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Running Head. Longitudinal Boosting Behaviors Profiles

A Longitudinal Person-Centered Investigation of Individual Employees' Team Boosting Behaviors

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Abstract

This person-centered investigation sought to identify the nature of employees' profiles of boosting behaviors (i.e., energizing, mood-enhancing, and uniting behaviors seeking to support the functioning of their team). We also examined the stability of these profiles over time, and of their associations with a series of predictors (i.e., availability expectations, social challenge stressors, telepressure, and harassment) and outcomes (i.e., affective commitment to the organization and to coworkers, and organizational citizenship behaviors directed towards individuals). We identified five distinct profiles among a sample of 415 employees who completed the same set of measures twice across a time interval of three months: Very Low Boosting Behaviors, High Boosting Behaviors, Low Boosting Behaviors, Very High Boosting Behaviors, and Average Boosting Behaviors. These profiles were moderately to highly stable over time. Social challenge stressors and telepressure were associated with a lower likelihood of membership into the Very Low Boosting Behaviors profile. All outcomes also differed across profiles, with the most adaptive outcomes being associated with the Very High Boosting Behaviors profile and the most maladaptive outcomes being associated with the Very Low Boosting Behaviors profile.

Key words: Boosting behaviors; job demands; information and communications technology; affective commitment; latent transition analyses; citizenship behaviors

Recent research has highlighted the possible importance of studying team boosting behaviors (i.e., behaviors via which individual employees help support the informal functioning of their team) to fully understand how employees' working within teams can help to informally support the healthy psychological functioning of their teammates (Fortuin et al., 2021, 2023). However, thus far, research on these behaviors have solely focused on correlational patterns of associations between variables (i.e., a variable-centered approach), thus failing to capture the more complex reality through which individual employees rely on distinct combinations of team boosting behaviors, each of which with their own potential implications. In the present study, we rely on a complementary person-centered approach to examine how distinct subpopulations (or profiles) of employees jointly engage in three types of team boosting behaviors. More specifically, we consider employees' mood-enhancing (e.g., joking around or telling funny stories), energizing (e.g., coming up with games or starting up a friendly competition during tedious moments), and uniting (e.g., having informal conversations with colleagues or asking about their interests) behaviors (Fortuin et al., 2021, 2023).

These three types of behaviors are assumed to be distinct, and each of them has been found to share unique relations with a variety of outcomes (Fortuin et al., 2021). Although their role has typically been studied in a purely additive manner, their effects have never been conceptualized as mutually exclusive or simply additive. Rather, employees are expected to rely on different combinations of these behaviors (Fortuin et al., 2021, 2023), and these combinations are assumed to play a role that is greater than the simple sum of these behaviors. The adoption of a person-centered perspective (Morin et al., 2018) allows us to consider the possibility that each of these behaviors can create a context that modifies the implications of the other behaviors. For instance, mood-enhancing behaviors can have different implications (e.g., relieving tension) when they occur on their own than when they occur in combination with uniting behaviors (e.g., relieving tensions to maintain team unity). Unfortunately, previous research conducted on these behaviors has ignored their inherent multidimensionality by combining them into a single global indicator of team boosting behaviors. This approach is self-contradictory. On the one hand, arguing that different types of behaviors should be considered to fully grasp team boosting highlights the need to study them separately. On the other hand, combining them into a single indicator assumes that distinctions are irrelevant. While both possibilities are possible, current research evidence makes it impossible to assess which perspective is optimal. The adoption of a person-centered perspective makes it possible to contrast these two possibilities. Indeed, identifying profiles displaying uniquely differentiated configurations of team boosting behaviors (e.g., one profile dominated by mood-enhancing behaviors, another profile dominated by mood-enhancing and energizing behaviors, etc.) would support the first perspective (multidimensional), whereas observing profiles that solely differ from one another globally (displaying high, moderate, or low levels across all three behaviors) would support the second perspective (unidimensional) (Gillet et al., 2017; Morin & Marsh, 2015; Morin et al., 2021).

Beyond addressing this key question about the dimensionality of these behaviors, the person-centered approach is also likely to help generate a clearer understanding of the team boosting behaviors profiles that are most optimal for employees, their teams, and their organization. For instance, do workers need to simultaneously display high levels of mood-enhancing, energizing, and uniting behaviors to produce the most positive effects? In contrast, is a specific team boosting behavior (e.g., mood-enhancing) more critical than others (e.g., uniting) from an outcome perspective? By addressing these questions, this study represents a necessary step in our understanding of how employees behave to support the informal functioning of their teams. At a time when many organizations are rethinking how to preserve and enhance employees' health, involvement, and performance, this study is thus likely to yield important insights for the development of interventions focused on boosting behaviors. Person-centered results also have the key advantage of being naturally aligned with managers' tendency to think about employees as members of different categories (person-centered) rather than in terms of complex variable associations (variable-centered; Morin et al., 2011, 2018).

Importantly, existing studies of team boosting behaviors (Fortuin et al., 2021, 2023) have yet to rely on longitudinal designs to study how team boosting behaviors, and profiles of team boosting behaviors, evolve over time (Gillet et al., 2018; Huyghebaert-Zouaghi et al., 2022a; Sandrin et al., 2020). The adoption of a longitudinal person-centered perspective makes it possible to assess multiple types of stability that cannot be captured by variable-centered methods (Gillet et al., 2019a; Morin et

al., 2016b; Sandrin et al., 2020). First, will the same set of profiles be identified over time (i.e., within-sample stability)? Second, will individual employees retain the same profile over time (within-person stability)? From a practical perspective, the first type of stability – when assessed over a time interval (i.e., three months in the present study) during which no major internal or external change is likely to happen to most employees – helps document the generalizability and robustness of our results. It would be unreasonable to attempt developing profile-based interventions without some evidence that these profiles generalize. Likewise, the design of person-based interventions has to be able to assume that profile membership will remain relatively stable over time in the absence of intervention. Otherwise, why try to change something that is unlikely to be maintained on its own? Beyond documenting stability, the current study also extends upon previous research (Fortuin et al., 2021, 2023) by considering a wider range of individual predictors and outcomes of profile membership, and the stability of these associations over time. Once again, this information is critical to the design of person-centered interventions (e.g., Meyer & Morin, 2016) seeking to improve team boosting behaviors, as it helps document possible levers of interventions (predictors) and to identify which profiles should be nurtured or targeted for modification (outcomes).

More precisely, the present study aims to: (1) offer the first person-centered investigation of team boosting behaviors profiles to help us better capture the dimensionality of these behaviors; (2) offer the first longitudinal investigation of the within-sample and within-person stability of team boosting behaviors profiles; and (3) document the construct validity of these profiles by examining their associations with theoretically-relevant predictors (availability expectations: AE, telepressure, harassment, and social challenge stressors) and outcomes (affective commitment to organization: ACO, affective commitment to colleagues: ACC, and organizational citizenship behaviors directed at individuals: OCB-I). Therefore, we consider three main research questions: (1) Can we identify several team boosting behaviors profiles at the individual level, and will these profiles display different configurations of team boosting behaviors (multidimensionality) or be characterized by matching levels across behaviors (unidimensionality)? (2) Will these profiles be replicated over time and will workers belong to the same profile over time? (3) Will these profiles relate to theoretically-relevant predictors and outcomes in a way that is consistent with theoretical expectations?

A Person-Centered Perspective on Team Boosting Behaviors

Although we are not aware of previous studies on team boosting behaviors profiles, past person-centered research suggests that workplace behaviors should not be studied in isolation. For instance, Klotz et al. (2018) conducted two studies revealing that some profiles of employees (three profiles in both studies) relied on organizational citizenship behaviors at a similar level across types of behaviors (e.g., altruism, civic virtue), whereas other profiles displayed a more differentiated configuration (two profiles in both studies). Similar results were obtained by Zhang et al. (2023) in two person-centered studies (six profiles were identified in Study 1, seven profiles in Study 2, and roughly three of these profiles displayed a similar level across indicators) of person-group fit characteristics (e.g., value congruence, shared interests, common workstyle). In contrast, a recent study by Gillet et al. (2023a) identified five profiles of workplace behaviors characterized by distinct configurations of presenteeism, performance, counterproductive work behaviors, and absenteeism [i.e., *Withdrawn (Presenteeism)*, *Involved*, *Deviant-Presenteeism*, *Problematic*, and *Average (Maladaptive)*] and showed that these profiles had well-differentiated outcome implications that would have been missed by a variable-centered representation.

Given the novelty of research on team boosting behaviors, no person-centered theoretical framework has yet been developed to guide research and help scholars formulate precise hypotheses about the nature of the profiles and underlying psychological mechanisms. However, based on the person-centered studies of employees' behaviors described previously (Klotz et al., 2018; Gillet et al., 2023a; Zhang et al., 2023), we expect the identification of five to seven profiles. We also expect at least three profiles with similar levels across team boosting behaviors (i.e., *Low*, *Average*, and *High Boosting Behaviors*). The *High Boosting Behaviors* profile refers to employees who propose new ideas to their teams while trying to entertain them and to strengthen social ties among colleagues, potentially to help support the efficiency of their teams, but also to maximize the likelihood that all team members will enjoy their work. Conversely, the *Low Boosting Behaviors* profile refers to employees who do not rely (or rely on low levels of) on behaviors designed to informally support their teams, potentially because they see these behaviors as unnecessary or because they simply prefer to limit informal connections with teammates. Finally, the *Average Boosting Behaviors* profile refers to employees who display average

levels of mood-enhancing, energizing, and uniting behaviors, possibly by limiting their team boosting efforts to those required to ensure team efficacy without necessarily trying to build up strong interpersonal connections. In these three profiles, we expect levels of team boosting behaviors to be mainly congruent across each three types of behaviors. Should all profiles have a similar shape (showing alignment across behaviors), then results would support a unidimensional conceptualization of team boosting behaviors, suggesting that differentiating them may not be relevant.

To be able to support the value of considering team boosting behaviors as distinct from one another, then additional profiles, displaying clearer differences in terms of configuration (i.e., dominated by a subset of behaviors) would be required. If we consider previous person-centered research on different types of work behaviors (Klotz et al., 2018; Gillet et al., 2023a; Zhang et al., 2023), it seems likely that at least a subset of the identified profiles will present unique configurations of team boosting behaviors. However, lacking previous evidence specific to team boosting behaviors, it is not possible at this stage to anticipate the nature of these profiles, other than to say that their configuration will involve different levels across all three types of behaviors. Importantly, this lack of clear expectations is consistent with the methodologically inductive nature of person-centered analyses (Morin et al., 2018). Based on all aforementioned considerations, we propose that:

Hypothesis 1. Five to seven profiles of team boosting behaviors will be identified.

Hypothesis 2. At least three of these profiles will display similar levels of team boosting behaviors across all three indicators (*Low, Average, and High Boosting Behaviors*).

Hypothesis 3. Additional profiles will display discrepant levels of team boosting behaviors across indicators.

A Longitudinal Person-Centered Perspective

Thus far, research on team boosting behaviors has been cross-sectional (Fortuin et al., 2021, 2023). However, variable-centered longitudinal studies on similar constructs (e.g., work behaviors) have typically revealed high levels of stability over periods of three to four months. For instance, past results revealed high stability in positive affect ($r = .86$; Sandrin et al., 2020) and self-efficacy ($r = .87$; Houle et al., 2022) ratings over four months. Huyghebaert-Zouaghi et al. (2022b) reported similar estimates of rank-order stability in job crafting behaviors (r between .88 and .91) over a three-month interval. Short-term studies may not be optimal for tests of profile stability especially when the time interval is small enough to allow employee to remember their previous responses. Thus, the present study specifically examines the stability of the identified profiles over a three-month period.

This specific time lag was selected based on theoretical, methodological, and empirical considerations. Prior longitudinal studies on the effects of work behaviors vary substantially in their chosen time lags, from a few days to many years (e.g., Sagherian et al., 2017; Xu et al., 2021). However, beyond this diversity, other studies have also selected a three-month interval as being particularly relevant to our understanding of these effects (e.g., Kampf et al., 2021; Gillet et al., 2024). Based on these previous studies, we believe that this time lag is appropriate because it is not limited to daily variations and is long enough to offset memory biases (Klasmeier & Rowold, 2022), while remaining short enough to ensure a proper measurement of stability under conditions that can generally be expected to be reasonably stable for most employees (Gillet et al., 2019a). It also remains short enough to capture changes that might be missed over longer time spans (Dormann & Griffin, 2015) and thus facilitates examinations of the dynamism and pace of within-person changes (Kaltainen et al., 2020). Furthermore, work behaviors are known to evolve over time and to be modifiable via relatively short-term interventions (Costa, 2024; Gaudine & Saks, 2001), making it important to study them when considering time intervals relevant to these interventions. Lastly, past investigations have shown that employees' functioning (e.g., ACO, OCB) can fluctuate over periods as short as three months (e.g., Houle et al., 2022; Tóth-Király et al., 2023). We thus assumed that a three-month period would be appropriate. Based on all of these considerations, we propose that:

Hypothesis 4. The same number of profiles, with the same structure, the same level of within-profile variability, and the same size will be identified across a three-month interval.

Hypothesis 5: The profiles will display a moderate to high level of within-person stability.

Predictors of Profile Membership

In the present study, we wanted to examine how different types of job demands could predict membership into team boosting behaviors profiles. More specifically, we considered job demands related to information and communication technologies (telepressure and AE) and interpersonal

interactions (exposure to harassment and social challenge stressors). Job demands require employees to invest psychological and/or physical efforts in their work, which can have health-related consequences if employees are unable to properly replenish the personal resources expended to handle demands (Bakker & Demerouti, 2017). However, LePine et al. (2005) showed that not all job demands are necessarily harmful and highlighted the need to distinguish hindrance and challenge types of demands. Hindrances (such as telepressure, AE, and exposure to harassment) are demands that hinder personal growth and goal attainment by interfering with employees' ability to properly do their work, and are likely to lead employees to experience a health-impairment process. Challenges (such as social challenge stressors) are demands that offer opportunities for growth, learning, and achievement, and are likely to lead employees to experience a motivational process.

Telepressure is a self-imposed type of job demands pushing employees to respond quickly to work-related communications even when they occur outside of regular work hours (Barber & Santuzzi, 2015). As a result, telepressure leads employees to persistently invest high levels of efforts and energy in their work, even outside of their regular work hours, which in turn is likely to interfere with their ability to recover the resources (Hobfoll, 2011) they need to engage in team boosting behaviors (Gillet et al., 2023c). By interfering with work recovery, telepressure can lead employees to feel overwhelmed and unable to overcome obstacles and to experience more negative emotional states, thereby interfering with their ability to informally support their team by engaging in team boosting behaviors (Barber & Santuzzi, 2015). Similar to telepressure in its finality (i.e., responding quickly to work-related communications irrespective of timing), AE is an externally imposed type of job demands that also interferes with work recovery, proactivity and positive mood (Derks et al., 2015), thereby limiting employees' desire and ability to engage in team boosting behaviors.

Employees' perceptions of exposure to harassment at work and social challenge stressors represent two types of interpersonal job demands likely to influence the quality of interpersonal relationships within a work team (French et al., 2019; Kern et al., 2021). Indeed, exposure to acts of harassment at work is assumed to put a strain on employees' resources, thereby leading them down a health impairment pathway (Bakker & Demerouti, 2017). Moreover, the experienced strain also limits employees' ability to properly recover, and maintain, their resources, thereby leading to withdrawal behaviors (i.e., pushing them away from their teams) and lower levels of commitment at work (French et al., 2019; Kern et al., 2021), making team boosting behaviors less likely. In contrast, social challenge stressors may represent stimulating opportunities for employees to learn and grow, thereby allowing them to anticipate future gains in their professional careers (Crawford et al., 2010). More precisely, employees exposed to challenging job demands (e.g., social challenge stressors such as coordinating colleagues in difficult situations or moderating a discussion when a problem has no clear solution) are likely to improve their competence and achievement as a result of this challenging situation (LePine et al., 2005). This type of job demands has been reported to engage a motivational process (Bakker & Demerouti, 2017) leading to primarily desirable outcomes, such as team boosting behaviors. Indeed, employees successfully dealing with social challenge stressors tend to display higher levels of goal achievement and need satisfaction, resulting in higher levels of personal development and growth (Kern et al., 2021). These positive outcomes make it more likely for them that they will have access to the resources required by team boosting behaviors (Hobfoll, 2011). We thus propose that:

Hypothesis 6. Telepressure, AE, and harassment will be associated with membership into profiles characterized by lower levels of team boosting behaviors (e.g., *Low Boosting Behaviors*) relative to profiles characterized by higher levels of team boosting behaviors (e.g., *High Boosting Behaviors*).

Hypothesis 7. Social challenge stressors will be associated with membership into profiles characterized by higher levels of team boosting behaviors (e.g., *High Boosting Behaviors*) relative to profiles characterized by lower levels of team boosting behaviors (e.g., *Low Boosting Behaviors*).

Implications of Team Boosting Behaviors Profiles for Employees' Functioning

Prior research highlights the critical role of team boosting behaviors for employees', teams', and organizations' functioning (Fortuin et al., 2021, 2023). To complement these prior variable-centered investigations, we focus on the implications of the team boosting behaviors profiles for employees' attitudes (ACO and ACC) and behaviors (OCB-I). These outcomes are known to be highly relevant to

employees, teams, and organizations' success. For instance, ACO and ACC have been positively related to various indicators of career success and work performance and are associated with lower intentions to leave (e.g., Perreira et al., 2018). Likewise, OCB-I may fuel a virtuous cycle between employees and is negatively linked to multiple undesirable work outcomes such as distress, absenteeism, interpersonal conflicts, and deviant behaviors (e.g., Henderson et al., 2020).

From a theoretical perspective (Fortuin et al., 2021), the positive impact of team boosting behaviors is expected to occur via work engagement (Fortuin et al., 2023). More specifically, team boosting behaviors contribute to work engagement as they are associated with increased positive affective states and energy, and better social connections. Interestingly, high levels of ACO and ACC are also core characteristics of engaged employees. Employees who engage in team boosting behaviors have high levels of energy, concentration, and involvement in their work, helping them to experience positive emotions, which ultimately contribute to a greater emotional bond with their organization and colleagues (i.e., ACO and ACC; Halbesleben, 2010). Similarly, OCB-I require energy and resources due to their discretionary nature (Henderson et al., 2020). Employees who engage in team boosting behaviors are full of energy and fulfill their in-role obligations, while being able to go the extra mile beyond the boundaries of job responsibilities (Fortuin et al., 2021, 2023). This is because they are immersed and passionate about the effective execution of duties but also have a strong desire to help their colleagues, while taking a personal interest in other employees and taking the time to listen to them (i.e., OCB-I; Matta et al., 2015). We thus propose that:

Hypothesis 8. The profile characterized by the highest levels of team boosting behaviors (*High Boosting Behaviors*) will be associated with the most adaptive functioning (i.e., highest levels of ACO, ACC, and OCB-I), followed by the *Average Boosting Behaviors* profile, and finally by the *Low Boosting Behaviors* profile.

Method

Participants and Procedure

Participants were asked to complete an online questionnaire twice during a three-month period through the *Prolific Academic* platform. We followed online survey reporting guidelines (Sischka et al., 2022; Turk et al., 2018). Participants were invited by individual survey links through an announcement posted on the platform. Before accessing the survey, they were told that they could stop participating at any time without consequences, and that participation was confidential and voluntary. They could also contact the first author at any time by e-mail to ask any questions about the study. Participants were only allowed to answer the questionnaire once and could not change their answers after completing it for the first time. However, they were not “forced” to answer all questions and could skip questions of their choice. The IP address of participants' computer was not used to identify potential duplicate entries from the same user. However, participants were identified using the unique identifier provided by the *Prolific Academic* platform, which was also used by Prolific to compensate the participants. Participants received £2.25 for their participation at each data collection.

Recruitment was limited to participants who spoke English as their main language, who worked in a team, and who were employed by an organization (excluding students, self-employed, and unemployed individuals). We stopped our data collection three days after the questionnaire became available on the platform with a targeted sample size of 400 (following current recommendations for person-centered analyses: Nylund-Gibson & Choi, 2018; Sinha et al., 2021; Spurk et al., 2020; Weller et al., 2020). The final sample included 415 participants (60.2% females) at Time 1 (T1), and 327 participants (60.0% females) at Time 2 (T2). Of those, 180 reported mainly working onsite, and 235 reported mainly working remotely. Participants lived and worked in the UK (75.1%) or USA (24.9%), and 70.8% held a university degree. They had a mean age of 40.19 years ($SD = 10.22$) and a mean tenure in their position of 6.95 years ($SD = 6.45$). Most held a permanent (98.3%) full-time (85.5%) position and worked in the private sector (55.2%). More precisely, they worked in non-market services (54.0%), market services (31.6%), industry (8.4%), construction (4.1%), or other sectors (1.9%). No information was collected on their employing organizations, with the exception of their sector, or on the teams within the same organization. Data was only collected at the individual level.

Measures

All items were rated on a five-point scale except for boosting behaviors items which were rated on a seven-point scale. These questionnaires were selected on the basis of their satisfactory psychometric properties, as reported in previous studies (e.g., Barber & Santuzzi, 2015; Derks et al., 2015; Fortuin

et al., 2021; French et al., 2019; Henderson et al., 2020; Kern et al., 2021; Perreira et al., 2018), and because they were all relatively short to complete.

Team boosting behaviors. Mood-enhancing (six items; e.g., “I break a negative atmosphere in our team with a joke”; $\alpha_{T1} = .93$; $\alpha_{T2} = .92$), energizing (six items; e.g., “I take initial action to set our team in motion”; $\alpha_{T1-T2} = .94$), and uniting (six items; e.g., “I assess the atmosphere in our team”; $\alpha_{T1-T2} = .91$) behaviors were measured using the scale developed by Fortuin et al. (2021).

AE. We used a six-item scale (e.g., “If I do not respond to messages from my colleagues, my position in the group is threatened”; $\alpha_{T1-T2} = .88$) developed by Derks et al. (2015).

Telepressure. We used a six-item scale (e.g., “When using message-based technology for work purposes, I cannot stop thinking about a message until I have responded”; $\alpha_{T1} = .94$; $\alpha_{T2} = .93$) created by Barber and Santuzzi (2015).

Exposure to harassment at work. Two items developed by French et al. (2019) were used (e.g., “How often do your supervisors or boss (item 1) / How often do your coworkers (item 2) use ethnic, racial, or sexual slurs or jokes?”; $r_{T1} = .76$; $r_{T2} = .61$).

Social challenge stressors. We used an eight-item scale (e.g., “How often are you required to mediate between colleagues in order to ensure the working process?”; $\alpha_{T1} = .90$; $\alpha_{T2} = .91$) by Kern et al. (2021).

ACO and ACC. ACO (e.g., “I am proud to say that I work for my organization”; $\alpha_{T1} = .91$; $\alpha_{T2} = .89$) and ACC (e.g., “When I talk to my friends about my coworkers, I describe them as great people to work with”; $\alpha_{T1} = .90$; $\alpha_{T2} = .93$) were measured with a scale developed by Perreira et al. (2018).

OCB-I. OCB-I were assessed using a three-item scale (e.g., “I helped others with heavy workloads”; $\alpha_{T1} = .68$; $\alpha_{T2} = .69$) developed by Henderson et al. (2020).

Results

Preliminary Analyses

We first relied on preliminary factor analyses to verify the psychometric properties of all multi-item measures. The specification of these analyses (pages S2-S3) and their results (Tables S1 to S5) are reported in the online supplements (i.e., factor structure, composite reliability, measurement invariance over time, and latent correlations). Our main analyses were based on factor scores extracted from these preliminary models in standardized units ($SD = 1$; $M = 0$) and specified as invariant over time to ensure their comparability over time (Millsap, 2011).

Main Analyses

The specifications of all main analyses are presented in the online supplements (pages S4 to S7).

Number of profiles. The model fit indicators associated with the time-specific latent profile analyses are reported in Table S6 (also see Figures S1 and S2) of the online supplements. These results tentatively supported a solution including seven profiles at both T1 (lowest CAIC value) and T2 (lowest CAIC and BIC values). However, the elbow plots presented in Figures S1 and S2 revealed a first plateau between two and three profiles, and a second plateau between four and five profiles at both time points. Based on this information and on our expectations, we carefully examined solutions including three to six profiles. These solutions were already very similar over time and revealed that additional profiles brought value up to five profiles, at both time points. However, considering a sixth profile led to the division of one profile into smaller ones with a similar configuration. Therefore, the five-profile solution was selected at both time points, thereby supporting Hypothesis 1.

Similarity over time. The model fit indicators associated with the longitudinal models are reported in Table 1. Relative to the initial solution of *configural* similarity (same number of profiles), the following solutions of *structural* (same profile structure), *dispersion* (same within-profile variability), and *distributional* (same profile size) similarity all resulted in lower values on the BIC, CAIC, and ABIC. The model of *distributional* similarity was thus selected as our final model and retained for interpretation. The results from this model are graphically displayed in Figure 1 and parameter estimates are reported in Tables S7 and S8 of the online supplements. This model was associated with a high classification accuracy (see Table S8: 89.3% to 100.0% at T1; 89.3% to 96.9% at T2), consistent with a high entropy of .851. These results support Hypothesis 4.

Profile description. Profile 1 displayed very low levels of mood-enhancing, energizing, and uniting behaviors. This *Very Low Boosting Behaviors* profile characterized 7.79% of the participants. Profile 2 represented participants reporting high levels across dimensions. This *High Boosting Behaviors* profile corresponded to 23.85% of the participants. Profile 3 represented participants

reporting low levels across dimensions. This *Low Boosting Behaviors* profile corresponded to 26.38% of the participants. Profile 4 represented participants reporting very high levels across dimensions. This *Very High Boosting Behaviors* profile corresponded to 6.95% of the participants. Finally, Profile 5 displayed average levels across dimensions. This *Average Boosting Behaviors* profile corresponded to 35.03% of the participants. These results support Hypothesis 2, but not Hypothesis 3.

Within-person stability. Membership into Profiles 5 (*Average Boosting Behaviors*: Stability of 90.5%) and 2 (*High Boosting Behaviors*: Stability of 83.7%) was the most stable over time. Membership into Profiles 1 (*Very Low Boosting Behaviors*: Stability of 69.4%), 3 (*Low Boosting Behaviors*: Stability of 79.0%), and 4 (*Very High Boosting Behaviors*: Stability of 73.2%) was not as stable (see Table S8 of the online supplements). These results support Hypothesis 5.

Demographics. In relation to demographics (sex, age, level of education, tenure in the current position, contract, working time, sector, and country), the results reported in Table 1 show that all information criteria were at their lowest for the null effects model (see the online supplements for details on these analyses). These results thus revealed a lack of associations between demographics and the profiles at both time points, a conclusion that is also consistent with the parameter estimates from all models. Thus, demographics were not retained for subsequent analyses.

Predictors. The results reported in Table 1 are consistent with the generalizability of associations between theoretical predictors and profiles over time (i.e., *predictive* similarity). The results from this solution are reported in Table S10 of the online supplements and first revealed that AE and harassment shared no association with profile membership. In contrast, social challenge stressors were positively associated with membership into the *Very High Boosting Behaviors* (4) and *Average Boosting Behaviors* (5) profiles relative to the *Very Low Boosting Behaviors* (1) and *Low Boosting Behaviors* (3) profiles. They were also positively associated with membership into the *High Boosting Behaviors* (2) profile relative to the *Very Low Boosting Behaviors* (1), *Low Boosting Behaviors* (3), and *Average Boosting Behaviors* (5) profiles. Finally, telepressure was positively associated with membership into the *Low Boosting Behaviors* (3) profile relative to the *Very Low Boosting Behaviors* (1) profile¹. These results partially support Hypothesis 6 and support Hypothesis 7.

Outcomes. The results reported in Table 1 support the model of *explanatory similarity* (i.e., revealing outcome associations that generalized over time), which was associated with the lowest values on all information criteria. Mean outcome levels in each profile are reported in Table S11 of the online supplements. The highest levels of ACO and ACC were found among members of the *Very High Boosting Behaviors*, while the lowest levels were found in the *Very Low Boosting Behaviors* profile. The *High Boosting Behaviors* profile was also associated with higher levels of ACO and ACC than the *Low Boosting Behaviors* profile. The highest levels of OCB-I were found in the *Very High Boosting Behaviors* profile, followed by the *High Boosting Behaviors* profile, the *Average Boosting Behaviors* profile, the *Low Boosting Behaviors* profile, and finally by the *Very Low Boosting Behaviors* profile². These results support Hypothesis 8.

Discussion

Our results revealed five distinct team boosting behaviors profiles displaying low to very low (*Low Boosting Behaviors* and *Very Low Boosting Behaviors*), average (*Average Boosting Behaviors*), and high to very high (*High Boosting Behaviors* and *Very High Boosting Behaviors*) levels of team boosting behaviors across dimensions. These profiles were replicated over time, as well as across subsamples of remote and onsite employees (see footnote 2). This evidence of generalizability suggests that these profiles capture core mechanisms involved in team boosting behaviors that remain applicable over time and across work settings. Although Fortuin et al. (2021) previously highlighted the need to account for multiple, and conceptually distinct, components of team boosting behaviors (i.e., energizing, mood-enhancing, and uniting behaviors), the present research suggests that there is only limited value in differentiating among these three components, which systematically were

¹ In line with recent studies (Huyghebaert-Zouaghi et al., 2022a), we examined if predictions varied between remote (coded 1) and onsite (coded 0) employees by incorporating interactions between work type and predictors. These results (see the online supplements) showed that predictors and work type did not interact.

² In line with recent studies (Huyghebaert-Zouaghi et al., 2022a), we considered whether results differed across subsamples of employees working onsite or remotely. These results are detailed in the online supplements and showed that the profile-outcome associations were common to remote and onsite employees.

aligned with one another within all profiles, especially for energizing and uniting behaviors, as levels of mood-enhancing behaviors tended to deviate (albeit slightly) from those of other behaviors in most profiles. This conclusion is aligned with previous reports revealing strong correlations between these components (Fortuin et al., 2021). From a practical perspective, our results thus suggest that, to achieve a comprehensive picture of team boosting behaviors profiles, it may be more informative and parsimonious to consider energizing, mood-enhancing, and uniting behaviors jointly rather than separately. However, additional studies are required to identify contexts in which it might be worth considering these boosting behaviors as distinct (or not) from one another.

However, it remains important to acknowledge that mood-enhancing behaviors did display a somewhat distinct pattern of results. Indeed, in four of the five team boosting behaviors profiles identified in this study (to a larger extent in the *Very High Boosting Behaviors* profile), levels of mood-enhancing behaviors deviated from those of energizing and uniting behaviors. Such findings suggest that workers are unlikely to display all types of team boosting behaviors at a similarly high level. They also underline the need to differentiate mood-enhancing behaviors from energizing and uniting behaviors rather than using a global score of boosting behaviors (e.g., Fortuin et al., 2021), as they confirm that these behaviors are conceptually distinct from the others. In spite of these considerations, levels of mood-enhancing behaviors were not radically distinct from those of energizing and uniting behaviors. Therefore, perhaps the best solution is not to oppose energizing and uniting behaviors on the one hand, and mood-enhancing behaviors on the other, but rather to encourage researchers to rely on a person-centered approach to identify boosting behaviors profiles with different configurations of boosting behaviors across dimensions. It would also seem important to systematically investigate whether and how similar profiles would be identified across diversified occupational groups (e.g., service workers, technicians) or cultures (e.g., South America, Asia).

In terms of within-person stability, profile membership was moderately to highly stable (69.4% to 90.5%). These stability rates match previous reports showing that similar work behaviors were also moderately to highly stable over comparable periods of time (e.g., three months; Houle et al., 2022; Huyghebaert-Zouaghi et al., 2022b). These stability rates support the value of profile-based interventions, suggesting that the current set of team boosting behaviors profiles neither captures rigid conditions, nor entirely ephemeral tendencies (Meyer & Morin, 2016). Membership into the *Very Low Boosting Behaviors* profile was the least stable over time, which may suggest that it might be hard to maintain very low levels of team boosting behaviors over time (even for a period as short as three months). Although our results do not formally test this possibility, prior research suggests that the difficulty associated with maintaining very low levels of team boosting behaviors could be related to employees' need to work in an environment in which they feel fulfilled and close to others (Jiang et al., 2024). Given the undesirability of this profile, it would be important for organizations to consider intervening to help employees with more desirable profiles maintain these profiles over time, possibly by interviewing them to assess which practices they see as most beneficial (or harmful). Such interventions could then be expanded to assist employees optimize their team boosting behaviors.

Predictors of Team Boosting Behaviors Profiles

Our results demonstrated that team boosting behaviors profiles were independent from employees' demographic characteristics but were related to some of our work-related predictors (AE, telepressure, harassment, and social challenge stressors). As such, our results have theoretical and practical implications likely to provide helpful guidance to upcoming research and intervention efforts.

Our results first showed that social challenge stressors seemed to both increase employees' likelihood of engaging in average to very high levels of team boosting behaviors while decreasing their likelihood of engaging in low to very low levels of these behaviors. However, this effect was not linear. Indeed, beyond its ability to predict membership into profiles displaying "satisfactory" (average, high, and very high) versus unsatisfactory (low and very low) levels of team boosting behaviors, this predictor did not help achieve finer differentiations within these two categories of profiles. These observations support previous evidence showcasing the positive role of social challenge stressors, which may lead employees to motivate themselves and invest more energy in their work (Kern et al., 2021). More generally, they confirm that social challenge stressors represent a "challenge" type of job demands likely to provide employees with opportunities for growth, achievement, and learning, thereby facilitating their engagement in a motivational process (Crawford et al., 2010; LePine et al., 2005). However, our results also suggest that other predictors may be more

likely to predict differences in terms of degree (e.g., average *versus* high *versus* very high; low *versus* very low) rather than kind (i.e., moderate-to-high *versus* low). Future research will be needed to examine the role of personal (e.g., self-efficacy) or job (e.g., supervisor support) resources, as well as other types of job demands, in the prediction of profile membership.

Unexpectedly, AE and exposure to harassment shared no association with profile membership on their own, while telepressure predicted an increased likelihood of membership into the *Low Boosting Behaviors* profile relative to the *Very Low Boosting Behaviors* profile. These results confirm that telepressure represents a “hindrance” type of job demands requiring employees to invest significant efforts likely to weaken their personal resources (Hobfoll, 2011). More generally, telepressure obstructs goal attainment and personal growth, and is associated with a health-impairment process (Bakker & Demerouti, 2017). The present results thus confirm the validity of some critical theoretical propositions from the job demands-resources model (Bakker & Demerouti, 2017; Crawford et al., 2010; LePine et al., 2005), which assumes the presence of two complementary health-impairment and motivational processes. However, taken together, these results fail to support Hypothesis 6 and suggest that AE and exposure to harassment may not be critical in explaining team boosting behaviors. Future investigations would gain in considering the role of other personal characteristics (e.g., work motivation) and of challenge (e.g., role complexity) and hindrance (e.g., role conflict) demands in the prediction of team boosting behaviors profiles.

Outcomes of Profile Membership

Our results revealed clear outcome associations. The *Very Low Boosting Behaviors* profile displayed the most problematic outcomes (i.e., the lowest levels of ACO, ACC, and OCB-I), followed by the *Low Boosting Behaviors* profile, by the *Average Boosting Behaviors* profile, by the *High Boosting Behaviors* profile, and finally by the *Very High Boosting Behaviors* profile which displayed the highest levels of ACO, ACC, and OCB-I. These observations support the previously reported benefits of team boosting behaviors (Fortuin et al., 2021, 2023). However, regarding ACO and ACC, no significant differences were found between the *High Boosting Behaviors* and *Average Boosting Behaviors* profiles, and between the *Low Boosting Behaviors* and *Average Boosting Behaviors* profiles, while there were significant differences in OCB-I between these profiles. These results thus suggest that the effects of the team boosting behaviors profiles may be somewhat different depending on the nature of the outcomes considered. Additional negative (e.g., turnover, absenteeism) and positive (e.g., creativity, performance) outcomes could be included in future research to better disentangle the implications of team boosting behaviors profiles.

Limitations and Future Directions

First, we relied solely on self-report questionnaires, which implies that social desirability biases may play a role in our results. To alleviate these concerns, future research could include informant ratings (e.g., supervisor, customers, colleagues) of team boosting behaviors. It would also be useful for future studies to consider incorporating objective measures of employees’ functioning (e.g., organizational data on work performance and absenteeism). Second, although our focus was placed on behaviors, predictors, and outcomes that were meaningful individual-level variables (Morin et al., 2022, 2023) among a sample of employees recruited individually and unlikely to come from the same workgroups or organizations (making it unnecessary to control for nesting), it remains that team boosting behaviors explicitly seek to influence team level processes and are also likely to be influenced by team-level characteristics. Although we felt that our focus on individual employees was justified in this first application of person-centered methods to the investigation of team boosting behaviors in which we explicitly assessed predictors and outcomes that were meaningful at the individual level, it would be important for future research to expand upon the current investigation in a multilevel manner in order to properly consider how team-level processes can add to the individual-level processes uncovered in this study (Morin et al., 2022, 2023). For instance, integrating team-level variables such as team cohesion or collective efficacy could help increase our understanding of how individual employees’ team boosting behaviors combine (support or interfere with one another) at the team level to influence team outcomes (e.g., team performance and creativity). In doing so, we could answer questions such as: Do a Very High Boosting Behaviors profile have a stronger impact on outcomes in cohesive teams versus fragmented ones? Similarly, considering predictors at the collective level (e.g., organizational culture, leadership behaviors) could help better understand the role played by such factors in shaping profiles with higher levels of team boosting behaviors.

Third, this study only relied on a convenience sample of workers who lived and worked in the USA or the UK, with a predominance of women (relative to men) and UK (relative to USA) workers. Although our results demonstrated that these demographic characteristics did not influence our results, it would be important for future studies to rely on more representative samples, and to formally assess the replicability of our results across a variety of work settings, cultures, languages, and countries (especially Eastern European, Asian, and non-WEIRD countries). Fourth, profile stability was assessed over a period of three months, during which no specific transition or systematic change occurred for most participants. Stability could be weaker if longer time intervals (e.g., one year), or intervals encompassing interventions or changes (e.g., professional training, artificial intelligence implementation), were considered. Future studies should thus examine the extent to which our findings would generalize to longer periods of time, transitions, interventions, and changes (Huyghebaert-Zouaghi et al., 2022a). In addition, although we provided information regarding the temporal stability of distinct combinations of boosting behaviors and their longitudinal implications, future research relying on longitudinal designs is needed to achieve a clearer picture of the dynamic nature of boosting behaviors and the directionality of the observed associations.

Fifth, Morin and Marsh (2015) demonstrated the importance of accounting for the variance globally shared across profile indicators to achieve a more precise estimate of their unique contribution. Building upon this initial rationale, Morin et al. (2016a, 2017) showcased the value of bifactor modeling as a preliminary step likely to result in the identification of profiles displaying more clearly differentiated configurations. Although our main analyses could not rely on factor scores extracted from bifactor models (e.g., poor fit indices, low loadings on the global factor), as suggested by these authors, the moderately high correlations observed among our profile indicators ($M_r = .74$; see Table S5 in the online supplements) suggest that this methodological approach could be an interesting way forward in person-centered research on team boosting behaviors. Finally, we only considered the predictive role of AE, telepressure, harassment, and social challenge stressors. Future research may investigate how other job (e.g., colleagues and supervisor support) and personal (e.g., regulatory focus, proactive personality) characteristics are linked to these profiles (e.g., Caesens et al., 2020). Likewise, negative (e.g., counterproductive behaviors, absenteeism) and positive (e.g., creativity, organizational citizenship behaviors) coupled with psychological mechanisms (e.g., psychological need states) could be included to better understand the implications of the boosting behaviors profiles (e.g., Gillet et al., 2019b; Huyghebaert-Zouaghi et al., 2023).

Implications for Practice

To prevent the harmful outcomes associated with low to very low levels of team boosting behaviors, organizations and managers might be tempted to promote social challenge stressors. However, it is important to bear in mind that this might act as a double-edged sword. On the one hand, social challenge stressors could limit the reliance on low to very low levels of team boosting behaviors. On the other hand, exposure to social challenge stressors may also be associated with negative outcomes (e.g., emotional exhaustion; Kern et al., 2021). It thus seems unwise to encourage the promotion of social challenge stressors in and of themselves. Conversely, job crafting interventions have been successfully implemented and can be useful in reinforcing employees' training and development. For instance, after a job crafting intervention (starting with a workshop, followed by job crafting implementation during a four-week period, and ending with an evaluative session), workers reported seeking more challenges at work, displayed more positive attitudes toward change and safety behaviors, and experienced lower levels of exhaustion (Demerouti et al., 2021). Uglanova and Dettmers (2023) also showed that a four-week online job crafting intervention, consisting of one training session and three reflection sessions (e.g., listing work values, interests, and personal strengths, setting a concrete goal to be implemented, reflecting on potential obstacles within the goal achievement process), was effective at improving job crafting strategies and decreasing employees' irritation. Furthermore, de Jong et al. (2024) demonstrated the effectiveness of a proactive team motivation intervention based on six workshop components (e.g., a clear message from management and supervisors, collectively clarifying the team's goals, creating a safe climate, a work design analysis). More specifically, results revealed that the intervention was associated with changes in three dimensions of team crafting (task team crafting, relational team crafting, and cognitive team crafting) at both six months and one year after the intervention. They also confirmed the mediating role of change in the three team-level crafting dimensions in explaining the association between the

intervention and change in team performance six months (with the exception of relational team crafting) and one year after the intervention. Such studies provide valuable insights for managers and organizations seeking to stimulate job crafting and organizations might propose similar interventions to foster the development of higher levels of team boosting behaviors.

It would also be interesting to encourage organizations and managers to act on other potential levers to facilitate the emergence and maintenance of team boosting behaviors. For instance, telling employees that they do not have to do everything themselves could help them understand the importance of prioritizing, and supervisors could support them in the identification of tasks that could be delegated to other team members. Supervisors could also be encouraged to become familiar with their employees' skills and resources, which should facilitate the distribution of tasks while ensuring that they are assigned to the right persons (Caesens et al., 2020). Interventions seeking to improve organizational support might also be useful (e.g., offering organizational benefits, policies, and programs for all employees, building a family-friendly organizational culture). Organizations could promote a supportive culture to help supervisors break down the walls between themselves and employees. In such environments, supervisors and employees come to share power and to be more attuned to each other identity and culture, resulting in higher opportunities for the co-creation of learning experiences and knowledge. Promoting procedural justice (e.g., by including employees in decision-making, reflecting and thoroughly selecting a communication strategy, being sensitive to negative or positive experiences employees have had) is also a meaningful way to increase organizational support (Kurtessis et al., 2017). Finally, organizations could offer training to help employees understand and adopt team boosting behaviors. They could also rely on employees or managers as role models for such behaviors (Fortuin et al., 2023).

However, although our results revealed that our profiles and their associations with outcomes were replicated across subsamples of remote and onsite employees, organizations and managers might have to adapt their actions depending on whether employees work remotely or onsite. It is unclear whether working remotely can be considered to represent a job resource, a job demand, or both (Wang et al., 2021). However, the effects of individual and job characteristics on team boosting behaviors profiles might vary across employees working remotely or onsite. For instance, the extent to which work passion predicts team boosting behaviors profiles can be expected to be contingent on working remotely or onsite (Gillet et al., 2023b). On the one hand, remote work, by providing harmoniously passionate employees with more control of when and how they transition between their work and their nonwork roles, should thus be more aligned with their preferences (Huyghebaert-Zouaghi et al., 2022a) and therefore increase their likelihood of membership into a Very High Boosting Behaviors profile. On the other hand, obsessive passion implies that employees devote an excessive amount of time and effort to their work at the expense of their family role (Vallerand & Houliort, 2019). For these workers, remote working in which the boundaries between the work and family roles are blurred, might contribute to increase the detrimental effect of obsessive passion (Wang et al., 2021), leading to an increased likelihood of membership into a Very Low Boosting Behaviors profile.

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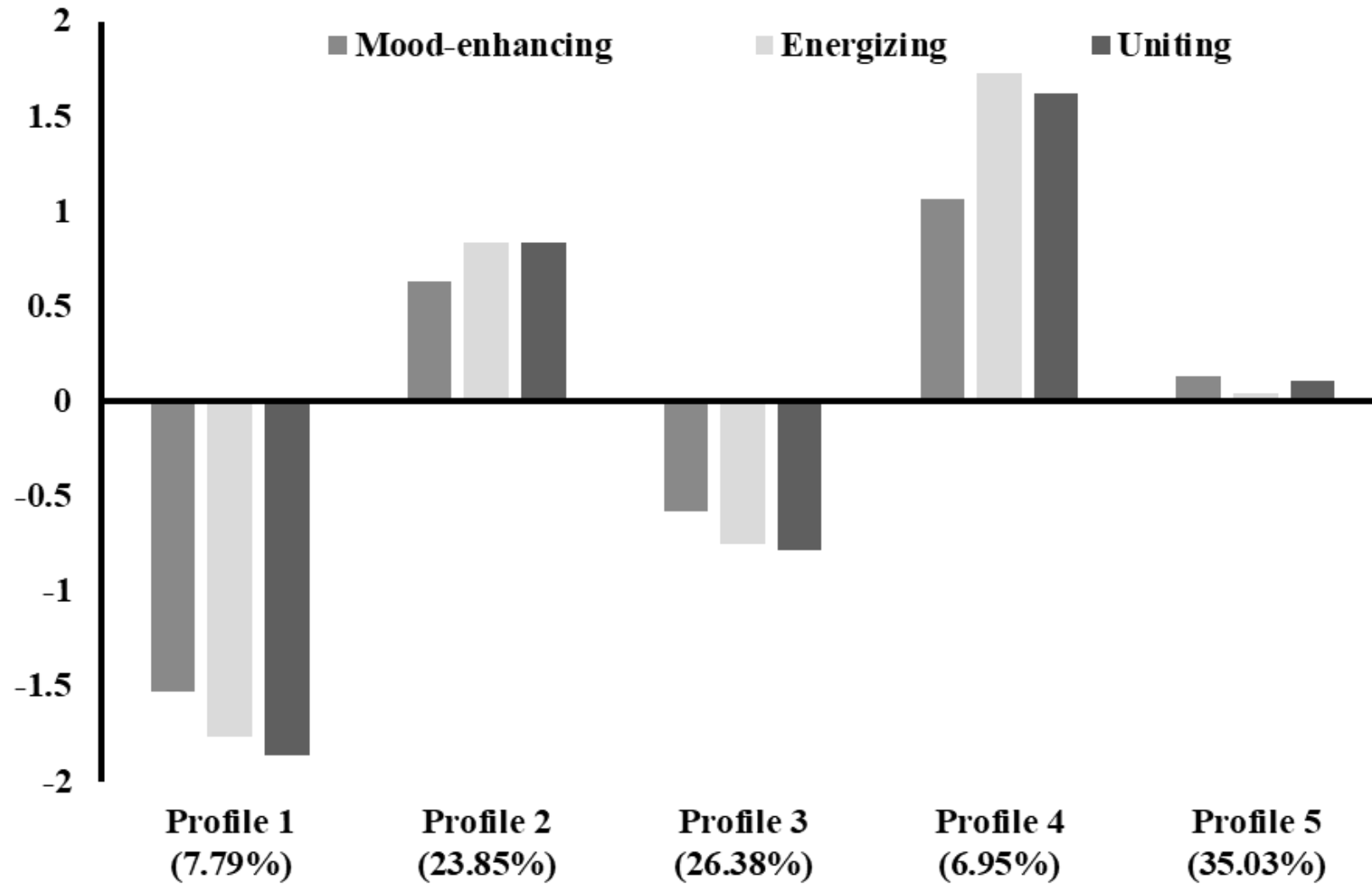


Figure 1. Final Five-Profile Solution

Note. Profile 1: *Very Low Boosting Behaviors*; Profile 2: *High Boosting Behaviors*; Profile 3: *Low Boosting Behaviors*; Profile 4: *Very High Boosting Behaviors*; and Profile 5: *Average Boosting Behaviors*.

Table 1*Results from the Time-Specific and Longitudinal Models*

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy
<i>Final Latent Profile Analyses</i>								
Time 1	-1294.643	34	1.088	2657.286	2828.247	2794.247	2686.357	.868
Time 2	-1204.174	34	1.121	2476.347	2647.309	2613.309	2505.418	.863
<i>Longitudinal Latent Profile Analyses</i>								
Configural Similarity	-2498.817	68	1.104	5133.633	5475.556	5407.556	5191.775	.866
Structural Similarity	-2512.224	53	1.382	5130.447	5396.946	5343.946	5175.764	.852
Dispersion Similarity	-2517.526	38	1.675	5111.053	5302.127	5264.127	5143.544	.853
Distributional Similarity	-2518.881	34	1.873	5105.762	5275.723	5242.723	5134.833	.851
<i>Predictive Similarity: Demographics</i>								
Null Effects Model	-3025.409	68	1.259	6186.818	6528.741	6460.741	6244.960	.853
Profile-Specific Free Relations with Predictors	-2933.505	292	5.896	6451.010	7919.267	7627.267	6700.679	.894
Free Relations with Predictors	-2978.994	132	1.104	6221.987	6885.720	6753.720	6334.852	.910
Equal Relations with Predictors	-3001.266	100	1.168	6202.531	6705.359	6605.359	6288.034	.857
<i>Predictive Similarity: Predictors</i>								
Null Effects Model	-4413.427	68	1.164	8962.854	9304.777	9236.777	9020.996	.853
Profile-Specific Free Relations with Predictors	-4321.341	180	.839	9002.682	9907.772	9727.772	9156.588	.891
Free Relations with Predictors	-4345.260	100	1.084	8890.520	9393.547	9293.547	8976.023	.910
Equal Relations with Predictors	-4360.129	84	1.183	8888.258	9310.633	9226.633	8960.080	.860
<i>Explanatory Similarity</i>								
Free Relations with Outcomes	-3844.595	60	1.093	7809.190	8110.887	8050.887	7860.492	.886
Equal Relations with Outcomes	-3847.413	45	1.381	7784.825	8011.098	7966.098	7823.302	.899

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

Online Supplements for:

A Longitudinal Person-Centered Investigation of Individual Employees' Team Boosting Behaviors

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

Analyses

Given our reliance on complex longitudinal models involving multiple constructs, we conducted preliminary analyses separately for the team boosting behaviors, and predictors and outcomes (availability expectations, social challenge stressors, telepressure, harassment, affective commitment to the organization and coworkers, and organizational citizenship behaviors directed at individuals). These preliminary analyses relied on Mplus 8.9 (Muthén & Muthén, 2023) and the maximum likelihood robust (MLR) estimator. We also relied on full information maximum likelihood (FIML; Enders, 2010) to deal with missing data, allowing us to save factor scores including no missing data. Factor scores are partially corrected for random measurement error (Skrondal & Laake, 2001) and maintain the properties of the measurement model (e.g., invariance) better than scale scores (Morin et al., 2016a). As the chi-square test of exact fit (χ^2) is oversensitive to minor misspecifications, omitted variables, and sample size (e.g., Marsh et al., 2005), models were assessed and compared using sample-size independent fit indices (Hu & Bentler, 1999): The Tucker-Lewis index (TLI), comparative fit index (CFI), and root mean square error of approximation (RMSEA) coupled with its 90% confidence interval. Values above .90 are acceptable for TLI and CFI, although values above .95 are recommended. Values less than .08 are acceptable for the RMSEA, although values less than .05 are preferred. Likewise, tests of measurement invariance relied on changes in fit indices (Chen, 2007; Cheung & Rensvold, 2002). A Δ CFI/TLI of .010 or less and a Δ RMSEA of .015 or less between a model and the previous model indicates that the invariance is supported. We also report composite reliability coefficients (omega: ω) calculated from the standardized parameters (McDonald, 1970):

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

In this formula, $|\lambda_i|$ reflects the standardized factor loadings, and δ_i , the item uniquenesses.

For team boosting behaviors, we relied on a confirmatory factor analysis (CFA) model with three correlated factors (mood-enhancing, energizing, and uniting behaviors) at both Time 1 (T1) and Time 2 (T2). All items were used to assess their a priori factor, with no cross-loading or correlated uniqueness. Similarly, the model used to represent the multi-item predictors and outcomes included seven factors (availability expectations through information technology communication, social challenge stressors, workplace telepressure, harassment, affective commitment to organization, affective commitment to coworkers, and organizational citizenship behaviors directed towards individuals) defined solely by their a priori items, with no cross-loading or correlated uniqueness. These seven factors were also allowed to freely correlate with one another.

We then proceeded to test of measurement invariance of each of these solutions over time (Millsap, 2011): (i) configural invariance; (ii) weak (loadings) invariance; (ii) strong (loadings and intercepts) invariance; (iv) strict (loadings, intercepts/thresholds, and uniquenesses) invariance; (v) invariance of the latent variance-covariance matrix; and (vi) latent means invariance.

Results

The model fit of all team boosting behaviors solutions is presented in Table S1, and confirmed the adequacy of the CFA model underlying the team boosting behaviors, as well as the configural, weak, strong, strict, latent variances-covariances, and latent means invariance of this solution over time. For our main analyses, factor scores were saved from this final model (latent means invariance), for which parameter estimates are reported in Table S2. These results revealed that mood-enhancing ($\lambda = .637$ to $.899$, $\omega = .927$), energizing ($\lambda = .789$ to $.902$, $\omega = .940$), and uniting ($\lambda = .720$ to $.903$, $\omega = .911$) behaviors were all well-defined by satisfactory factor loadings and composite reliability coefficients.

The model fit of the models including the predictors and outcomes is presented in Table S3 and confirms the adequacy of these measurement models, as well as their configural, weak, strong, strict, latent variances-covariances, and latent means invariance over time. For our main analyses, factor scores were saved from this final model (latent means invariance), for which parameter estimates are reported in Table S4. The factors representing availability expectations through information technology communication ($\lambda = .550$ to $.889$, $\omega = .876$), social challenge stressors ($\lambda = .643$ to $.817$, $\omega = .904$), affective commitment to organization ($\lambda = .795$ to $.914$, $\omega = .890$), affective commitment to coworkers ($\lambda = .877$ to $.894$, $\omega = .915$), organizational citizenship behaviors directed towards individuals ($\lambda = .548$ to $.734$, $\omega = .702$), telepressure ($\lambda = .740$ to $.916$, $\omega = .935$), and harassment ($\lambda =$

.788 to .906, $\omega = .837$) were well-defined by satisfactory factor loadings and composite reliability coefficients. Correlations among all variables are shown in Table S5.

Main Analyses

Latent Profile Analyses

Our main analyses relied on *Mplus 8.9* (Muthén & Muthén, 2023), the maximum likelihood robust estimator, and full information maximum likelihood procedures to handle missing data (Enders, 2010). This approach allowed us to estimate all models using the responses from all participants who completed at least one time point ($n = 415$), rather than relying on the problematic listwise elimination of participants who did not complete both time points ($n = 88$). Time-specific latent profile analytic models including one to eight profiles were estimated while allowing the means and variances of the three team boosting behaviors to be estimated freely across profiles (Morin & Litalien, 2019). These models used 5000 sets of random start values, 1000 iterations, and 200 final optimizations (Hipp & Bauer, 2006). These values were increased to 10000, 1000, and 500 in the latter longitudinal models.

Identifying the optimal number of profiles to retain is a complex decision that needs to be taken while considering multiple sources of information, including (Marsh et al., 2009; McLachlan & Peel, 2000): (a) whether each added profile brings a meaningful contribution to the solution; (b) whether each added profile is theoretically consistent; (c) whether each added profile results in a statistically proper solution (e.g., convergence, lack of negative variance estimates); and (d) a variety of statistical indicators which are available to guide this decision. For these last criteria, a lower value on the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Consistent AIC (CAIC), and sample-size Adjusted BIC (ABIC) indicate better fitting models. Moreover, a statistically significant Bootstrap Likelihood Ratio Test (BLRT) and adjusted Lo, Mendell, and Rubin's (2001) Likelihood Ratio Test (aLMR) both support a model relative to one including fewer profiles. However, statistical research has shown that the BIC, CAIC, ABIC, and BLRT, but not the AIC and aLMR, were efficient at guiding the identification of the optimal number of latent profiles (Diallo et al., 2016, 2017). For this reason, we only report the AIC and aLMR to ensure complete disclosure, and will not use them for purposes of model comparison. In addition, these tests all present a strong sample size dependency (Marsh et al., 2009) and thus often fail to converge on a specific solution. When this happens, scores on the AIC, BIC, CAIC, and ABIC as a function of the number of profiles should be graphically presented in the form of an elbow plot, where the observation of a plateau in the decrease in these values helps to pinpoint the optimal solution (Morin et al., 2011). In practice (e.g., Meyer & Morin, 2016; Morin & Litalien, 2019), the statistical indicators are considered first to help pinpoint a range of acceptable solutions, which are then examined to eliminate those that are statistically improper, before being contrasted in terms of meaningfulness and theoretical conformity. Lastly, we also report an indicator of classification accuracy, the entropy, which should not be used to select the optimal number of profiles (Lubke & Muthén, 2007).

Longitudinal Tests of Profile Similarity

As long as the same number of profiles is identified at both time points, the two time-specific solutions can be integrated into a single longitudinal latent profile model, which can be used to test the similarity of these solutions over time (Morin & Litalien, 2017; Morin et al., 2016b). These tests are realized in sequence, starting by the verification of whether the same number of profiles is identified over time. Both time-specific solutions are then integrated into a single model of *configural* similarity to which equality constraints are then imposed in sequence on the within-profile means (*structural* similarity), variances (*dispersion* similarity), and size (*distributional* similarity). Model comparisons rely on the BIC, CAIC, and ABIC, and profile similarity is supported when two of these indices decrease in a model relative to the previous one in the sequence (Morin et al., 2016b).

Latent Transition Analyses

A latent transition specification (allowing T1 profile membership to predict T2 profile membership) was added to the most similar longitudinal solution to investigate within-person stability and transitions (Collins & Lanza, 2010). This solution and all upcoming analyses were estimated via the manual three-step approach (Asparouhov & Muthén, 2014; Morin & Litalien, 2017). Participants initially presenting very low levels of team boosting behaviors, when they transitioned to another profile at T2, retained low levels of team boosting behaviors. Indeed, 30.6% of the members of the *Very Low Boosting Behaviors* profile at T1 transitioned to the *Low Boosting Behaviors* profile at T2. For members of the *High Boosting Behaviors* profile at T1, transitions involved the *Average Boosting*

Behaviors (13.6%) and *Very High Boosting Behaviors* (2.7%) profiles at T2. For members of the *Low Boosting Behaviors* profile at T1, transitions involved the *Average Boosting Behaviors* (12.9%), *Very Low Boosting Behaviors* (5.4%), and *High Boosting Behaviors* (2.7%) profiles at T2. For members of the *Very High Boosting* profile at T1, transitions involved the *High Boosting Behaviors* (20.9%) and *Average Boosting Behaviors* (5.9%) profiles at T2. Finally, when they transitioned to a new profile at T2, members of the *Average Boosting Behaviors* profile transitioned to the *High Boosting Behaviors* (4.6%), *Low Boosting Behaviors* (3.7%), and *Very Low Boosting* (1.2%) profiles at T2.

Predictors of Profile Membership

We initially investigated the need to incorporate demographics (sex, age, level of education, tenure in the current position, contract, working time, sector, and country) as controls. These variables were incorporated to the solution through a multinomial logistic regression link, and four alternative models were contrasted. The first (null) model assumed no associations between demographics and profile membership. The second model allowed effects to differ over time and the prediction of T2 profile membership to differ across T1 profiles (i.e., reflecting the effect of these variables on specific transitions). The third model only allowed these predictions to vary over time. The last model (*predictive* similarity) constrained these associations to equality over time. Relations between the predictors and profile membership were then assessed using the same sequence.

Outcomes of Profile Membership

Time-specific outcome measures were then incorporated to the solution, and their levels were allowed to differ across profiles and time points. In these analyses, the outcome measures taken at T2 were controlled for their shared variance with the T1 outcome measures (i.e., stability). A second model of *explanatory* similarity was then estimated by fixing these associations to equality across time points. The statistical significance of between-profile differences in outcome levels was assessed using the multivariate delta method (Raykov & Marcoulides, 2004).

Generalizability to Remote and Onsite Workers

Work type was first considered across a series of four models in which its association with profile membership was specified using a multinomial logistic regression link function. First, we estimated a null model assuming no relations between work type and profile membership. Second, the effects of work type were freely estimated, and allowed to vary over time and as a function of T1 profile membership (i.e., effects on transitions). Third, predictions were allowed to differ over time only. Finally, a model of predictive similarity was estimated by constraining these associations to be equal over time. As shown in Table S12, the lowest values on all information criteria were associated with the null model, consistent with a lack of associations between profile membership and work type. This interpretation was supported by an examination of the parameter estimates of these models, which revealed a lack of associations between work type and the profiles.

To investigate whether the role of predictors (availability expectations, social challenge stressors, telepressure, and harassment) differed for employees working onsite or remotely, we also investigated whether the effects of these predictors on profile membership interacted with work type. As shown in Table S12, the lowest values on all information criteria were associated with the null model, consistent with a lack of statistically significant interaction effects.

To further investigate whether associations between the outcomes and the profiles generalized to onsite and remote workers, we first confirm the configural, structural, dispersion, and distributional similarity of the five-profile solution across the two groups of workers at T1 and T2 (see Table S12). Outcomes were then integrated separately to the two time-specific multi-group solutions of distributional similarity. The T1 and T2 results both supported the explanatory similarity of this solution across samples of employees working remotely or onsite, consistent with the presence of outcome associations corresponding to those reported in the main manuscript across groups.

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Table S1*Goodness-of-Fit Statistics for the Estimated Models (Team Boosting Behaviors)*

Description	χ^2 (df)	CFI	TLI	RMSEA	90% CI	CM	$\Delta\chi^2$ (df)	Δ CFI	Δ TLI	Δ RMSEA
<i>Team Boosting Behaviors</i>										
Time 1	528.981 (132)*	.917	.904	.085	[.078; .093]	-	-	-	-	-
Time 2	475.936 (132)*	.912	.899	.089	[.081; .098]	-	-	-	-	-
<i>Team Boosting Behaviors: Longitudinal Invariance</i>										
M1. Configural invariance	1383.797 (561)*	.923	.914	.059	[.056; .063]	-	-	-	-	-
M2. Weak invariance	1399.996 (576)*	.923	.916	.059	[.055; .063]	M1	7.890 (15)	.000	+0.002	.000
M3. Strong invariance	1416.613 (591)*	.923	.918	.058	[.054; .062]	M2	13.383 (15)	.000	+0.002	-.001
M4. Strict invariance	1422.111 (609)*	.924	.922	.057	[.053; .061]	M3	11.197 (18)	+0.001	+0.004	-.001
M5. Variance-covariance invariance	1427.459 (615)*	.924	.923	.056	[.053; .060]	M4	4.584 (6)	.000	+0.001	-.001
M6. Latent means invariance	1428.895 (618)*	.925	.923	.056	[.052; .060]	M5	.465 (3)	+0.001	.000	.000

Note. * $p < .01$; 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 Team Boosting Behaviors)

Items	Mood-enhancing λ	Energizing λ	Uniting λ	δ
Mood-enhancing				
Item 1	.871			.241
Item 2	.893			.203
Item 3	.899			.191
Item 4	.816			.334
Item 5	.804			.353
Item 6	.637			.594
Energizing				
Item 1		.858		.264
Item 2		.845		.286
Item 3		.789		.378
Item 4		.819		.330
Item 5		.902		.187
Item 6		.887		.213
Uniting				
Item 1			.831	.309
Item 2			.724	.476
Item 3			.720	.481
Item 4			.756	.429
Item 5			.823	.323
Item 6			.903	.185
ω	.927	.940	.911	
Factor Correlations				
Mood-enhancing	-			
Energizing	.589	-		
Uniting	.656	.855	-	

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

Table S3*Goodness-of-Fit Statistics for the Estimated Models (Predictors and Outcomes)*

Description	χ^2 (df)	CFI	TLI	RMSEA	90% CI	CM	$\Delta\chi^2$ (df)	Δ CFI	Δ TLI	Δ RMSEA
<i>Predictors and Outcomes</i>										
Time 1	1077.183 (414)*	.907	.895	.062	[.058; .067]	-	-	-	-	-
Time 2	995.336 (414)*	.898	.885	.066	[.060; .071]	-	-	-	-	-
<i>Predictors and Outcomes: Longitudinal Invariance</i>										
M1. Configural invariance	3158.604 (1709)*	.908	.898	.045	[.043; .048]	-	-	-	-	-
M2. Weak invariance	3163.819 (1732)*	.909	.901	.045	[.042; .047]	M1	17.753 (23)	+0.001	+0.003	.000
M3. Strong invariance	3199.044 (1757)*	.908	.901	.044	[.042; .047]	M2	34.024 (25)	-0.001	.000	-0.001
M4. Strict invariance	3228.152 (1788)*	.909	.903	.044	[.042; .046]	M3	39.012 (31)	+0.001	+0.002	.000
M5. Variance-covariance invariance	3275.437 (1810)*	.907	.903	.044	[.042; .047]	M4	47.141 (22)*	-0.002	.000	.000
M6. Latent means invariance	3288.091 (1816)*	.907	.903	.044	[.042; .047]	M5	12.843 (6)*	.000	.000	.000

Note. * $p < .05$; 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 Predictors and Outcomes)

Items	AE λ	SS λ	ACO λ	ACC λ	OCB-I λ	TEL λ	HAR λ	δ
Availability expectations								
Item 1	.878							.229
Item 2	.889							.209
Item 3	.644							.585
Item 4	.642							.588
Item 5	.550							.698
Item 6	.776							.398
Social stressors								
Item 1		.658						.567
Item 2		.692						.521
Item 3		.793						.371
Item 4		.817						.332
Item 5		.807						.349
Item 6		.766						.413
Item 7		.696						.516
Item 8		.643						.586
ACO								
Item 1			.914					.164
Item 2			.885					.217
Item 3			.795					.368
ACC								
Item 1				.882				.222
Item 2				.877				.231
Item 3				.894				.202
OCB-I								
Item 1					.734			.461
Item 2					.700			.510
Item 3					.548			.699
Telepressure								
Item 1						.744		.446
Item 2						.740		.452
Item 3						.822		.324
Item 4						.900		.190
Item 5						.916		.161
Item 6						.902		.186
Harassment								
Item 1							.906	.180
Item 2							.788	.379
ω	.876	.904	.890	.915	.702	.935	.837	
Factor Correlations								
AE								
SS	.344							
ACO	<i>-.017</i>	<i>.001</i>						
ACC	<i>.013</i>	<i>.008</i>	.607					
OCB-I	.227	.425	.315	.469				
TEL	.335	.206	.055	.094	.142			
HAR	.171	.076	-.219	-.199	.079	.012		

Note. λ : Factor loading; δ : Item uniqueness; ω : Omega coefficient of composite reliability; AE: Availability expectations through information technology communication; SS: Social challenge stressors; ACO: Affective commitment to organization; ACC: Affective commitment to colleagues; OCB-I: Organizational citizenship behaviors directed towards individuals; TEL: Telepressure; HAR: Harassment; non-significant parameters ($p > .05$) are marked in italics.

Table S5
Correlations between Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Sex	-																
2. Age	.120*	-															
3. Working time	-.251**	.081	-														
4. Sector	-.182**	.041	.084	-													
5. Country	.156**	-.063	-.158**	-.169**	-												
6. Education	.024	-.127**	-.098*	.088	.014	-											
7. Tenure	.072	.381**	.120*	.085	-.011	-.177**	-										
8. Contract	.008	-.001	.056	-.004	-.030	.044	-.092	-									
9. Work type	.053	-.034	-.138**	-.111*	-.050	.091	-.099*	.038	-								
10. Mood-enhancing (T1)†	-.056	-.123*	-.045	-.018	-.078	-.114*	-.062	-.026	-.086	-							
11. Energizing (T1)†	.001	-.061	-.087	-.090	-.013	.003	.009	-.022	-.018	.618**	-						
12. Uniting (T1)†	-.056	-.043	-.068	-.047	-.036	-.009	-.005	-.015	-.025	.699**	.891**	-					
13. AE (T1)†	-.043	-.111*	.036	-.081	.016	.021	.019	-.049	-.076	.070	.198**	.172**	-				
14. Social stressors (T1)†	.030	-.049	-.104*	-.013	-.032	.138**	-.069	.053	-.020	.170**	.411**	.336**	.381**	-			
15. ACO (T1)†	-.075	.002	.039	.014	-.056	.008	.025	-.045	.032	.271**	.332**	.379**	.001	-.007	-		
16. ACC (T1)†	-.047	-.070	.024	.016	-.039	-.066	.052	.021	.022	.410**	.343**	.484**	.023	.000	.638**	-	
17. OCB-I (T1)†	-.085	-.132**	.012	-.020	-.102*	-.071	-.020	.029	-.150**	.480**	.589**	.646**	.280**	.490**	.354**	.525**	-
18. Telepresssure (T1)†	-.190**	-.126*	-.053	-.039	-.129**	.041	-.046	-.069	.106*	.027	.079	.085	.394**	.221**	.042	.051	.152**
19. Harassment (T1)†	.010	-.048	-.029	-.095	.025	-.133**	-.010	-.056	-.119*	-.003	-.049	-.060	.203**	.079	-.263**	-.238**	.081
20. Mood-enhancing (T2)†	-.111*	-.127**	-.014	.029	-.120*	-.139**	-.050	-.038	-.090	.885**	.586**	.642**	.105*	.181**	.283**	.408**	.495**
21. Energizing (T2)†	-.006	-.039	-.067	-.066	-.051	-.018	-.001	.028	.001	.544**	.887**	.811**	.196**	.389**	.326**	.324**	.564**
22. Uniting (T2)†	-.070	-.019	-.019	-.020	-.072	-.058	.013	.018	-.021	.607**	.799**	.864**	.201**	.333**	.356**	.420**	.612**
23. AE (T2)†	-.075	-.126*	-.004	-.019	-.017	.000	-.020	-.021	-.106*	.077	.163**	.140**	.864**	.379**	-.008	-.009	.214**
24. Social stressors (T2)†	.066	-.038	-.105*	.018	-.003	.123*	-.067	.046	-.028	.133**	.369**	.281**	.379**	.872**	-.003	.025	.385**
25. ACO (T2)†	-.066	.002	.050	.001	-.047	.030	.056	-.043	.042	.274**	.351**	.395**	.053	.025	.952**	.637**	.358**
26. ACC (T2)†	-.102*	-.029	.067	.052	-.084	-.038	.052	.020	-.001	.401**	.350**	.482**	.066	.040	.655**	.789**	.498**
27. OCB-I (T2)†	-.120*	-.118*	.020	.017	-.105*	-.056	-.017	.035	-.131**	.438**	.553**	.603**	.195**	.366**	.451**	.485**	.839**
28. Telepressure (T2)†	-.168**	-.095	-.052	.076	-.159**	.063	-.069	.032	.126**	.083	.128**	.153**	.310**	.246**	.018	.108*	.157**
29. Harassment (T2)†	.057	-.012	-.081	-.068	.016	-.148**	-.041	-.042	-.115*	.013	-.011	-.024	.137**	.075	-.215**	-.174**	.114*

	18	19	20	21	22	23	24	25	26	27	28	29
18. Telepressure (T1)†	-											
19. Harassment (T1)†	.029	-										
20. Mood-enhancing (T2)†	.050	-.012	-									
21. Energizing (T2)†	.081	-.064	.629**	-								
22. Uniting (T2)†	.090	-.060	.695**	.905**	-							
23. AE (T2)†	.333**	.154**	.147**	.194**	.185**	-						
24. Social stressors (T2)†	.203**	.042	.169**	.403**	.343**	.384**	-					
25. ACO (T2)†	.013	-.249**	.293**	.344**	.387**	-.018	.022	-				
26. ACC (T2)†	.022	-.265**	.443**	.359**	.497**	.010	.032	.696**	-			
27. OCBI-I (T2)†	.131**	.020	.504**	.594**	.654**	.193**	.380**	.507**	.587**	-		
28. Telepressure (T2)†	.687**	-.016	.119*	.118*	.153**	.333**	.240**	.061	.141**	.206**	-	
29. Harassment (T2)†	.032	.747**	.021	.010	-.006	.178**	.081	-.250**	-.252**	.019	-.011	-

Note. * $p < .05$; ** $p < .01$; † variables estimated from factor scores with a mean of 0 and a standard deviation of 1; AE: Availability expectations through information technology communication; ACO: Affective commitment to organization; ACC: Affective commitment to coworkers; sex was coded 0 for women and 1 for men; working time was coded 0 for employed full-time and 1 for employed part-time; sector was coded 0 for private sector and 1 for public sector; country was coded 0 for UK and 1 for USA; education was coded 0 for non-university students and 1 for students with a university degree; contract was coded 0 for permanent contract and 1 for temporary contract; and work type was coded 0 for onsite workers and 1 for remote workers.

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
<i>Time 1</i>										
1 Profile	-1745.820	6	.955	3503.639	3533.809	3527.809	3508.769	Na	Na	Na
2 Profiles	-1512.548	13	1.123	3051.096	3116.464	3103.464	3062.212	.812	< .001	< .001
3 Profiles	-1411.824	20	1.613	2863.648	2964.214	2944.214	2880.749	.808	.303	< .001
4 Profiles	-1340.356	27	1.212	2734.712	2870.476	2843.476	2757.798	.849	.046	< .001
5 Profiles	-1294.643	34	1.088	2657.286	2828.247	2794.247	2686.357	.868	.060	< .001
6 Profiles	-1255.960	41	1.079	2593.919	2800.079	2759.079	2628.976	.862	.062	< .001
7 Profiles	-1231.473	48	1.034	2558.946	2800.303	2752.303	2599.987	.864	.033	< .001
8 Profiles	-1209.106	55	.936	2528.212	2804.767	2749.767	2575.239	.880	.005	< .001
<i>Time 2</i>										
1 Profile	-1673.986	6	.991	3359.972	3390.141	3384.141	3365.102	Na	Na	Na
2 Profiles	-1445.072	13	1.177	2916.145	2981.512	2968.512	2927.260	.794	< .001	< .001
3 Profiles	-1333.591	20	1.385	2707.182	2807.747	2787.747	2724.282	.821	.147	< .001
4 Profiles	-1252.952	27	1.105	2559.904	2695.667	2668.667	2582.990	.859	.014	< .001
5 Profiles	-1204.174	34	1.121	2476.347	2647.309	2613.309	2505.418	.863	.043	< .001
6 Profiles	-1173.851	41	1.013	2429.702	2635.862	2594.862	2464.759	.872	< .001	< .001
7 Profiles	-1152.961	48	1.011	2401.922	2643.280	2595.280	2442.964	.875	.076	< .001
8 Profiles	-1136.568	55	.942	2383.136	2659.691	2604.691	2430.162	.889	.100	< .001

Note. LL: Model loglikelihood; #fp: Number of free parameters; scaling: Scaling correction factor associated with robust maximum likelihood estimates; AIC: Akaike 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.

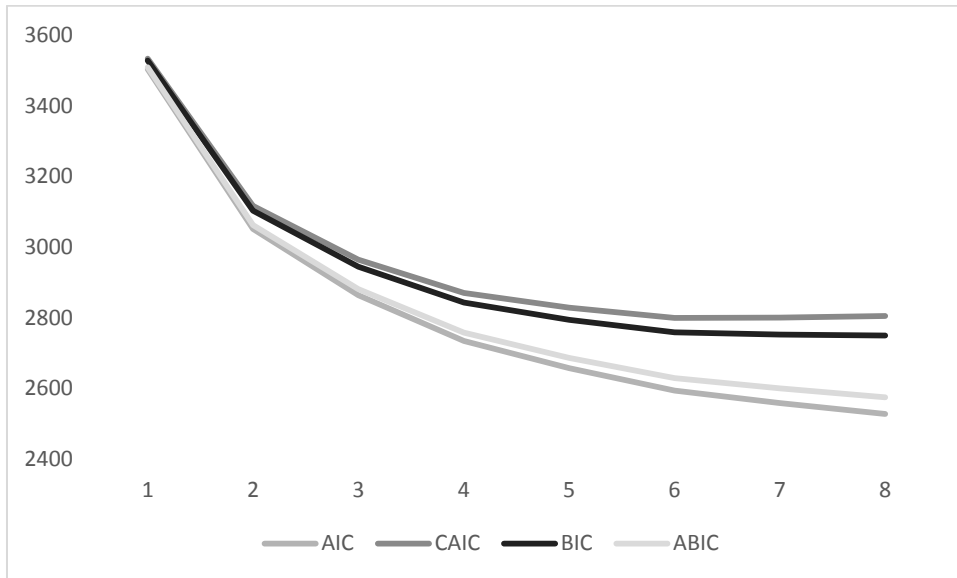


Figure S1
Elbow Plot of the Value of the Information Criteria for Solutions Including Different Numbers of Latent Profiles at Time 1

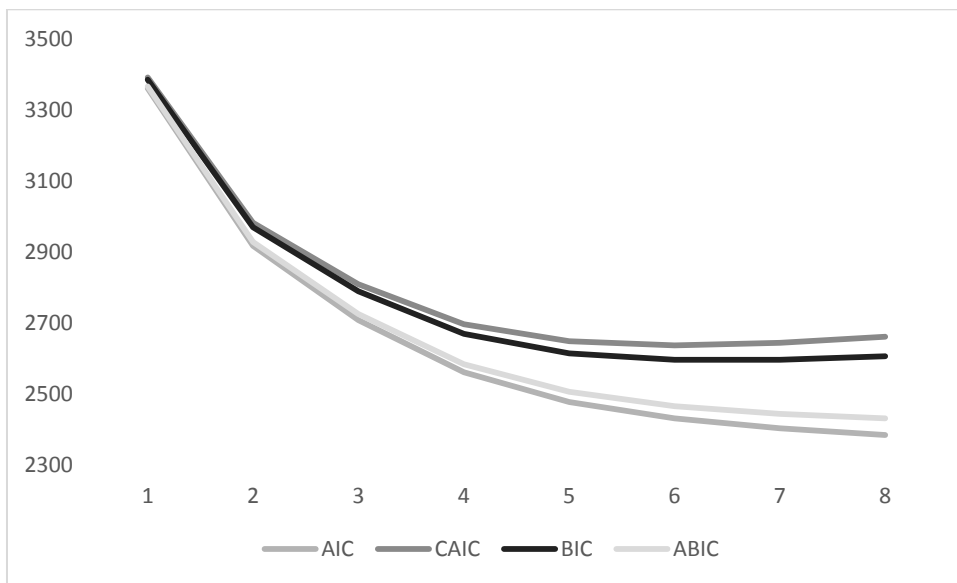


Figure S2
Elbow Plot of the Value of the Information Criteria for Solutions Including Different Numbers of Latent Profiles at Time 2

Table S7*Detailed Parameter Estimates from the Final LPA Solution (Distributional Similarity)*

	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
	Mean [CI]	Mean [CI]	Mean [CI]	Mean [CI]	Mean [CI]
Mood-enhancing	-1.526 [-1.888; -1.164]	.633 [.434; .832]	-.575 [-.779; -.371]	1.067 [.632; 1.502]	.131 [-.159; .420]
Energizing	-1.764 [-2.068; -1.459]	.835 [.456; 1.215]	-.751 [-.985; -.517]	1.724 [1.396; 2.052]	.047 [-.256; .350]
Uniting	-1.864 [-2.207; -1.521]	.834 [.523; 1.146]	-.779 [-1.033; -.524]	1.619 [1.251; 1.986]	.111 [-.191; .413]
	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
	Variance [CI]	Variance [CI]	Variance [CI]	Variance [CI]	Variance [CI]
Mood-enhancing	.481 [.236; .726]	.486 [.369; .603]	.359 [.254; .463]	.708 [.347; 1.068]	.484 [.373; .596]
Energizing	.246 [.175; .317]	.133 [.084; .182]	.154 [.119; .188]	.077 [.013; .141]	.173 [.110; .236]
Uniting	.330 [.199; .461]	.080 [.056; .105]	.134 [.091; .178]	.051 [-.047; .149]	.109 [.078; .141]

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: *Very Low Boosting Behaviors*; Profile 2: *High Boosting Behaviors*; Profile 3: *Low Boosting Behaviors*; Profile 4: *Very High Boosting Behaviors*; and Profile 5: *Average Boosting Behaviors*.

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
<i>Time 1</i>					
Profile 1	1.000	.000	.000	.000	.000
Profile 2	.000	.893	.044	.063	.000
Profile 3	.000	.061	.939	.000	.000
Profile 4	.000	.038	.000	.925	.037
Profile 5	.000	.000	.000	.078	.922
<i>Time 2</i>					
Profile 1	.969	.031	.000	.000	.000
Profile 2	.033	.921	.046	.000	.000
Profile 3	.000	.042	.893	.000	.065
Profile 4	.000	.000	.000	.957	.043
Profile 5	.000	.000	.068	.037	.895

Note. Profile 1: *Very Low Boosting Behaviors*; Profile 2: *High Boosting Behaviors*; Profile 3: *Low Boosting Behaviors*; Profile 4: *Very High Boosting Behaviors*; and Profile 5: *Average Boosting Behaviors*.

Table S9*Transition Probabilities*

	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
Profile 1	.694	.000	.306	.000	.000
Profile 2	.000	.837	.000	.027	.136
Profile 3	.054	.027	.790	.000	.129
Profile 4	.000	.209	.000	.732	.059
Profile 5	.012	.046	.037	.000	.905

Note. Profile 1: *Very Low Boosting Behaviors*; Profile 2: *High Boosting Behaviors*; Profile 3: *Low Boosting Behaviors*; Profile 4: *Very High Boosting Behaviors*; and Profile 5: *Average Boosting Behaviors*.

Table S10*Results from the Predictive Analyses*

Predictors	Profile 1 vs 5		Profile 2 vs 5		Profile 3 vs 5	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Availability expectations	-.310 (.217)	.733	-.120 (.169)	.887	-.259 (.163)	.772
Social stressors	-1.027 (.356)**	.358	.439 (.142)**	1.551	-.674 (.173)**	.510
Telepressure	-.159 (.202)	.853	.146 (.171)	1.157	.258 (.147)	1.295
Harassment	.196 (.211)	1.216	.213 (.139)	1.238	.233 (.138)	1.262
Predictors	Profile 4 vs 5		Profile 1 vs 4		Profile 2 vs 4	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Availability expectations	.262 (.251)	1.299	-.572 (.307)	.564	-.382 (.271)	.683
Social stressors	.402 (.242)	1.495	-1.429 (.417)**	.240	.037 (.248)	1.038
Telepressure	-.241 (.243)	.786	.083 (.297)	1.086	.387 (.270)	1.473
Harassment	-1.337 (1.249)	.263	1.533 (1.260)	4.631	1.550 (1.250)	4.713
Predictors	Profile 3 vs 4		Profile 1 vs 3		Profile 2 vs 3	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Availability expectations	-.521 (.269)	.594	-.051 (.217)	.950	.139 (.173)	1.150
Social stressors	-1.075 (.268)**	.341	-.354 (.360)	.702	1.113 (.182)**	3.042
Telepressure	.500 (.258)	1.648	-.417 (.205)*	.659	-.112 (.170)	.894
Harassment	1.570 (1.251)	4.805	-.037 (.207)	.964	-.019 (.133)	.981
Predictors	Profile 1 vs 2					
	Coef. (SE)	OR				
Availability expectations	-.191 (.235)	.826				
Social stressors	-1.466 (.367)**	.231				
Telepressure	-.305 (.228)	.737				
Harassment	-.018 (.209)	.983				

Note. * $p < .05$; ** $p < .01$; SE: Standard error of the coefficient; OR: Odds ratio; the coefficients and OR reflect the effects of the predictors on the likelihood of membership into the first listed profile relative to the second listed profile; availability expectations through information and communication technology, social challenge stressors, telepressure, and harassment are estimated from factor scores with a standard deviation of 1 and a mean of 0; Profile 1: *Very Low Boosting Behaviors*; Profile 2: *High Boosting Behaviors*; Profile 3: *Low Boosting Behaviors*; Profile 4: *Very High Boosting Behaviors*; and Profile 5: *Average Boosting Behaviors*.

Table S11*Associations between Profile Membership and the Outcomes Taken from the Model of Explanatory Similarity (Equal across Time Points)*

	Profile 1 M [CI]	Profile 2 M [CI]	Profile 3 M [CI]	Profile 4 M [CI]	Profile 5 M [CI]	Summary of Statistically Significant Differences
Commitment to the organization	-1.451 [-1.976; -.926]	.350 [.059; .642]	.029 [-.357; .415]	.945 [.777; 1.113]	-.093 [-.513; .327]	1 < 2 = 5 < 4; 3 = 5; 1 < 3 < 2 < 4
Commitment to coworkers	-1.707 [-2.21; -1.192]	.350 [.078; .622]	-.019 [-.340; .302]	.984 [.790; 1.177]	.011 [-.330; .352]	1 < 2 = 5 < 4; 3 = 5; 1 < 3 < 2 < 4
OCB-I	-1.270 [-1.595; -.945]	.524 [.340; .708]	-.400 [-.595; -.204]	1.121 [.823; 1.418]	.031 [-.205; .267]	1 < 3 < 5 < 2 < 4

Note. M: Mean; CI: 95% confidence interval; OCB-I: Organizational citizenship behaviors directed towards individuals; indicators of affective commitment to organization and coworkers, and organizational citizenship behaviors directed towards individuals are factor scores with a mean of 0 and a standard deviation of 1; Profile 1: *Very Low Boosting Behaviors*; Profile 2: *High Boosting Behaviors*; Profile 3: *Low Boosting Behaviors*; Profile 4: *Very High Boosting Behaviors*; and Profile 5: *Average Boosting Behaviors*.

Table S12*Results from the Multi-Group Models*

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy
<i>Predictive Similarity: Work Type</i>								
Null Effects Model	-1245.247	26	.615	2542.493	2673.228	2647.228	2564.724	.853
Profile-Specific Free Relations with Predictor	-1238.454	54	.548	2584.908	2856.435	2802.435	2631.079	.859
Free Relations with Predictor	-1240.493	34	.746	2548.986	2719.947	2685.947	2578.057	.859
Equal Relations with Predictor	-1244.684	30	.669	2549.637	2700.216	2670.216	2575.018	.853
<i>Predictive Similarity: Predictors x Work Type</i>								
Null Effects Model	-5740.776	214	1.418	11909.552	12985.603	12771.603	12092.529	.861
Profile-Specific Free Relations with Predictors	-5670.335	446	2.253	12232.669	14475.281	14029.281	12614.014	.896
Free Relations with Predictors	-5692.851	266	1.230	11917.702	13255.224	12989.224	12145.141	.918
Equal Relations with Predictors	-5733.855	230	1.387	11927.710	13084.214	12854.214	12124.367	.861
<i>Multi-Group Tests of Similarity (Time 1)</i>								
Configural Similarity	-1544.630	69	1.041	3227.259	3574.210	3505.210	3286.256	.905
Structural Similarity	-1566.875	54	1.000	3241.751	3513.278	3459.278	3287.923	.887
Dispersion Similarity	-1577.809	39	1.091	3233.618	3429.721	3390.721	3266.964	.869
Distributional Similarity	-1578.644	35	1.085	3227.287	3403.277	3368.277	3257.214	.868
<i>Multi-Group Explanatory Similarity (Time 1)</i>								
Free Relations with Outcomes	-3019.109	33	1.003	6104.218	6270.151	6237.151	6132.434	.885
Equal Relations with Outcomes	-3035.447	18	1.132	6106.893	6197.402	6179.402	6122.284	.885
<i>Multi-Group Tests of Similarity (Time 2)</i>								
Configural Similarity	-1460.469	69	1.008	3058.938	3405.890	3336.890	3117.936	.897
Structural Similarity	-1480.468	54	.996	3068.937	3340.464	3286.464	3115.109	.870
Dispersion Similarity	-1487.480	39	1.093	3052.961	3249.063	3210.063	3086.307	.863
Distributional Similarity	-1488.174	35	1.117	3046.349	3222.338	3187.338	3076.275	.863
<i>Multi-Group Explanatory Similarity (Time 2)</i>								
Free Relations with Outcomes	-2941.543	33	1.478	5949.086	6115.019	6082.019	5977.302	.875
Equal Relations with Outcomes	-2959.282	18	1.303	5954.563	6045.072	6027.072	5969.954	.869

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