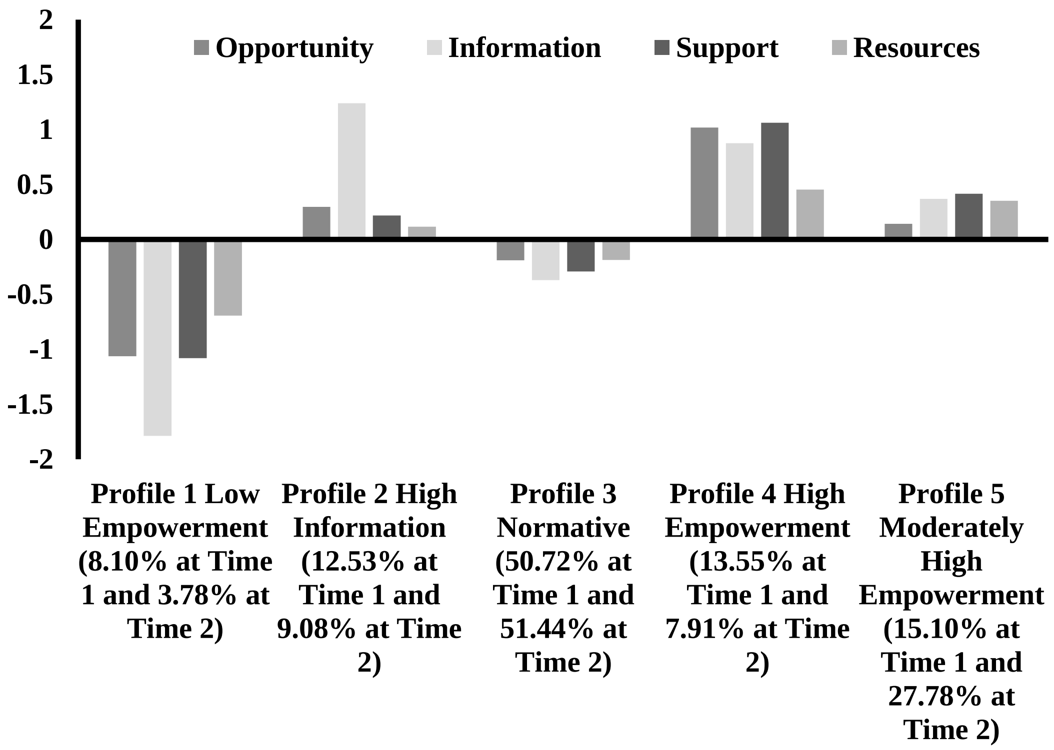

Figure 1. Final Five-Profile Solution

Table 1

Results from the Time-Specific and Longitudinal Models

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy
Final Latent Profile Analyses								
Time 1	-3033.280	44	1.502	6154.561	6394.381	6350.381	6210.686	.824
Time 2	-2678.975	44	1.022	5445.950	5685.770	5641.770	5502.075	.779
Longitudinal Latent Profile Analyses								
Configural Similarity	-5723.357	88	1.153	11622.714	12102.356	12014.356	11734.965	.759
Structural Similarity	-5752.204	68	1.119	11640.409	12011.041	11943.041	11727.148	.759
Dispersion Similarity	-5779.451	48	1.282	11654.902	11916.525	11868.525	11716.129	.822
Distributional Similarity	-5797.063	44	1.370	11682.126	11921.946	11877.946	11738.251	.821
Multi-Group Latent Profile Analyses T1								
Configural Similarity	-3325.746	89	.955	6829.491	7314.583	7225.583	6943.017	.772
Structural Similarity	-3394.358	69	1.005	6926.716	7302.799	7233.799	7014.730	.833
Partial Structural Similarity	-3379.624	70	1.009	6899.248	7280.781	7210.781	6988.538	.830
Dispersion Similarity	-3397.319	50	1.267	6894.639	7167.162	7117.162	6958.418	.831
Distributional Similarity	-3408.002	46	1.144	6908.004	7158.725	7112.725	6966.680	.770
Multi-Group Latent Profile Analyses T2								
Configural Similarity	-2997.649	89	1.056	6173.298	6658.390	6569.390	6286.824	.826
Structural Similarity	-3058.031	69	1.051	6254.063	6630.145	6561.145	6342.077	.773
Dispersion Similarity	-3072.007	49	1.077	6242..014	6509.087	6460.087	6304.517	.784
Distributional Similarity	-3081.192	45	1.022	6252.383	6497.654	6452.654	6309.784	.779
Predictive Similarity: Demographics								
Null Effects Model	-3559.898	44	.939	7207.795	7447.616	7403.616	7263.920	.795
Profile-Specific Free Relations with Predictors	-3475.138	184	.633	7318.277	8321.163	8137.163	7552.982	.825
Free Relations with Predictors	-3515.336	84	.962	7198.672	7656.511	7572.511	7305.820	.805
Equal Relations with Predictors	-3531.335	64	.976	7190..670	7539.500	7475.500	7272.307	.798
Explanatory Similarity								
Free Relations with Outcomes	-6293.517	60	1.414	12707.034	13034.063	12974.063	12783.569	.839
Equal Relations with Outcomes	-6300.629	45	1.545	12691.258	12936.529	12891.529	12748.659	.824

Note. LL: Model loglikelihood; #fp: Number of free parameters; Scaling: Scaling correction factor associated with robust maximum likelihood estimates; AIC: Akaïke information criteria; CAIC: Constant AIC; BIC: Bayesian information criteria; ABIC: Sample size adjusted BIC.

Table 2

Transitions Probabilities

	Profile 1 *Low Empowerment*	Profile 2 *High Information*	Profile 3 *Normative*	Profile 4 *High Empowerment*	Profile 5 *Moderately High Empowerment*
Profile 1	.197	.000	.705	.000	.098
Profile 2	.009	.204	.127	.129	.532
Profile 3	.036	.054	.832	.000	.078
Profile 4	.000	.120	.124	.435	.320
Profile 5	.017	.141	.007	.043	.791

Table 3

Associations between Profile Membership and the Outcomes Taken from the Model of Explanatory Similarity (Equal across Time Points)

	Profile 1 *Low Empowerment* M [CI]	Profile 2 *High Information* M [CI]	Profile 3 *Normative* M [CI]	Profile 4 *High Empowerment* M [CI]	Profile 5 *Moderately High Empowerment* M [CI]	Summary of Statistically Significant Differences
Positive affect	-1.529 [-1.923; -1.136]	-.290 [-.690; .109]	-.068 [-.340; .205]	.945 [.820; 1.071]	.001 [-.622; .624]	4 > 2 = 3 = 5 > 1
Negative affect	1.572 [1.259; 1.884]	.285 [-.098; .668]	.067 [-.224; .358]	-.911 [-1.031; -.791]	-.050 [-.687; .586]	1 > 2 = 3 = 5 > 4
Quality of care	5.754 [5.165; 6.344]	7.243 [6.827; 7.660]	7.317 [7.058; 7.575]	8.220 [8.008; 8.432]	7.424 [6.977; 7.871]	4 > 2 = 3 = 5 > 1

Note. M: Mean; CI: 95% confidence interval; the indicators of positive affect and negative affect are estimated from factor scores with a mean of 0 and a standard deviation of 1.

Online Supplements for:

A Longitudinal Investigation of Structural Empowerment Profiles among Healthcare Employees

Authors' note

These online technical appendices are to be posted on the journal website and hot-linked to the manuscript. If the journal does not offer this possibility, these materials can alternatively be posted on one of our personal websites (we will adjust the in-text reference upon acceptance).

We would also be happy to have some of these materials brought back into the main manuscript, or included as published appendices if you deem it useful. We developed these materials to provide additional technical information and to keep the main manuscript from becoming needlessly long.

Preliminary Measurement Models

Due to the complexity of the longitudinal models underlying all constructs assessed in the present study, preliminary analyses were conducted separately for the structural empowerment variables and for the multi-item outcome measures (positive and negative affect). These longitudinal measurement models were estimated in Mplus 8.7 (Muthén & Muthén, 2021), using the maximum likelihood robust (MLR) estimator. This estimator provides parameter estimates, standard errors, and goodness-of-fit that are robust to the non-normality of the response scales used in this study. These models were estimated with full information maximum likelihood (FIML; Enders, 2010) to handle missing data.

Confirmatory factor analyses (CFA) and exploratory structural equation modeling (ESEM) models were first separately tested at Time 1 (T1) and Time 2 (T2). In the CFA models, items were only allowed to define their a priori factors, factors were allowed to correlate, and no cross-loadings were estimated. In the ESEM models, the factors were defined as in the CFA models, and all cross-loadings were freely estimated but assigned a target value of zero using an oblique target rotation procedure (Browne, 2001). Given the known oversensitivity of the chi-square test of exact fit (χ^2) to sample size and minor model misspecifications (e.g., Marsh et al., 2005), we relied on sample-size independent goodness-of-fit indices to describe the fit of the alternative models (Hu & Bentler, 1999): The comparative fit index (CFI), the Tucker-Lewis index (TLI), as well as the root mean square error of approximation (RMSEA) and its 90% confidence interval. Values greater than .90 for the CFI and TLI indicate adequate model fit, although values greater than .95 are preferable. Values smaller than .08 or .06 for the RMSEA respectively support acceptable and excellent model fit.

The goodness-of-fit results from all structural empowerment models are reported in Table S1. These results clearly support the adequacy of the ESEM solution (with all CFI and TLI ≥ .90, and all RMSEA ≤ .08) and its superiority relative to its CFA counterpart (ΔCFI = .040 to .047; ΔTLI = .038 to .045; ΔRMSEA = .017 to .025). This solution was thus retained for sequential tests of measurement invariance (Millsap, 2011): (1) configural invariance; (2) weak invariance (loadings); (3) strong invariance (loadings and intercepts); (4) strict invariance (loadings, intercepts, and uniquenesses); (5) invariance of the latent variance-covariance matrix (loadings, intercepts, uniquenesses, correlated uniquenesses, and latent variances-covariances); and (6) latent means invariance (loadings, intercepts, uniquenesses, correlated uniquenesses, latent variances-covariances, and latent means). These tests were conducted across measurement occasions (longitudinal invariance) and groups of healthcare employees (nurses and nursing assistants versus other employees) at both time points. Like the chi square, chi square difference tests are oversensitive to sample size and minor misspecifications. For this reason, invariance was assessed by considering changes in CFI and RMSEA (Chen, 2007; Cheung & Rensvold, 2002). A ΔCFI/TLI of .010 or less and a ΔRMSEA of .015 or less between a more restricted model and the previous one support the invariance hypothesis.

The results from these tests, reported in Table S1, supported the configural, weak, strong, partial strict (equality constraints had to be relaxed on the uniqueness of one information item which reduced over time, as shown in Table S2), latent variance-covariance, and latent means invariance of the model across time points. Factor scores were extracted from the final longitudinal model of latent means invariance. Parameter estimates from this final longitudinal model of latent means invariance are reported in Table S2. Composite reliability coefficients associated with each of the a priori factors are calculated from the model standardized parameters using McDonald (1970) omega (ω) coefficient:

$$\omega = \frac{(\sum|\lambda_i|)^2}{[(\sum|\lambda_i|)^2 + \sum\delta_i]}$$

where $|\lambda_i|$ are the standardized factor loadings associated with a factor in absolute values, and δi, the item uniquenesses. These results show that all factors are well-defined by satisfactory factor loadings (λ = .463 to .963) and composite reliability coefficients (ω = .668 to .872).

The results from the tests of multi-group invariance (Table S1) also supported the configural, weak, partial strong (equality constraints had to be relaxed on the intercepts of one opportunity item and one resources item), strict, and latent variance-covariance invariance of the model across groups of healthcare employees at T1 (see Table S1). The latent means invariance of the model was not supported, revealing lower average levels of information (-.346 SD) and higher average levels of support (.605 SD) among nurses and nursing assistants relative to other healthcare employees. Similarly, the results from the tests of multi-group invariance also supported the configural, weak, partial strong (equality constraints had to be relaxed on the intercept of one opportunity item), partial strict (equality constraints had to be relaxed on the uniquenesses of one opportunity item and one resources item), and latent variance-covariance invariance of the model across groups of healthcare employees at T2. The latent means invariance of the model was not supported, revealing lower average levels of information (-.271 SD) and resources (-.305 SD), and higher average levels of support (.483 SD) among nurses and nursing assistants relative to other healthcare employees. These results are aligned with those from prior research showing that nurses may face challenges in dealing with patients due to a limited access to important information (Cha & Park, 2021) and a lack of resources (Dewey & Allwood, 2022). In contrast, nurses may be more likely to feel supported as a result of working in very cohesive teams in which they can share their most stressful clinical experiences, and in which they have easily access to their supervisor (e.g., Jun & Lee, 2017).

CFA and ESEM models were also estimated for the multi-item outcome variables at both T1 and T2, and included a total of two factors (positive and negative affect) at each time point. The goodness-of-fit results for these models are reported in Table S3. These results support the superiority of the CFA model (with all CFI/TLI $\geq$ .90), as well as the configural, weak, strong, strict, latent variance-covariance, and latent mean invariance of this model across time points (ΔCFI $\leq$ .010; ΔTLI $\leq$ .010; and ΔRMSEA $\leq$ .015). The parameter and composite reliability estimates obtained from the most invariant longitudinal measurement model (latent means invariance) are reported in Table S4. These results show that all factors are well-defined by satisfactory factor loadings (λ = .660 to .851) and composite reliability coefficients (ω = .689 to .804). Factor scores were saved from this most invariant measurement model. The correlations between all variables are reported in Table S5.

The results from the tests of multi-group invariance (Table S3) also supported the configural, weak, partial strong (equality constraints had to be relaxed on the intercept of one positive affect item), strict, latent variance-covariance, and latent means invariance of the CFA model across groups of healthcare employees both at T1 and T2.

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Table S1

Goodness-of-Fit Statistics for the Estimated Models (Structural Empowerment)

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	CM	$\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
Structural Empowerment										
CFA Time 1	142.194 (48)*	.953	.935	.056	[.045; .066]	-	-	-	-	-
ESEM Time 1	38.658 (24)*	.993	.980	.031	[.010; .048]	-	-	-	-	-
CFA Time 2	151.391(48)*	.935	.911	.071	[.059; .084]	-	-	-	-	-
ESEM Time 2	53.498 (24)*	.982	.949	.054	[.035; .073]	-	-	-	-	-
Structural Empowerment: Longitudinal Invariance										
M1. Configural invariance	195.361 (164)*	.993	.988	.017	[.002; .026]	-	-	-	-	-
M2. Weak invariance	236.024 (196)*	.991	.987	.018	[.007; .026]	M1	40.598 (32)	-.002	-.001	+.001
M3. Strong invariance	262.400 (204)*	.986	.981	.021	[.013; .028]	M2	28.833 (8)*	-.005	-.006	+.003
M4. Strict invariance	340.354 (216)*	.971	.962	.030	[.024; .036]	M3	68.879 (12)*	-.015	-.019	+.009
M4’. Partial strict invariance	311.119 (215)*	.977	.971	.027	[.020; .033]	M3	45.498 (11)*	-.009	-.010	+.006
M5. Variance-covariance invariance	333.125 (225)*	.974	.969	.028	[.021; .034]	M4’	21.261 (10)	-.003	-.002	+.001
M6. Latent means invariance	362.891 (229)*	.968	.962	.030	[.024; .036]	M5	35.809 (4)*	-.006	-.007	+.002
Structural Empowerment: Multi-Group Invariance T1										
M7. Configural invariance	78.498 (48)*	.985	.959	.045	[.026; .062]	-	-	-	-	-
M8. Weak invariance	119.148 (80)*	.981	.968	.039	[.023; .053]	M7	40.846 (32)	-.004	+.009	-.006
M9. Strong invariance	168.054 (88)*	.961	.941	.054	[.041; .066]	M8	52.083 (8)*	-.020	-.027	+.015
M9’. Partial strong invariance	131.654 (86)*	.977	.965	.041	[.026; .054]	M8	12.621 (6)*	-.004	-.003	+.002
M10. Strict invariance	147.347 (98)*	.976	.967	.040	[.026; .053]	M9’	16.136 (12)	-.001	+.002	-.001
M11. Variance-covariance invariance	176.171 (108)*	.966	.959	.045	[.032; .056]	M10	29.945 (10)*	-.010	-.008	+.005
M12. Latent means invariance	261.923 (112)*	.926	.913	.065	[.055; .075]	M11	86.973 (4)*	-.040	-.046	+.020
Structural Empowerment: Multi-Group Invariance T2										
M13. Configural invariance	84.163 (48)*	.978	.940	.060	[.038; .081]	-	-	-	-	-
M14. Weak invariance	107.020 (80)*	.984	.973	.040	[.016; .059]	M13	28.901 (32)	+.006	+.033	-.020
M15. Strong invariance	135.770 (88)*	.971	.957	.051	[.033; .067]	M14	33.027 (8)*	-.013	-.016	+.011
M15’. Partial strong invariance	119.198 (87)*	.981	.971	.042	[.020; .059]	M14	12.552 (7)	-.003	-.002	+.002
M16. Strict invariance	149.087 (99)*	.970	.960	.049	[.032; .065]	M15’	27.942 (12)*	-.011	-.011	+.007
M16’. Partial strict invariance	140.417 (97)*	.974	.964	.046	[.028; .062]	M15’	19.971 (10)*	-.007	-.007	+.004
M17. Variance-covariance invariance	154.980 (107)*	.971	.964	.046	[.029; .061]	M16’	14.567 (10)	-.003	.000	.000
M18. Latent means invariance	208.033 (111)*	.942	.931	.064	[.051; .078]	M17	52.794 (4)*	-.029	-.033	+.018

Note. * $p < .05$; CFA: Confirmatory factor analysis; ESEM: Exploratory structural equation modeling; χ^2: Scaled chi-square test of exact fit; *df*: Degrees of freedom; CFI: Comparative fit index; TLI: Tucker-Lewis index; RMSEA: Root mean square error of approximation; 90% CI: 90% confidence interval; CM: Comparison model; and Δ: Change in fit relative to the CM.

Table S2

Standardized Factor Loadings (λ) and Uniquenesses (δ) for the M6 Solution (Longitudinal Latent Means Invariance)

Items	Opportunity λ	Information λ	Support λ	Resources λ	δ
Opportunity					
Item 1	**.566**	*.053*	-*.015*	-.063	.672
Item 2	**.717**	-*.024*	*.023*	.057	.468
Item 3	**.606**	-*.025*	*.025*	-*.007*	.633
Information					
Item 1	*.018*	**.649**	.078	*.021*	.515
Item 2	-*.004*	**.963**	-.060	-*.022*	.128
Item 3	-*.008*	**.774 / .858**	*.016 / .018*	*.008 / .009*	.392 / .253
Support					
Item 1	*.013*	.046	**.750**	-*.036*	.413
Item 2	-.078	-.049	**.938**	-.049	.317
Item 3	.144	*.053*	**.463**	.156	.617
Resources					
Item 1	-.080	.044	.055	**.787**	.359
Item 2	-*.004*	-*.013*	-.092	**.899**	.227
Item 3	.093	-*.036*	.079	**.474**	.735
Factor Correlations	Opportunity	Information	Support	Resources	
Opportunity	-				
Information	.363	-			
Support	.384	.399	-		
Resources	.177	.250	.227	-	
	Opportunity	Information	Support	Resources	
ω	.668	.846 / .872	.775	.779	

Note. λ: Factor loading; δ: Item uniqueness; ω: Omega coefficient of composite reliability; target factor loadings are indicated in bold; non-significant (p > .05) parameters are marked in italics.

Table S3

Goodness-of-Fit Statistics for the Estimated Models (Outcomes)

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	CM	$\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
Outcomes										
CFA Time 1	28.637 (8)*	.983	.968	.064	[.040; .090]	-	-	-	-	-
ESEM Time 1	28.200 (4)*	.980	.925	.098	[.066; .134]	-	-	-	-	-
CFA Time 2	34.989 (8)*	.963	.931	.090	[.060; .121]	-	-	-	-	-
ESEM Time 2	31.436 (4)*	.962	.859	.128	[.088; .171]	-	-	-	-	-
Outcomes: Longitudinal Invariance										
M1. Configural invariance	100.970 (42)*	.975	.960	.047	[.035; .059]	-	-	-	-	-
M2. Weak invariance	107.937 (46)*	.973	.962	.046	[.035; .058]	M1	7.412 (4)	-.002	+.002	-.001
M3. Strong invariance	110.786 (50)*	.974	.966	.044	[.033; .055]	M2	2.288 (4)	+.001	+.004	-.002
M4. Strict invariance	118.611 (56)*	.973	.968	.042	[.032; .053]	M3	7.219 (6)	-.001	+.002	-.002
M5. Variance-covariance invariance	129.514 (59)*	.970	.966	.044	[.033; .054]	M4	9.554 (3)	-.003	-.002	+.002
M6. Latent means invariance	132.405 (61)*	.969	.967	.043	[.033; .053]	M5	2.866 (2)	-.001	+.001	-.001
Outcomes: Multi-Group Invariance T1										
M7. Configural invariance	46.040 (16)*	.975	.954	.077	[.052; .104]	-	-	-	-	-
M8. Weak invariance	50.064 (20)*	.975	.963	.069	[.045; .093]	M7	4.205 (4)	.000	+.009	-.008
M9. Strong invariance	69.797 (24)*	.963	.953	.078	[.057; .099]	M8	20.834 (4)*	-.012	-.010	+.009
M9’. Partial strong invariance	59.874 (23)*	.970	.961	.071	[.049; .094]	M8	10.121 (3)*	-.005	-.002	+.002
M10. Strict invariance	72.863 (29)*	.964	.963	.069	[.050; .089]	M9’	13.081 (6)*	-.006	+.002	-.002
M11. Variance-covariance invariance	74.811 (32)*	.965	.967	.065	[.046; .085]	M10	1.441 (3)	+.001	+.004	-.004
M12. Latent means invariance	75.352 (34)*	.966	.970	.062	[.043; .081]	M11	.237 (2)	+.001	+.003	-.003
Outcomes: Multi-Group Invariance T2										
M13. Configural invariance	45.333 (16)*	.963	.930	.093	[.062; .126]	-	-	-	-	-
M14. Weak invariance	50.433 (20)*	.961	.942	.085	[.056; .115]	M13	5.137 (4)	-.002	+.012	-.008
M15. Strong invariance	65.230 (24)*	.948	.934	.090	[.064; .117]	M14	15.476 (4)*	-.013	-.008	-.005
M15’. Partial strong invariance	55.785 (23)*	.958	.946	.082	[.055; .110]	M14	5.139 (3)	-.003	+.004	-.003
M16. Strict invariance	68.045 (29)*	.950	.949	.080	[.055; .105]	M15’	12.063 (6)	-.008	+.003	-.002
M17. Variance-covariance invariance	78.174 (32)*	.941	.945	.083	[.060; .106]	M16	9.675 (3)*	-.009	-.004	+.003
M18. Latent means invariance	88.812 (34)*	.931	.939	.087	[.065; .110]	M17	10.625 (2)*	-.010	-.006	+.004

Note. * $p < .01$; CFA: Confirmatory factor analysis; ESEM: Exploratory structural equation modeling; χ^2: Scaled chi-square test of exact fit; *df*: Degrees of freedom; CFI: Comparative fit index; TLI: Tucker-Lewis index; RMSEA: Root mean square error of approximation; 90% CI: 90% confidence interval; CM: Comparison model; and Δ: Change in fit relative to the CM.

Table S4

Standardized Factor Loadings (λ) and Uniquenesses (δ) for the M6 Solution (Longitudinal Latent Means Invariance)

Items	Positive affect λ	Negative affect λ	δ
Positive affect			
Item 1	.665		.557
Item 2	.851		.275
Item 3	.755		.429
Negative affect			
Item 1		.831	.309
Item 2		.660	.564
Item 3		.721	.480
ω	.804	.689	
Factor Correlations	Positive affect	Negative affect	
Positive affect	-		
Negative affect	-.717	-	

Note. λ: Factor loading; δ: Item uniqueness; ω: Omega coefficient of composite reliability; all parameters are significant (p < .001).

Table S5

Correlations Between Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Sex	-																		
2. Age	-.067	-																	
3. Status	.153**	.061	-																
4. Position	.116**	.368**	.209**	-															
5. Job type	-.303**	.001	-.148**	-.120**	-														
6. Opportunity (T1)†	-.108**	-.088*	-.095*	-.149**	.109**														
7. Information (T1)†	-.041	.096*	-.053	-.031	.148**	.422**	-												
8. Support (T1)†	.115**	-.003	.009	-.046	-.242**	.445**	.407**	-											
9. Resources (T1)†	-.004	.075	.050	-.003	.004	.215**	.274**	.226**	-										
10. Positive affect (T1)†	-.116**	.076	.105**	.074	.030	.310**	.189**	.187**	.381**	-									
11. Negative affect (T1)†	.105**	-.069	-.096*	-.047	-.025	-.299**	-.187**	-.182**	-.386**	-.837**	-								
12. Quality of care (T1)	-.113**	.053	.057	-.026	.089*	.241**	.165**	.105**	.280**	.345**	-.314**	-							
13. Opportunity (T2)†	-.104**	-.084*	-.106**	-.110**	.133**	.678**	.222**	.182**	.063	.211**	-.200**	.180**	-						
14. Information (T2)†	-.045	.083*	-.050	-.008	.114**	.368**	.622**	.291**	.103**	.145**	-.159**	.115**	.462**	-					
15. Support (T2)†	.083*	.035	-.016	.001	-.203**	.304**	.302**	.680**	.071	.113**	-.141**	.075	.445**	.490**	-				
16. Resources (T2)†	-.010	.041	.079*	-.025	.071	.183**	.208**	.235**	.726**	.334**	-.357**	.248**	.210**	.265**	.280**	-			
17. Positive affect (T2)†	-.101*	.022	.063	.033	.135**	.235**	.171**	.132**	.272**	.578**	-.631**	.225**	.289**	.227**	.159**	.442**	-		
18. Negative affect (T1)†	.136**	-.028	-.066	-.015	-.118**	-.242**	-.153**	-.131**	-.296**	-.550**	.710**	-.235**	-.304**	-.236**	-.205**	-.471**	-.799**	-	
19. Quality of care (T2)	-.066	.103*	.035	.052	.172**	.234**	.151**	.077	.108*	.316**	-.301**	.391**	.290**	.190**	.132**	.247**	.314**	-.303**	-

Note. * $p < .05$; ** $p < .01$; † variables estimated from factor scores with mean of 0 and a standard deviation of 1; sex was coded 0 for men and 1 for women; status was coded 0 for employed full-time and 1 for employed part-time; position was coded 0 for temporary workers and 1 for permanent workers; and job type was coded 0 for nurses and nursing assistants and 1 for other healthcare employees.

Table S6

Results from the Latent Profile Analysis Models at Times 1 and 2

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
Time 1										
1 Profile	-3367.608	8	1.020	6751.215	6794.819	6786.819	6761.420	Na	Na	Na
2 Profiles	-3183.250	17	1.132	6400.499	6493.157	6476.157	6422.184	.643	< .001	< .001
3 Profiles	-3132.105	26	1.314	6316.210	6457.922	6431.922	6349.374	.720	.221	< .001
4 Profiles	-3084.465	35	1.149	6238.930	6429.696	6394.696	6283.575	.732	.037	< .001
5 Profiles	-3033.280	44	1.502	6154.561	6394.381	6350.381	6210.686	.824	.616	< .001
6 Profiles	-2989.282	53	2.850	6084.564	6373.438	6320.438	6152.169	.838	1.000	< .001
7 Profiles	-2943.256	62	1.161	6010.511	6348.441	6286.441	6089.597	.838	.023	< .001
8 Profiles	-2909.280	71	1.252	5960.560	6347.544	6276.544	6051.126	.807	.676	< .001
Time 2										
1 Profile	-3027.496	8	1.117	6070.992	6114.596	6106.596	6081.196	Na	Na	Na
2 Profiles	-2857.440	17	1.343	5748.880	5841.538	5824.538	5770.565	.703	.001	< .001
3 Profiles	-2771.595	26	1.109	5595.189	5736.901	5710.901	5628.354	.722	< .001	< .001
4 Profiles	-2720.055	35	1.095	5510.110	5700.876	5665.876	5554.755	.782	< .001	< .001
5 Profiles	-2678.975	44	1.022	5445.950	5685.770	5641.770	5502.075	.779	< .001	< .001
6 Profiles	-2647.627	53	1.154	5401.254	5690.129	5637.129	5468.859	.753	.414	< .001
7 Profiles	-2622.028	62	1.129	5368.056	5705.985	5643.985	5447.142	.776	.270	< .001
8 Profiles	-2598.478	71	1.058	5338.955	5725.939	5654.939	5429.521	.758	.156	< .001

Note. LL: Model loglikelihood; #fp: Number of free parameters; scaling: Scaling correction factor associated with robust maximum likelihood estimates; AIC: Akaïke information criteria; CAIC: Constant AIC; BIC: Bayesian information criteria; ABIC: Sample size adjusted BIC; aLMR: Adjusted Lo-Mendel-Rubin likelihood ratio test; and BLRT: Bootstrap likelihood ratio test.

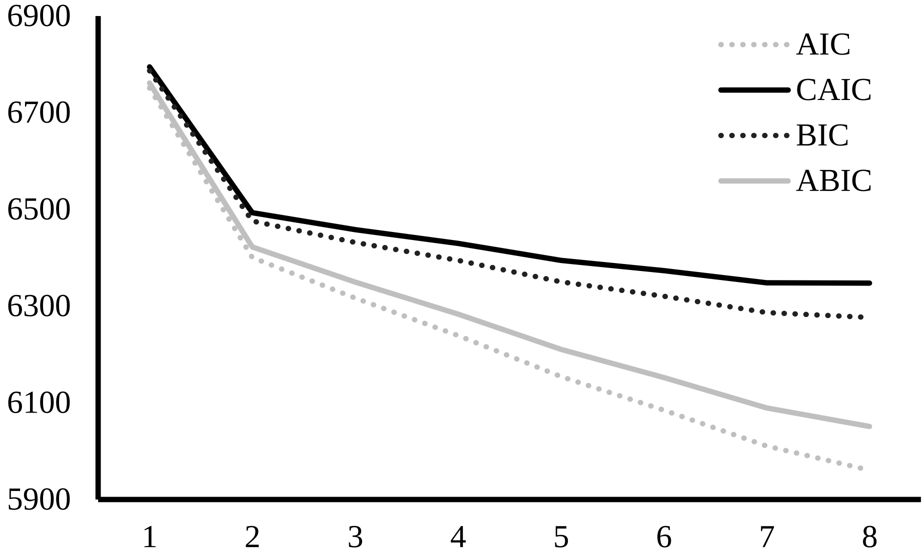

Figure S1

Elbow Plot of the Value of the Information Criteria for Solutions Including Different Numbers of Latent Profiles at Time 1

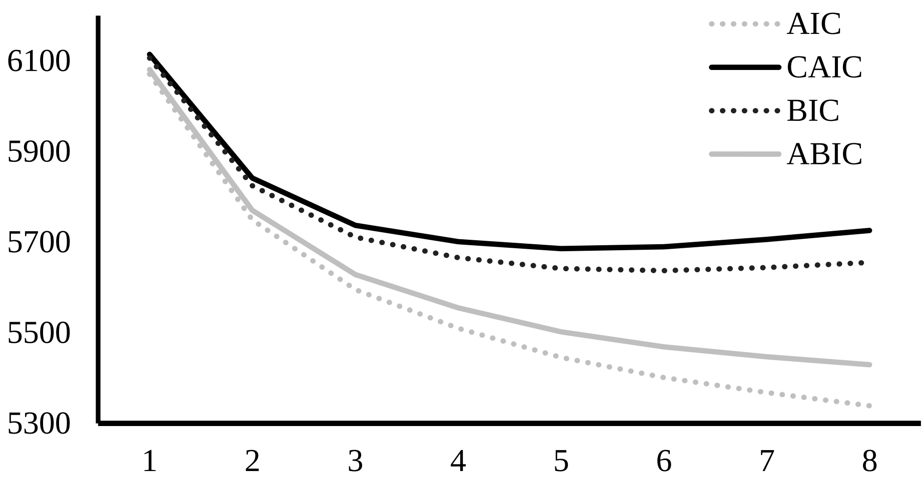

Figure S2

Elbow Plot of the Value of the Information Criteria for Solutions Including Different Numbers of Latent Profiles at Time 2

Table S7

Detailed Parameter Estimates from the Final LPA Solution (Dispersion Similarity)

	Profile 1 Mean [CI]	Profile 2 Mean [CI]	Profile 3 Mean [CI]	Profile 4 Mean [CI]	Profile 5 Mean [CI]
Opportunity	-1.062 [-1.409; -.714]	.297 [.131; .463]	-.189 [-.272; -.107]	1.018 [.871; 1.165]	.142 [.038; .246]
Information	-1.788 [-1.849; -1.727]	1.239 [1.186; 1.291]	-.369 [-.477; -.260]	.875 [.573; 1.178]	.368 [.335; .400]
Support	-1.080 [-1.496; -.664]	.219 [.043; .394]	-.292 [-.380; -.205]	1.063 [.867; 1.259]	.416 [.296; .537]
Resources	-.693 [-.978; -.408]	.117 [-.069; .303]	-.188 [-.281; -.094]	.455 [.211; .699]	.353 [.207; .499]
	Profile 1 Variance [CI]	Profile 2 Variance [CI]	Profile 3 Variance [CI]	Profile 4 Variance [CI]	Profile 5 Variance [CI]
Opportunity	1.210 [.769; 1.651]	.345 [.178; .512]	.532 [.450; .614]	.110 [.053; .166]	.165 [.057; .272]
Information	.018 [.007; .029]	.023 [.013; .033]	.354 [.237; .472]	.716 [.481; 952]	.026 [.017; .036]
Support	.936 [.593; 1.279]	.477 [.323; .632]	.591 [.521; .660]	.294 [.152; .436]	.243 [.173; .313]
Resources	.589 [.154; 1.024]	.695 [.544; .846]	.587 [.497; .676]	1.030 [.840; 1.221]	.680 [.578; .783]

Note. CI = 95% confidence interval; the profile indicators are estimated from factor scores with a mean of 0 and a standard deviation of 1; Profile 1: *Low Empowerment*; Profile 2: *High Information*; Profile 3: *Normative*; Profile 4; *High Empowerment*; and Profile 5: *Moderately High Empowerment*.

Table S8

Classification Accuracy: Average Probability of Membership into Each Latent Profile (Column) as a Function of the Most Likely Profile Membership (Row)

	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
Time 1					
Profile 1	.884	.000	.116	.000	.000
Profile 2	.000	.864	.067	.065	.004
Profile 3	.014	.003	.927	.022	.033
Profile 4	.000	.077	.076	.804	.043
Profile 5	.000	.000	.151	.043	.806
Time 2					
Profile 1	.871	.000	.129	.000	.000
Profile 2	.000	.863	.062	.070	.004
Profile 3	.007	.006	.924	.013	.050
Profile 4	.000	.103	.016	.828	.054
Profile 5	.000	.001	.146	.032	.822

Note. Profile 1: *Low Empowerment*; Profile 2: *High Information*; Profile 3: *Normative*; Profile 4; *High Empowerment*; and Profile 5: *Moderately High Empowerment*.