Longitudinal Trajectories of Perceived Organizational Support: A Growth Mixture Analysis

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Abstract

This research aims to identify trajectories of employees' perceptions of organizational support (POS) over the course of an eight-month period, and to document associations between these longitudinal trajectories and several outcomes related to employees' well-being (i.e., job satisfaction), attitudes (i.e., turnover intentions, affective commitment) and behaviors (i.e., voice behaviors). POS ratings provided each four months by a sample of 747 employees were analyzed using person-centered growth mixture analyses. Results revealed that longitudinal heterogeneity in POS trajectories were best captured by the identification of four distinct profiles of employees. Two of these profiles followed stable high (67.2%) and low (27.3%) POS trajectories, whereas the remaining profiles were characterized by increasing (2.2%) or decreasing (3.3%) POS trajectories. Our results showed that, by the end of the follow up period, the most desirable outcome levels were associated, in order, with the increasing, high, low, and decreasing trajectories. This research has important implications by showing that perceptions of organizational support fluctuate over time for some employees and help better predicting valuable work-related outcomes. These findings shed a new perspective on organizational support theory by adopting a dynamic perspective, and revealing that changes over time in POS are more potent predictors of valuable work-related outcomes than stable POS levels.
Keywords: POS, trajectories, growth mixture analyses, job satisfaction, turnover intentions.

Longitudinal Trajectories of Perceived Organizational Support: A Growth Mixture Analysis

Organizational support theory (OST) suggests that employees' perceptions regarding the extent to which the organization values their contributions and cares about their well-being (perceived organizational support; POS) are an important determinant of their performance and well-being (e.g., Eisenberger and Stinglhamber, 2011). Supporting this, meta-analytic evidence has demonstrated clear associations between POS and a variety of positive organizational and individual outcomes, such as well-being and desirable work attitudes and behaviors (e.g., Kurtessis *et al.*, 2017). The majority of these prior studies conducted on POS has been cross-sectional, thus limiting the examination of POS as a static construct and ignoring its intrinsically dynamic nature. Furthermore, prior research on POS has been mainly limited to the adoption of a variable centered approach, assuming that all employees come from the same underlying population, and that the obtained results can be generalized to all members of this population (Caesens *et al.*, 2019). Little is known about how POS evolves over time, how this evolution differs across subpopulations of employees, and what consequences are associated with these systematic time-structured variations.

Indeed, Caesens and Stinglhamber (2020) recently reinforce the need for scholars to explore POS dynamically using longitudinal research designs, while paying special attention to inter-individual variations in the shape of these trajectories. More precisely, they noted the need to "analyze whether employees who generally perceive high levels of POS may react more negatively to a slight decrease in their POS over time, as compared to employees who are characterized by stable perceptions of moderate support from their organization over time" (p.476). To our knowledge, this idea has never been empirically verified.

This study was designed to address this call by examining how POS trajectories evolve dynamically over a period of eight months among distinct subpopulations of employees. To achieve this, we rely on growth mixture analyses (GMM) of POS ratings obtained in a three-wave longitudinal study with four-month intervals. Additionally, this study investigates how these identified POS trajectories will differ in their associations with the three main categories of outcomes considered in OST (Eisenberger *et al.*, 2020), namely employees' subjective well-being (i.e., job satisfaction), attitudes (i.e., turnover intentions, and affective organizational commitment), and behaviors (i.e., voice behaviors).

By doing so, this research contributes to the existing literature in at least three important ways. First, this research enriches OST by providing a more comprehensive understanding of POS as a dynamic construct, which is closer to employees' true time structured reality. Second, this research responds to the recent call to more systematically examine inter-individual variations in the shape of POS trajectories as they unfold over time, and the consequences of these variations (Caesens and Stinglhamber, 2020). Third, by providing a better understanding of the effects of POS trajectories on several key outcomes, this research seeks to contribute to informing practitioners on how to best allocate POS as part of improved interventions programs targeting distinct subpopulations of employees.

POS as a Dynamic Process

OST (e.g., Eisenberger and Stinglhamber, 2011) positions POS as a key determinant of their performance and well-being at work. Anchored in the norm of reciprocity and social exchange theory, OST suggests that POS initiates a social exchange process wherein employees come to feel an obligation to reciprocate for POS by helping the organization to reach its goals, in turn leading to more positive attitudes and behaviors. Second, POS is proposed to help fulfill employees' basic socioemotional needs (need for esteem, emotional support), in turn leading to subjective well-being. Supporting this, several variable-centered studies have shown that POS is related to higher levels of levels of work performance (e.g., Neves and Eisenberger, 2012), affective commitment (e.g., Rhoades *et al.*, 2001) and job satisfaction (e.g., Eisenberger *et al.*, 1997). So far, most of these studies were cross-sectional, measuring variables at one time point (e.g., Eisenberger *et al.*, 2020). The few longitudinal studies conducted to date have been limited to two measurement points (e.g., Eisenberger *et al.*, 2002), thus ignoring the dynamic nature of POS and its potential consequences.

Yet, POS is recognized to reflect a dynamic construct (Caesens, Stinglhamber and Ohana, 2016) that varies across employees within the same organization (e.g., Frear *et al.*, 2017), and that may change over time within specific employees (e.g., Eisenberger and Stinglhamber, 2011). Indeed, the social exchange process that is proposed to underpin POS explicitly positions POS as a dynamic process that should fluctuate over time in response to employees' perceptions of their treatment by the organization (Eisenberger and Stinglhamber, 2011). This dynamic view has led to the proposition that that "POS may be affected by more than just the level of certain antecedents but also by changes in antecedents due to variations in work experiences inherent to organizational life" (Caesens, Stinglhamber and Ohana, 2016, p.216). In line with this, it has been proposed that POS tends to drop during the first six months of employment (Eisenberger and Stinglhamber, 2011) and to fluctuate as a response of the changing workplace characteristics to which an employee is exposed (Caesens, Stinglhamber and Ohana, 2016). Furthermore, POS is assumed to present longitudinal stability, given that it is assumed to be "based on accumulated experience and reflects such a variety of experiences" (Ford *et al.*, 2018, p.177).

Empirically, most of previous longitudinal investigations of POS have sought to examine the directionality of longitudinal associations between POS and various antecedents (e.g., perceived supervisor support: Eisenberger *et al.*, 2002) or outcomes (e.g., proactive behaviors: Caesens, Marique *et al.*, 2016). These studies reported moderate estimates of rank-order stability (r=.34 to .42) over two to three years (e.g., Chen *et al.*, 2009; Neves and Eisenberger, 2012) that increase when shorter time lags are considered (e.g., 5 months: r=.52; Eisenberger *et al*., 2014; 3 months: r=.63; Eisenberger *et al.*, 2002; 4 months: r=.86; Caesens, Marique *et al.,* 2016). Importantly, these rank-order stability coefficients suggest some stability, but also that POS might still change over-time for a substantial portion of employees.

To our knowledge, a single study has relied on more than two measurement points, allowing for a consideration of intra-individual fluctuations in POS trajectories, and of inter-individual heterogeneity in these time-structured variations. In this study, Caesens, Stinglhamber and Ohana (2016) investigated momentary fluctuations in POS trajectories occurring weekly over the course of twelve weeks. In accordance with the dynamic perspective, their results revealed that 48 percent of the variance in POS ratings was due to within-person fluctuations. Interestingly, Caesens, Stinglhamber *et al.* (2016) showed that substantial variation remained at the between-person level. Part of this heterogeneity might be due to the presence of subpopulations of employees following distinct longitudinal trajectories of POS. However, a limitation of this study was that the exact shape of intra-individual trajectories, and the nature of inter-individual variations in the shape of these trajectories, were not directly examined. Yet, to fully understand the experience of POS, it is of upmost importance to examine how it fluctuates over time, and how these fluctuations may differ across distinct subpopulations of employees (Caesens and Stinglhamber, 2020).

More generally, prior research on POS has been mainly variable-centered in nature and limited to achieving a description of the average associations among constructs occurring in a specific sample (Caesens *et al.*, 2019). In contrast, a person-centered approach is much closer to employees' reality (Hofmans *et al.*, 2020) and provides a way to assess how these relations differ across subpopulations of employees (e.g., Marsh *et al.*, 2009). This study was designed to address this limitation by identifying the shape of POS trajectories occurring within distinct subpopulations of employees, via the reliance on person-centered growth mixture analyses (Morin, 2016).

A Longitudinal Person-Centered Perspective on POS

Applying a growth mixture analyses to a sample of employees who provided POS ratings three times over the course of eight months, this study aims to identify relatively homogenous subpopulations of employees following distinct POS trajectories. In the absence of prior guidance and research, it is unrealistic to formulate explicit hypotheses regarding the expected nature and the number of POS trajectories. Still, based on the high level of between- and within-person heterogeneity identified in previous research (e.g., Caesens, Stinglhamber and Ohana, 2016), we assume that three to five profiles will be necessary to depict POS trajectories. Additionally, based on the theoretical argument that POS is a rather stable perception (Ford *et al.*, 2018) and given the moderate (Eisenberger *et al.*, 2002; Eisenberger *et al.*, 2014) to high (Caesens, Marique *et al.*,2016) levels of rank-order stability identified in previous POS research relying on similar time intervals, we expect a majority of employees to follow reasonably stable POS trajectories (linear trajectories of stable low, average, or high POS). Yet, given the expected dynamic nature of POS (Caesens, Stinglhamber *et al.*, 2016), we expect to identify specific profiles of employees whose trajectories would reflect increases or decreases over time in POS levels. These trajectories might be characterized by a linear increase or decrease of POS over time.

Outcomes of POS Trajectories

Caesens and Stinglhamber (2020) recently reinforced the need for scholars to examine the nature of POS trajectories most commonly observed among distinct subpopulations of employees and, more critically, the outcome implications of these trajectories. Importantly, when person-centered analyses (such GMM) are used without the guidance of strong research hypotheses, it is crucial to document the construct validity of the distinct profiles of longitudinal trajectories by assessing their associations with theoretically-relevant outcome variables (Morin, 2016). Thus, our second objective was to analyze how the identified POS trajectories profiles would be associated with outcomes. Based on OST (e.g., Eisenberger *et al.*, 2020), we focused on three core categories of outcomes: (1) employees' well-being (i.e., job satisfaction), (2) work-related attitudes (i.e., turnover intentions and affective commitment), and (3) behaviors (i.e., voice behaviors).

Prior variable-centered studies have documented associations between POS and these outcomes (e.g., Eisenberger *et al.*,1997; Neves and Eisenberger, 2012). In accordance with these results and with the core theoretical underpinnings of OST (Eisenberger and Stinglhamber, 2011), the norm of reciprocity and social exchange theory, we expect that profiles of employees presenting longitudinal trajectories characterized by higher or increasing levels of POS will be associated with the more positive outcomes (i.e., higher levels of job satisfaction, affective commitment and voice behaviors, and lower levels of turnover intentions). Indeed, employees perceiving high level of POS would feel an obligation to reciprocate for the positive treatment received, notably by increasing their positive attitudes and behaviors at work (Eisenberger and Stinglhamber, 2011). Supporting this assertion, a recent study using a person-centered approach to social support at work (including POS, supervisor support and colleagues support) indicated that as a whole, profiles characterized by higher levels of support were associated with the most positive outcomes (Caesens *et al.*, 2019). On the contrary, the profiles characterized by profiles with low support were associated with the worst outcomes. Thus, we expect profiles presenting longitudinal trajectories characterized by lower or decreasing levels of POS to be associated with the least desirable outcomes.

Furthermore, psychological contract theory (Coyle-Shapiro and Conway, 2004) and social exchange theory suggest that "when the organization is perceived to break a promise, employees reciprocate by hurting organizational interests" (Bordia *et al.*, 2008, p.1105), thus reducing their positive attitudes and behaviors at work. Moreover, POS has been proposed to provide information to employees about their status within the organization, which allows them to develop a positive social identity when POS is high (Marique *et al.*, 2013). Therefore, employees perceiving decreases in POS might come to feel more threatened in their social identities than employees presenting more stable, albeit low, POS perceptions. They might react more negatively, as illustrated by lower levels of well-being, less positive attitudes, and less desirable behaviors (Caesens and Stinglhamber, 2020). Alternatively, increasing POS levels might lead to the development of a stronger sense of social identify as a valued member of the organization and should lead to a marked desire to reciprocate. In sum, we expect employees to react more positively or negatively to increasing or decreasing POS trajectories than to stable POS trajectories.

Method

Design and Sample

Prolific Academic was used to invite participants to complete an electronic questionnaire in November 2016 (Time 1), March 2017 (Time 2), and July 2017 (Time 3). The decision to rely on an eight-month period with four-month intervals is based on the results from prior research showing that POS ratings tend to be highly stable over short time lags (3 or 4 months*:* r=.63 to .83; Caesens, Marique *et al.*, 2016; Eisenberger *et al.*, 2002), and become less stable over longer intervals (5 to 8 months: r=.52 to .57; Eisenberger *et al.*, 2014; Kelley *et al.*, 2014), before reducing further over longer intervals (two to three years: r=.34 to .42; Chen *et al.*, 2009; Neves and Eisenberger, 2012). Besides being consistent with the time frame used in most of these previous longitudinal studies of POS, this timeframe was chosen to grasp both the stability and fluctuations of the POS construct.

At each measurement occasion, the goals of the study were explained to participants who were assured that they could stop their participation at any time and that their confidentiality was guaranteed (participants has to provide their own personal identifier used to connect their responses over time). Participants were allocated £1.50 upon completion of each of the three surveys (15 minutes). This research project received approval from the University Research Ethics committee.

Three pre-screening criteria were utilized to limit participation to individuals who: (1) had an approval score ≥ 90% based on their prior participations in Prolific Academic surveys, (2) were native English speakers, (3) had a full-time or part-time contract for an external organization. 799 participants provided responses at Time 1, 599 participants provided responses at Time 2 (74.97%), and 487 participants provided responses at Time 3 (60.95%). Some participants were excluded as they provided incorrect answers to one of two attentional check included to the survey at Time 1, 2 or 3 or reported that they did not work for an external organization at any point in time. Of the remaining 747 Time 1 respondents, 47.66% were women and most of them hold a bachelor degree (46.18%). The average age of this sample was 35.19 years old (SD=10.84) and organizational tenure was 6.04 years (SD=6.27).

Measures. For all variables, items were rated on a 7-point response scale (“strongly disagree” to “strongly agree”). Unless otherwise indicated, constructs were measured at all time points.

POS. POS was measured using 8 items (α=.94 to .96; e.g., *My organization really cares about my well-being)* of the Survey of Perceived Organizational Support (Eisenberger *et al.*, 1986).

Job satisfaction. Job satisfaction was assessed via 4 items (α=.93 to .94; e.g., *All in all, I am very satisfied with my current job*) (Eisenberger *et al.*, 1997).

Affective commitment (Time 2 and Time 3). Affective commitment was measured with six items (α=.92; e.g., *This organization has a great deal of personal meaning for me*) (Meyer *et al.*, 1993).

Turnover intentions. Turnover intentions were assessed using the three-item scale (α = .93 to .94; e.g., *I often think about quitting this organization*) developed by Jaros (1997).

Voice behaviors (Time 2 and Time 3). Voice behaviors were measured using 6 items (α=.94) adapted of Van Dyne and Lepine (1998) to change the group referent for the organization (e.g., *I speak up and encourage others in my organization to get involved in issues that affect the organization*).

Data Analyses

Estimation Procedures

Analyses were conducted using the robust Maximum Likelihood (MLR) estimator implemented in Mplus 8 (Muthén and Muthén, 2017). This estimator provides unbiased estimates even under conditions of non-normality. We relied on Full Information Maximum Likelihood (FIML) to handle missing responses (Graham, 2009). Precisely, among respondents who completed each time point, missing responses ranged between 0.13 and 1.33%. In total, we obtained 1604 time-specific ratings (*M*=2.15 per participant) from a total of 747 employees: 304 (40.70%) participated at all time points, 249 (33.33%) participated in two of the assessment periods, and 194 (26.97%) participated only once.

Preliminary Analyses

Analyses relied on factor scores estimated in standardized measurement units (*M*=0 and *SD*=1) from preliminary measurement models specified to be longitudinally invariant to ensure comparability over time (Millsap, 2011). When compared to more traditional scale scores obtained by summing or averaging items, factor scores: (a) incorporate a partial control for measurement errors (Skrondal and Laake, 2001); (b) are able to retain the specificities of the measurement model (e.g., invariance) (Morin *et al.*, 2016). Correlations between these factor scores and the other variables used in this study are reported in Table S5 of the online supplements. Readers seeking more information on these analyses, including information related to construct distinctiveness, are referred to the online supplements.

Growth Mixture Analyses (GMA)

GMA were performed following procedures outlined by Gillet *et al.* (2019; Gillet, Morin, Huart *et al.*, 2018; Gillet, Morin, Sandrin and Houle, 2018). GMA are an extension from latent growth models (Bollen and Curran, 2006) designed to identify subpopulations, or profiles, of respondents following different longitudinal trajectories. In a linear GMA model, growth trajectories are summarized by profile-specific random intercepts (i.e., reflecting the initial level of POS) and slope factors (i.e., reflecting the rate of change in POS level over time). To achieve this linear specification across the three equally-spaces measurement occasions considered in this study, time codes on the slope factor were respectively set to 0, 1, and 2 at the first, second and third measurement occasions. These models relied on the Mplus default parameterization according to which: (a) the latent variance-covariance matrix was specified to be invariant across profiles, (b) the time-specific residuals were specified as invariant across profiles but free to vary over time. Despite the documented advantage of more flexible GMA parameterizations (Diallo *et al.*, 2016; Morin *et al.*, 2011), these more flexible parameterizations often result in estimation problems (nonconvergence or convergence on improper solutions). When this occurs, which was the case in this study, researchers are advised to rely on simpler parameterizations (Diallo *et al.*, 2016), such as the one implemented here. Using these specifications, GMA models[1] including one to eight profiles were estimated using 10,000 sets of random start values (the best 500 of which were retained for optimization) which were each allowed 1000 iterations (Hipp and Bauer, 2006). A more technical presentation of GMA is provided in the online supplements.

To select the number of latent trajectory profiles, researchers have to consider the statistical adequacy, signification, and theoretical conformity of the solution (Bauer and Curran, 2003; Marsh *et al.*, 2009), as well as results on a variety of statistical indicators (McLachlan and Peel, 2000). These statistical indicators include the Akaïke Information Criterion (AIC) and its consistent version (CAIC), the Bayesian Information Criterion (BIC) and its sample-size adjusted version (ABIC), the adjusted Lo, Mendel, and Rubin's (2001) (aLMR) and Bootstrap Likelihood Ratio Tests (BLRT). Better fitting models are indicated by lower values on the information criteria (AIC, CAIC, BIC, and ABIC), and a statistically significant *p*-value on the aLMR and BLRT indicates that the model considered fits better than a model including one fewer profile. Statistical simulation studies have revealed that the CAIC, BIC, ABIC, and BLRT seem to be useful in identifying the optimal solution (e.g., Diallo *et al.*, 2016). The remaining indices (AIC, aLMR) will thus only be reported for purposes of transparency. Due to the sample-size dependency of these indicators (Marsh *et al.*, 2009) they frequently keep on suggesting adding profiles to the solution without converging on an optimal solution. When this happens, "elbow plots" should be used to better identify the point at which the added value of adding an additional profile tends to become negligible (Morin *et al.*,2011; Morin, 2016). Finally, we report the entropy which provides a 0 to 1 summary of the classification accuracy of the solution.

Controls. A series of tests seeking to determine the need to retain demographic controls (age, gender, education level, and organizational tenure) for the analyses were conducted. These controls were incorporated to the final retained unconditional model (Morin *et al.*, 2016) via a series of alternative specifications (e.g., Morin *et al.*, 2013). A null effects model was first estimated. In this model, the effects of the controls were set to be zero. The second model allowed these control variables to predict profile membership. The third model allowed these control variables to influence the intercepts and slopes of the trajectories, and the fourth model allowed these effects to differ across profiles.

Outcomes. Time-specific outcomes levels were incorporated to the final solution. Profile-specific outcome levels where then compared using Lanza *et al.*'s (2013) approach implemented in Mplus via the Auxiliary (DCON) function (Asparouhov and Muthén, 2014).

Results

Unconditional Models

The results from the unconditional GMA models are reported in the top section of Table 1. Examination of the results reveals that the AIC, ABIC, and BLRT kept on suggesting the addition of profiles, whereas the CAIC, BIC, and aMLR respectively supported solutions including 6, 7, and 3 profiles. Examination of the elbow plot used to summarize this information (Figure S2, online supplements) showed that the improvement in fit reached a plateau around 4 profiles. This 4-profile solution, together with the bordering 3- and 4- profile solutions, were carefully examined. This examination revealed that these solutions were statistically proper and that moving from a 3- to 4-profile solution resulted in the addition of a well-defined meaningful profile to the solution. However, adding a fifth profile only resulted in the arbitrary division an already existing profile into two similar ones. More importantly, one of these additional profiles was almost empty, and corresponded only to 0.4% of the sample. We thus decided to retain the 4-profile solution, which is illustrated in Figure 1 (exact parameter estimates are reported in Table S6, online supplements).

Profile 1 (*High*) characterized the majority of participants (67.2%) presenting initially high levels of POS that appeared to be quite stable over time. Even though the average slope factor associated with this profile is statistically significant, this slope indicates only a negligible decrease, corresponding to .026 SD units per time point. In contrast, Profile 2 (*Low*) characterized 27.3% of the participants presenting initially low levels of POS, which appeared to remain stable over time. Profile 3 (*Decreasing*) was the most concerning, as it characterized 3.3% of the participants presenting initially high levels of POS (lower, but comparable to those observed in Profile 1) which decreased markedly over time (leading them to reach a level comparable to that of Profile 2 by the end of the study). In contrast, Profile 4 (*Increasing*) characterized 2.2% of the participants presenting initially low levels of POS (comparable to those observed in Profile 2) which increased markedly over time (leading them to reach a level comparable to that of Profile 1 by the end of the study). As such, Profiles 2 and 3 can be interpreted as "switching" profiles (e.g., Morin *et al.*,2013), representing participants whose profile membership respectively "switch" from High to Low, and from Low to High, over time. The classification accuracy of the solution is reported in Table S7 of the online supplements, revealing a high level of classification accuracy, ranging from 79.7% for the *Decreasing* profile (3) to 95.1% for members of the *High* profile (1) consistent with a relatively high entropy value (.853).

Controls

The goodness-of-fit of the alternative solutions including the demographics control variables are reported in the lower section of Table 1. These results supported the null effects models. This conclusion is reinforced by a more careful examination of these solutions, which were all consistent with a lack of effects of these demographics' controls. These controls were thus excluded from further analyses.

Time-Varying Outcomes Levels

Results from the comparison of outcome levels across profiles are reported in Table 2. These results revealed clear outcome differences between the four profiles, and a pattern of differences that differed across outcome. At Time 1, all four profiles were well differentiated from an outcome perspective, with levels of turnover intentions and job satisfaction being respectively lowest, and highest, in the High profile, followed by the Decreasing profile, then by the Low profile, and finally by the Decreasing profile (all comparisons were statistically significant). At Time 2, differences became less pronounced. Levels of turnover intentions and job satisfaction were respectively lowest and highest in the *High* profile than in the other profiles, but impossible to differentiate across the remaining profiles. Results regarding affective commitment and voice behavior show a similar pattern, being highest in the *High* profile than in most other profiles (with the exception of the *Increasing* profile for voice behaviors). However, levels on both outcomes were significantly higher in the *Increasing* profile relative to the *Low* profile. Finally, by the end of the study, differences were again almost as pronounced as at Time 1. Precisely, the results showed that the most desirable levels on the outcome variables (low levels of turnover intentions and high levels of job satisfaction, affective commitment and voice behaviors) were associated with the *High* and *Increasing* profiles, followed by the *Low* profile, and then by the *Decreasing* profile, with this last difference being only statistically significant for three out of four outcomes (i.e., turnover intentions, job satisfaction, and affective commitment). Differences between the *High* and *Increasing* profiles differed as a function of the outcome: (a) these two profiles displayed equivalent levels of turnover intentions; (b) levels of voice behaviors and affective commitment were higher in *Increasing* profile relative to the *High* profile; (c) levels of job satisfaction were higher in *High* profile relative to the *Increasing* profile.

Discussion

Capitalizing on a three-wave longitudinal study of employees followed over the course of an eight-month period, this study relied on GMM to identify profiles of employees following distinct trajectories of POS, and to investigate the outcome implications of these trajectories in relation to job satisfaction, turnover intentions, affective commitment, and voice behaviors. The results revealed four profiles of employees following *High* and stable (67.2%), *Low* and stable (27.3%), *Increasing* (2.2%) and *Decreasing* (3.3%) longitudinal trajectories of POS. Interestingly, these trajectories were unrelated to participants' demographic characteristics (i.e., age, gender, education level, and organizational tenure). Our results also revealed that the *Increasing* POS trajectory was associated with the highest levels of affective commitment and voice behaviors, as well as with the lowest levels of turnover intentions by the end of the study. Furthermore, the members of the stable *High* POS trajectory reported relatively high levels of job satisfaction, affective commitment and voice behaviors, as well as low levels of turnover intentions across the whole study period. In contrast, more undesirable outcomes were associated with the stable *Low* and *Decreasing* POS trajectories, the former presenting the worst outcomes at Time 1, and the latter presenting the worst outcomes at Time 3.

Theoretical Implications

This research contributes to OST (Eisenberger *et al.*, 2020) by increasing knowledge on intra-individual and inter-individual differences in longitudinal POS trajectories. By applying a dynamic perspective, this study showed for the first time that employees' POS longitudinal trajectories follow one out of four possible configurations. On the one hand, these results show that POS perceptions tend to remain high for most employees, and that change is possible for employees displaying low levels of POS. On the other hand, these results show that change is not frequent for a substantial proportion of employees presenting initially low levels of POS (2.2% show increasing trajectories whereas 27.3% remain low). These findings are more supportive of the theoretical proposition that POS is a rather stable perception that employees form over time from a broad variety of experiences (e.g., Ford *et al.*, 2018), than with the perspective that it presents a high level of reactivity to social exchanges contingencies (e.g., Caesens, Stinglhamber and Ohana, 2016), but without excluding this latter possibility.

Furthermore, this research addressed a recent call (Caesens and Stinglhamber, 2020) to provide a more nuanced perspective on POS by examining the nature of its longitudinal trajectories, and their outcome implications. In this regard, our results support our expectations, based on prior research (e.g., Caesens *et al.*, 2019), suggesting that high levels of support tend to be associated with systematically more positive outcomes. More precisely, these results are consistent with the idea that employees with high levels of POS may feel an obligation to reciprocate positive treatments received from their organization through affective commitment, performance, and intentions to remain (e.g., Kurtessis *et al.*, 2017).

More importantly, our findings shed new light on these previous results in demonstrating the importance of considering changes in POS levels as an equally important determinant of these work outcomes. Indeed, the *Increasing* profile was related to the best organizational and individual outcomes by the end of the study (even more so than the *High* profile), while the *Decreasing* profile was associated with the worst outcomes at the end of the study (even more so than the *Low* profile). These results are aligned with the theoretical underpinnings of social exchange and psychological contract (Coyle-Shapiro and Conway, 2004) theories, suggesting that violations to the psychological contract linking employees to their organization, might be more potent drivers of attitudes and performance than balanced social exchanges relationships (e.g., Bordia *et al.*, 2008). More precisely, this study is the first to demonstrate that circumstantial failures to maintain high levels of support among employees can lead to potentially worse consequences than simply failing to support them in a stable manner. This finding indicates, for the first time in the history of research on POS, a potential drawback of POS which needs to be provided (or at least perceived) in a stable manner to yield proper benefits.

Practical Implications

This study has important practical implications. First, 27% of the participants in our sample reported stable low levels of POS while an additional 3.3% reported decreasing levels of POS. Importantly, these two trajectories were associated with the least desirable outcomes, reinforcing the importance of POS as a determinant of performance and retention. Managers should thus be particularly attentive to nurture POS among employees. Providing relevant training, offering individualized benefits, rewarding employees based on performance, and promoting strong social networks are all examples of effective means to foster POS (Eisenberger and Stinglhamber, 2011).

Furthermore, our findings suggested that managers should be particularly attentive to the fact that POS might fluctuate over time for some employees, and to the risks associated with decreasing POS levels. As noted by Caesens, Stinglhamber and Ohana (2016), fostering and maintaining POS requires ongoing efforts on the part of managers. To achieve this, managers should promote HR practices that signal strong and recurrent cues of POS and be attentive to potentially abrupt changes in work conditions. When such changes occur as a result of externally driven or uncontrollable events, managers could explain to employees the involuntary nature of these events and reinforce the availability of support to navigate these unexpected circumstances (Eisenberger and Stinglhamber, 2011). Finally, managers might consider tracking individuals' POS levels by using short and repeated evaluations of POS as part of routine employee surveys to obtain informative indicators of evolutions in POS.

Limitations and Perspectives for Future Research

This research has limitations. First, employees were followed over a period of eight months across four-month intervals. The high levels of stability that we identified in this study remain well-aligned with rank-order stability levels identified prior research conducted over similar time intervals (e.g., Chen *et al.*,2009). However, it is important to keep in mind that these results cannot be dissociated from the time lag considered, so that greater levels of fluctuations could be expected over longer time lags. Similarly, this study relied on a convenience sample of employees considered at different stages of their career and in a variety of organizational context. Far more potent investigations of changes in POS levels are likely to be made possible by the consideration of organizational newcomers, newly promoted employees, or employees exposed to different types of organizational changes. Clearly, future research would benefit from extending this design to a greater variety of time lags, types of employees, and organizational contexts.

Second, all data was collected using self-reported questionnaires. Because this research focused mainly on employees' perceptions, self-reported measures could not be avoided. Yet, self-reported measures could have been impacted by social desirability bias, and should be complemented, in future research, by more objective or informant-based measures of behavioral outcomes or organizational determinants. Furthermore, to keep our first questionnaire as short as possible (and to maximize participation), affective commitment and voice behaviors were only measured at Time 2 and 3, precluding an assessment of their associations with the POS trajectories at Time 1. Future research should replicate our findings while measuring all variables at all time points.

Third, participants were recruited on the Prolific Academic platform. Indeed, as noted by Landers and Behrend (2015), several concerns arise when using similar data collection platforms (e.g., MTurk) such as: (1) repeated participation, (2) the monetary compensation might influence motivation, (3) a potential over-selection bias for participants, and (4) representativeness of the sample. However, Landers and Behrend (2015) claimed that these platforms are "neither better nor worse than other more common convenient samples; they are merely different" (p.21), and that "if we intend to create theory broadly applicable across organizational contexts, MTurk and similar samples may prove superior to those collected from single convenient organizations" (p.18).

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Table 1

Results from the Growth Mixture Analyses

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
Growth Mixture Analyses										
1 Profile	-1542.909	6	2.0144	3101.818	3144.746	3138.746	3113.343	Na	Na	Na
2 Profiles	-1484.813	11	1.8223	2991.625	3053.402	3042.402	3007.473	.990	.022	< .001
3 Profiles	-1441.845	14	1.7111	2911.690	2990.315	2976.315	2931.860	832	< .001	< .001
4 Profiles	-1400.113	17	2.2251	2834.225	2929.699	2912.699	2858.717	.853	.520	< .001
5 Profiles	-1382.957	20	1.5870	2805.914	2918.235	2898.235	2834.727	.873	.058	< .001
6 Profiles	-1367.545	23	1.5218	2781.090	2910.259	2887.259	2814.225	.871	.229	< .001
7 Profiles	-1356.218	26	1.3787	2764.436	2910.454	2884.454	2801.894	.868	.064	< .001
8 Profiles	-1348.805	29	1.4517	2755.611	2918.477	2889.477	2797.391	.839	.622	.013
Models with Controls										
Null Effects	-1305.779	17	1.9358	2645.558	2739.408	2722.408	2668.431	.857	Na	Na
Effects on C	-1295.999	29	1.4812	2649.997	2810.095	2781.095	2689.017	.861	Na	Na
Effects on C, I (inv.)	-1292.987	33	1.4242	2651.974	2834.155	2801.155	2696.376	.863	Na	Na
Effects on C, I, S (inv.)	-1291.836	37	1.3661	2657.672	2861.935	2824.935	2707.456	.863	Na	Na
Effects on C, I (var.)	-1284.246	45	1.3080	2658.492	2906.920	2861.920	2719.040	.863	Na	Na
Effects on C, I, S (var.)	-1266.586	61	1.4202	2655.172	2991.929	2930.929	2737.248	.863	Na	Na

Note. LL: model loglikelihood; #fp: number of free parameters; scaling: scaling correction factor associated with robust maximum likelihood estimates; AIC: Akaïke information criteria; CAIC: constant AIC; BIC: Bayesian information criteria; ABIC: sample size adjusted BIC; aLMR: adjusted Lo-Mendel-Rubin likelihood ratio test; BLRT: bootstrap likelihood ratio test; Na: Not applicable; C: Profile membership; I: Intercept factor; S: Slope factor; inv.: predictions constrained to invariance across profiles; var.: predictions freely estimated across profiles.

Table 2

Time-Varying Associations between Profile Membership and the Outcomes

	Profile 1 (High) M [CI]	Profile 2 (Low) M [CI]	Profile 3 (Decreasing) M [CI]	Profile 4 (Increasing) M [CI]	Summary of Significant Differences
Turnover intentions*					
Time 1	-.435 [-.504; -.366]	.840 [.754; .923]	.278 [-.047; .603]	1.297 [1.081; 1.513]	4 > 2 > 3 > 1
Time 2	-.375 [-.444; -.306]	.722 [.632; .812]	.741 [.476; 1.006]	.377 [.010; .744]	2 = 3= 4 > 1
Time 3	-.338 [-.407; -.269]	.706 [.618; .794]	1.240 [1.087; 1.393]	-.309 [-.695; .077]	3 > 2 > 1 = 4
Job satisfaction*					
Time 1	.587 [.534; .640]	-.867 [-.959; -.775]	-.372 [-.680; -.064]	-1.317 [-1.642; -.992]	1 > 3 > 2 > 4
Time 2	.517 [.462; .572]	-.855 [-.945; -.765]	-.820 [-1.112; -.528]	-.661 [-1.018; -.304]	1 > 2 = 3 = 4
Time 3	.469 [.414; .524]	-.855 [-.949; -.761]	-1.135 [-1.386; -.884]	.074 [-.279; .427]	1 > 4 > 2 > 3
Affective commitment*					
Time 2	.440 [.379; .501]	-.807 [-.887; -.727]	-.780 [-1.047; -.513]	-.307 [-.642; .028]	1 > 4 > 2 = 3
Time 3	.437 [.378; .496]	-.783 [-.859; -.707]	-1.192 [-1.396; -.988]	1.066 [.699; 1.433]	4 > 1 > 2 >3
Voice behaviors*					
Time 2	.248 [.185; .311]	-.478 [-.598; -.358]	-.534 [-.910; -.158]	-.008 [-.388; .372]	1 > 2 = 3; 4 > 2; 1 = 4; 3 = 4
Time 3	.230 [.171; .289]	-.457 [-.571; -.343]	-.846 [-1.248; -.444]	1.098 [.759; 1.437]	4 > 1 > 2 = 3

Note. M: Mean; CI: 95% confidence interval.

*Variables estimated from factor scores with mean of 0 and a standard deviation of 1.

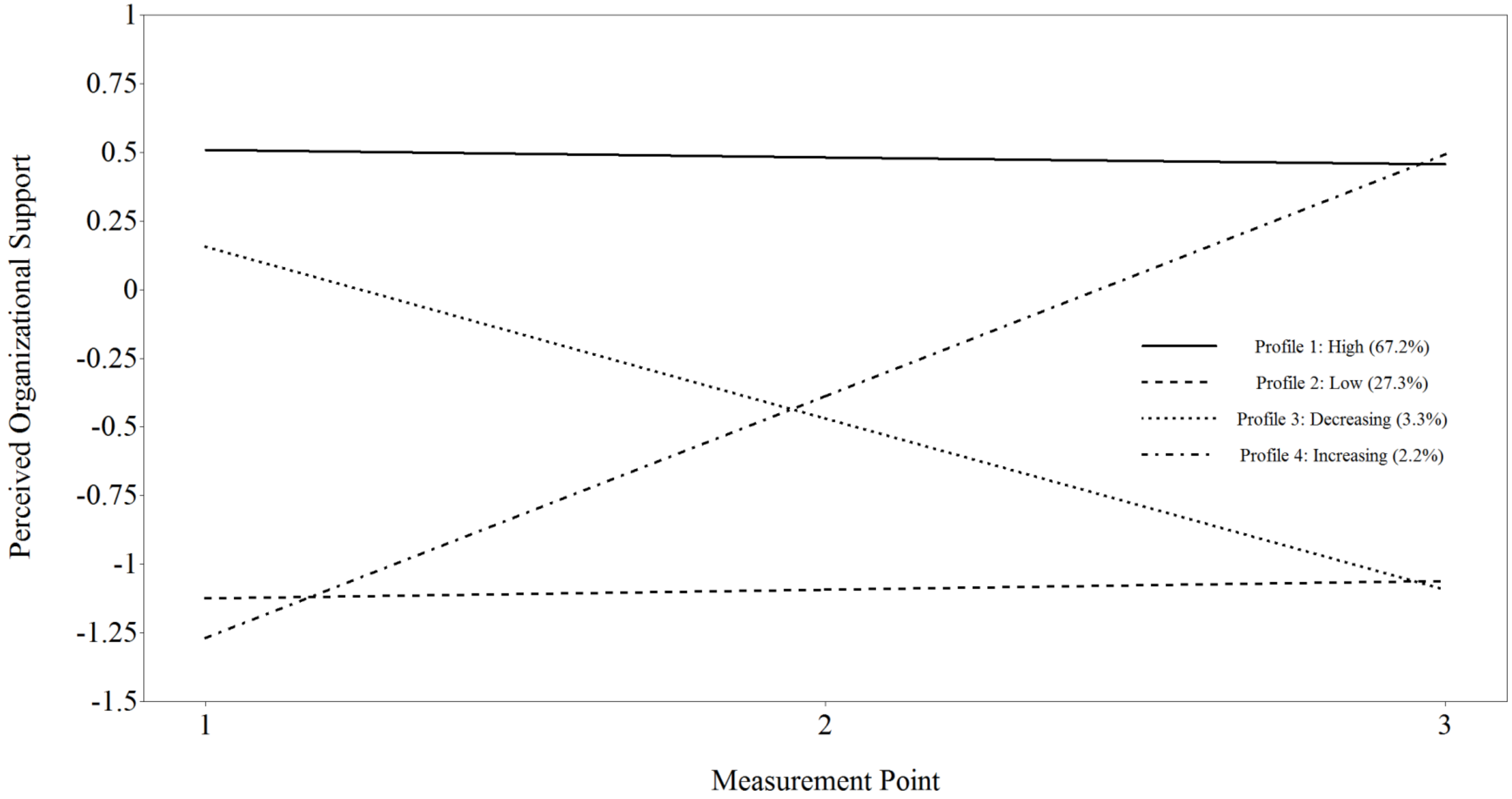

Figure 1. Estimated Growth Trajectories for the Four Perceived Organizational Support Profiles.

Note. Trajectories are estimated using time-invariant factor scores (M = 0; SD = 1) obtained from preliminary analyses (see online supplements for details).

Online Supplements for:
Longitudinal Trajectories of Perceived Organizational Support: A Growth Mixture Analysis

Footnotes

[1] The decision to rely on linear models is based on the initial comparison of linear versus multibase latent curve and GMA models, which revealed no evidence of non-linearity. Multibase models provide a way to test for the presence of non-linearity in models including three-time points through the free estimation of the second loading on the slope factor (i.e., time code). In addition, Metha and West (2000) showed that relying on uniform time codes when participants differ in age is proper when: (1) the regression of the intercept of a latent curve model on age is equal to the slope, and (2) the regression of the slope on age is equal to zero. In this study, participants are close in age, of the same grade level, and results supported both conditions, as shown by non-significant χ^2difference tests (condition 1: $\Delta\chi^2 = 0.183$, *df* = 1; Condition 2: $\Delta\chi^2 = 0.197$, *df* = 1; Conditions 1 and 2: $\Delta\chi^2 = 0.186$, *df* = 2).

Preliminary Measurement Models

Due to the complexity of the longitudinal models underlying all constructs assessed in the present study, preliminary analyses were conducted separately for the repeated measures of perceived organizational support (used to assess the longitudinal trajectories) and the outcomes (turnover intentions, job satisfaction, affective commitment to the organization, and voice behaviors). These longitudinal measurement models were estimated with the robust Maximum Likelihood (MLR) estimator implemented in Mplus 8 (Muthén & Muthén, 2017). This estimator provides unbiased estimates even under conditions of non-normality. We also relied on Full Information Maximum Likelihood (FIML) procedures to handle missing responses (for additional details on missing data, see the main manuscript).

We first estimated alternative measurement models at each time points, starting with our a priori 3-factor measurement model at Time 1 (POS, turnover intentions, and job satisfaction) and 5-factor measurement model at Times 2 and 3 (POS, turnover intentions, job satisfaction, affective commitment and voice behaviors). In addition, an orthogonal method factor was included to control for the negative wording of half of the POS items (Marsh, Scalas, & Nagengast, 2010) and one correlated uniqueness was included to the Time 2 and 3 models to account for the negative wording of two of the affective commitment items. A series of alternative models were then estimated, combining one pair of construct each time to ascertain the discriminant validity of the constructs.

Longitudinal models were then estimated across all three time waves and included a total of 3 factors (1 perceived organizational support factor x 3 time waves) for the perceived organizational support measure, 10 factors for the outcome measures (2 factors for turnover intentions and job satisfaction x 3 time waves + 2 factors for affective commitment and voice behaviors x 2 time waves). All factors were allowed to correlate within and across time-points. A priori correlated uniquenesses between matching indicators of the factors utilized at the different time-points were included in the longitudinal models to avoid inflated stability estimates (e.g., Marsh, 2007). In addition, an orthogonal method factor was included to the perceived organizational support model to control for the negative wording of half of the items (Marsh, Scalas, & Nagengast, 2010). For the same reason, one correlated uniqueness per time point was included to the outcome model to account for the negative wording of two of the affective commitment items. Before saving the factor scores for our main analyses, we verified that the measurement models operated in the same manner across time waves, through tests of measurement invariance (Millsap, 2011). For both models, we assessed the following forms of invariance (1) configural; (2) weak (loadings); (3) strong (loadings and intercepts); (4) strict (loadings, intercepts, and uniquenesses); (5) latent variance-covariance (loadings, intercepts, uniquenesses, and latent variances-covariances); and (6) latent means (loadings, intercepts, uniquenesses, latent variances-covariances, and latent means). An additional step was added to this sequence for the outcome model (between steps 4 and 5) to test the longitudinal invariance of the negatively-worded items correlated uniqueness.

We relied on sample-size independent goodness-of-fit indices to describe model fit (Hu & Bentler, 1999; Marsh, Hau, & Grayson, 2005): the comparative fit index (CFI), the Tucker-Lewis index (TLI), and the root mean square error of approximation (RMSEA). CFI and TLI values greater than .90 indicate adequate fit, whereas values greater than .95 indicate excellent fit. Values smaller than .09 or .06 for the RMSEA respectively support acceptable and excellent fit. For tests of invariance, we also considered changes in goodness-of-fit-indices (Chen, 2007; Cheung & Rensvold, 2002), with a ΔCFI/TLI of .010 or less and a ΔRMSEA of .015 or less taken to support the invariance of the model. Composite reliability coefficients associated with each of the a priori factors are calculated from the model standardized parameters using McDonald (1970) omega (ω) coefficient:

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

where $|\lambda_i|$ are the standardized factor loadings in absolute value, and δi, the item uniquenesses.

The goodness-of-fit results of the time-specific models are reported in Table S1, and support the adequacy of our time-specific a priori models (with all CFI/TLI ≥ .93 and all RMSEA ≤ .08), as well as their superiority relative to all alternative models in which pairs of constructs were combined. The goodness-of-fit results of the longitudinal models are then reported in Table S2. These results support the adequacy of the a priori measurement models (with all CFI/TLI ≥ .94 and all RMSEA ≤ .04). The results also support the configural, weak, strong, and strict measurement invariance of both models across time points, as well as the invariance of the latent variance-covariance matrix, latent means, and correlated uniqueness for the outcome model (ΔCFI/TLI ≤ .010; ΔRMSEA ≤ .015). These results globally show that the parameter estimates can be considered to be fully equivalent across time. The observation of latent mean invariance across time points indicates that, on the average, the sample is neither characterized by growth or decline in levels of perceived organizational support over time. However, observed levels of between-person variability in latent means and individual trajectories are consistent with the presence of substantial inter-individual variability in growth, supporting the use of methods designed to model this variability (i.e., latent curve models) and specific growth profiles (i.e., growth mixture analyses). Figure S1 graphically presents observed individual trajectories.

Parameter estimates and composite reliability from the most invariant model are reported in Tables S3 and S4. These results show that all factors are well-defined through satisfactory factor loadings (λ = .675 to .944), resulting in satisfactory model-based composite reliability coefficients, ranging from ω = .917 to .952. Factor scores were saved from this most invariant measurement model and used as profile indicators in the main research.

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A More Technical Presentation of Growth Mixture Analyses (GMA)

GMA aim to represent longitudinal heterogeneity by the identification of subgroups (i.e., profiles) of participants following distinct trajectories. A linear GMA for the repeated measure y_{it} for individual *i* at time *t* is estimated within *k* distinct levels (k = 1, 2, …, K) of an unobserved latent categorical variable *c* representing the profiles, with each individual having a probability (*p*) of membership in the *k* levels of this latent categorical variable.

$$y_{it} = \sum_{k=1}^{K} p_k [\alpha_{iyk} + \beta_{iyk} \lambda_t + \varepsilon_{yitk}] \quad (1)$$

$$\alpha_{iyk} = \mu_{\alpha yk} + \zeta_{\alpha yik} \quad (2)$$

$$\beta_{iyk} = \mu_{\beta yk} + \zeta_{\beta yik} \quad (3)$$

The *k* subscript indicates that most parameters can be freely estimated across profiles. In this equation, α_{iyk} and β_{iyk} represent the random intercept and random linear slope of the trajectory for individual *i* in profile *k*; $\mu_{\alpha yk}$ and $\mu_{\beta yk}$ represent the average intercept and linear slope in profile *k*, and $\zeta_{\alpha yik}$ and $\zeta_{\beta yik}$ represent the variability of the intercepts and slopes across cases within profiles. ε_{yitk} represents a diagonal matric of time- individual- and class- specific residuals. p_k defines the probability that an individual *i* belongs to class *k* with all $p_k \geq 0$ and $\sum_{k=1}^{K} p_k = 1$. The variance parameters ($\zeta_{\alpha yik}, \zeta_{\beta yik}$) have a mean of zero and a Φ_{yk} variance-covariance matrix:

$$\Phi_{yk} = \begin{bmatrix} \psi_{\alpha\alpha yk} & \\ \psi_{\alpha\beta yk} & \psi_{\beta\beta yk} \end{bmatrix} \quad (4)$$

In these models, Time is represented by λ_t , the factor loading matrix relating the time-specific indicators to the linear slope factor. Time is coded to reflect the passage of time and is thus a function of the intervals between measurement points. Given that the current study relies on three equally spaced measurement points, it is reasonable to set the intercept at Time 1 [$E(\alpha_{iyk}) = \mu_{y1k}$]. Thus, for a linear growth mixture model, time would be coded $\lambda_1 = 0$, $\lambda_2 = 1$, $\lambda_3 = 2$. As noted in the main manuscript, the current study relies on a more constrained estimation of GMA through which the latent variance-covariance matrix and the residual matrix were specified as invariant across profiles:

$$y_{it} = \sum_{k=1}^{K} p_k [\alpha_{iyk} + \beta_{iyk} \lambda_t + \varepsilon_{yit}] \quad (5)$$

$$\alpha_{iyk} = \mu_{\alpha yk} + \zeta_{\alpha yi} \quad (6)$$

$$\beta_{iyk} = \mu_{\beta yk} + \zeta_{\beta yi} \quad (7)$$

$$\Phi_{y} = \begin{bmatrix} \psi_{\alpha\alpha y} & \\ \psi_{\alpha\beta y} & \psi_{\beta\beta y} \end{bmatrix} \quad (8)$$

Table S1

Goodness-of-Fit Statistics for the Time-Specific Preliminary Measurement Models and Tests of Construct Distinctiveness.

	χ^2 (df)	CFI	TLI	RMSEA	RMSEA 90% CI
Time 1					
A Priori Model	418.589 (81)*	.949	.933	.078	.070; 085
Combining POS and IQ	1179.393 (84)*	.833	.792	.137	.131; .144
Combining POS and JS	1148.513 (84)*	.838	.798	.136	.129; .143
Combining IQ and JS	910.328 (84)*	.874	.843	.119	.112; .126
Time 2					
A Priori Model	915.878 (305)*	.939	.930	.063	.058; .068
Combining POS and JS	1616.668 (310)*	.870	.853	.091	.087; .096
Combining POS and commitment	1563.279 (309)*	.875	.858	.090	.085; .094
Combining POS and voice	2420.536 (310)*	.790	.762	.116	.112; .120
Combining IQ and JS	1353.830 (310)*	.896	.883	.082	.077; .086
Combining IQ and commitment	1397.824 (310)*	.892	.878	.083	.079; .088
Combining IQ and voice	2237.051 (310)*	.808	.783	.111	.107; .115
Combining JS and commitment	1367.682 (310)*	.895	.881	.082	.078; 087
Combining JS and voice	2663.909 (310)*	.766	.735	.123	.118; .127
Combining commitment and voice	2244.621 (310)*	.808	.782	.111	.107; 116
Time 3					
A Priori Model	778.920 (305)*	.943	.934	.061	.056; .067
Combining POS and JS	1392.674 (310)*	.870	.852	.092	.087; .097
Combining POS and commitment	1300.943 (309)*	.880	.864	.088	.083; .093
Combining POS and voice	2081.989 (310)*	.786	.758	.118	.113; .122
Combining IQ and JS	1095.704 (310)*	.905	.893	.078	.073; .083
Combining IQ and commitment	1168.203 (310)*	.897	.883	.082	.077; .087
Combining IQ and voice	1865.655 (310)*	.813	.788	.110	.105; .115
Combining JS and commitment	1100.664 (310)*	.905	.892	.078	.073; .084
Combining JS and voice	2136.171 (310)*	.780	.751	.119	.115; .124
Combining commitment and voice	1829.133 (310)*	.817	.793	.109	.104; .114

Note. * $p < .01$; POS: perceived organizational support; JS: job satisfaction; IQ: intentions to quit; 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.

Table S2

Goodness-of-Fit Statistics for the Longitudinal Preliminary Measurement Models

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	CM	$\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
Perceived Organizational Support										
M1. Configural invariance	425.274 (204)*	.975	.966	.038	[.033; .043]	-	-	-	-	-
M2. Weak invariance	458.768 (224)*	.973	.967	.037	[.033; .042]	M1	33.237 (20)*	-.002	+.001	-.001
M3. Strong invariance	469.017 (236)*	.974	.969	.036	[.032; .041]	M2	6.767 (12)	+.001	+.002	-.001
M4. Strict invariance	474.800 (252)*	.975	.972	.034	[.030; .039]	M3	16.277 (16)	+.001	+.003	-.002
M5. Var-Cov invariance	483.528 (256)*	.974	.972	.035	[.030; .039]	M4	8.713 (4)	-.001	.000	+.001
M6. Latent means invariance	487.693 (260)*	.974	.973	.034	[.030; .039]	M5	3.107 (4)	.000	+.001	-.001
Outcomes										
M7. Configural invariance	1905.618 (865)*	.947	.940	.040	[.038; .043]	-	-	-	-	-
M8. Weak invariance	1924.944 (885)*	.947	.941	.040	[.037; .042]	M7	12.399 (20)	.000	+.001	.000
M9. Strong invariance	1967.493 (905)*	.946	.941	.040	[.037; .042]	M8	42.386 (20)*	-.001	.000	.000
M10. Strict invariance	1967.589 (931)*	.947	.944	.039	[.036; .041]	M9	25.397 (26)	+.001	+.003	-.001
M11. Invariance of the correlated uniq.	1965.397 (932)	.948	.944	.039	[.036; .041]	M10	0.086 (1)	+.001	.000	.000
M12. Var-Cov invariance	1978.061 (645)*	.948	.945	.038	[.036; .041]	M11	8.288 (13)	.000	+.001	-.001
M13. Latent means invariance	1984.926 (951)*	.948	.945	.038	[.036; .041]	M12	6.127 (6)	.000	.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; Var-Cov: variance-covariance; CM: comparison model; Δ: change in fit relative to the CM.

Table S3

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

Items	λ	δ
Perceived Organizational Support		
Item 1	.903**	.185**
Item 2	.862**	.247**
Item 3	.875**	.234**
Item 4	.751**	.267**
Item 5	.824**	.322**
Item 6	.739**	.379**
Item 7	.758**	.217**
Item 8	.829**	.314**
ω	.952	

Note. ** $p < .001$. λ: factor loading; δ: item uniqueness; ω: omega coefficient of model-based composite reliability

Table S4

Standardized Factor Loadings (λ) and Uniquenesses (δ) for the M13 solution (Latent Means Invariance: Outcomes)

Items	Factor 1 λ	Factor 2 Λ	Factor 3 λ	Factor 4 Λ	δ
1. Turnover intentions					
Item 1	.839				.296
Item 2	.944				.109
Item 3	.934				.127
2. Job satisfaction					
Item 1		.863			.255
Item 2		.938			.121
Item 3		.894			.200
Item 4		.817			.332
3. Affective commitment					
Item 1			.747		.442
Item 2			.675		.544
Item 3			.802		.356
Item 4			.891		.206
Item 5			.863		.255
Item 6			.833		.305
4. Voice behaviors					
Item 1				.796	.367
Item 2				.888	.211
Item 3				.840	.295
Item 4				.850	.278
Item 5				.868	.246
Item 6				.867	.247
ω	.933	.931	.917	.941	

Note. λ: factor loading; δ: item uniqueness; ω: omega coefficient of model-based composite reliability.

Table S5

Correlations between Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Gender (T1)	-	$-.080^{*}$	.029	-.012	-.044	-.013	-.035	-.021	-.044	-.025	-.067	.071	-.016	-.033	-.029	-.056	.064
2. Age (T1)		-	-.026	$.520^{***}$	$-.089^{*}$	-.067	$-.081^{*}$	$-.084^{*}$	$-.104^{*}$	-.056	-.024	.038	$-.098^{*}$	-.072	-.070	-.029	.033
3. Education level (T1)			-	$-.091^{*}$	.014	-.007	.059	.026	.031	.041	.036	.058	.017	.030	.032	.028	.035
4. Organizational tenure (T1)				-	-.07	-.042	$-.096^{*}$	$-.11^{**}$	-.07	-.07	.03	$.076^{*}$	$-.104^{**}$	-.06	$-.09^{*}$	.024	.070
5. Perceived organizational support (T1)†					-	$-.634^{***}$	$.730^{***}$	$.910^{***}$	$-.532^{***}$	$.688^{***}$	$.665^{***}$	$.398^{***}$	$.853^{***}$	$-.506^{***}$	$.660^{***}$	$-.633^{***}$	$.351^{***}$
6. Turnover intentions (T1)†						-	$-.776^{***}$	$-.592^{***}$	$.847^{***}$	$-.744^{***}$	$-.678^{***}$	$-.303^{***}$	$-.563^{***}$	$.810^{***}$	$-.703^{***}$	$-.654^{***}$	$-.243^{***}$
7. Job satisfaction (T1)†							-	$.687^{***}$	$-.644^{***}$	$.916^{***}$	$.709^{***}$	$.383^{***}$	$.661^{***}$	$-.634^{***}$	$.880^{***}$	$.684^{***}$	$.329^{***}$
8. Perceived organizational support (T2)†								-	$-.596^{***}$	$.735^{***}$	$.719^{***}$	$.423^{***}$	$.942^{***}$	$-.567^{***}$	$.706^{***}$	$.685^{***}$	$.390^{***}$
9. Turnover intentions (T2)†									-	$-.775^{***}$	$-.744^{***}$	$-.335^{***}$	$-.574^{***}$	$.916^{***}$	$-.722^{***}$	$-.690^{***}$	$-.307^{***}$
10. Job satisfaction (T2)†										-	$.823^{***}$	$.435^{***}$	$.720^{***}$	$-.749^{***}$	$.952^{***}$	$.780^{***}$	$.403^{***}$
11. Affective commitment (T2)†											-	$.532^{***}$	$.709^{***}$	$-.699^{***}$	$.787^{***}$	$.940^{***}$	$.525^{***}$
12. Voice behaviors (T2)†												-	$.417^{***}$	$-.336^{***}$	$.418^{***}$	$.526^{***}$	$.897^{***}$
13. Perceived organizational support (T3)†													-	$-.610^{***}$	$.743^{***}$	$.733^{***}$	$.431^{***}$
14. Turnover intentions (T3)†														-	$-.787^{***}$	$-.756^{***}$	$-.347^{***}$
15. Job satisfaction (T3)†															-	$.831^{***}$	$.449^{***}$
16. Affective commitment (T3)†																-	$.564^{***}$
17. Voice behaviors (T3)†																	-

Note. * $p < .05$; ** $p < .01$, *** $p < .001$; †Variables estimated from factor scores with mean of 0 and a standard deviation of 1. Gender was coded 0 for women and 1 for men.

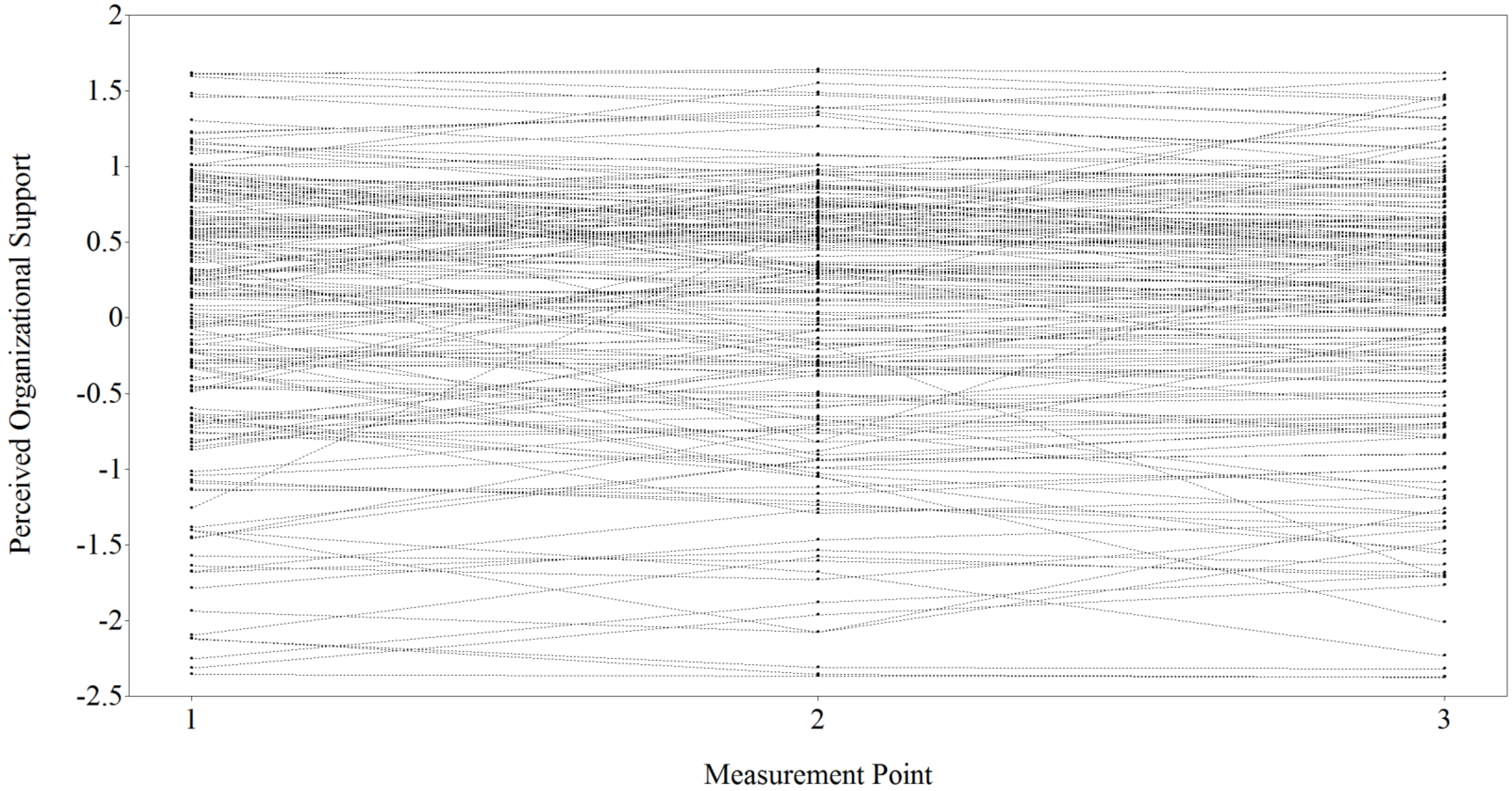

Figure S1. Observed Individual Trajectories of Perceived Organizational Support.
Note. Levels of perceived organizational support are factor scores with a mean of 0 and a standard deviation of 1.

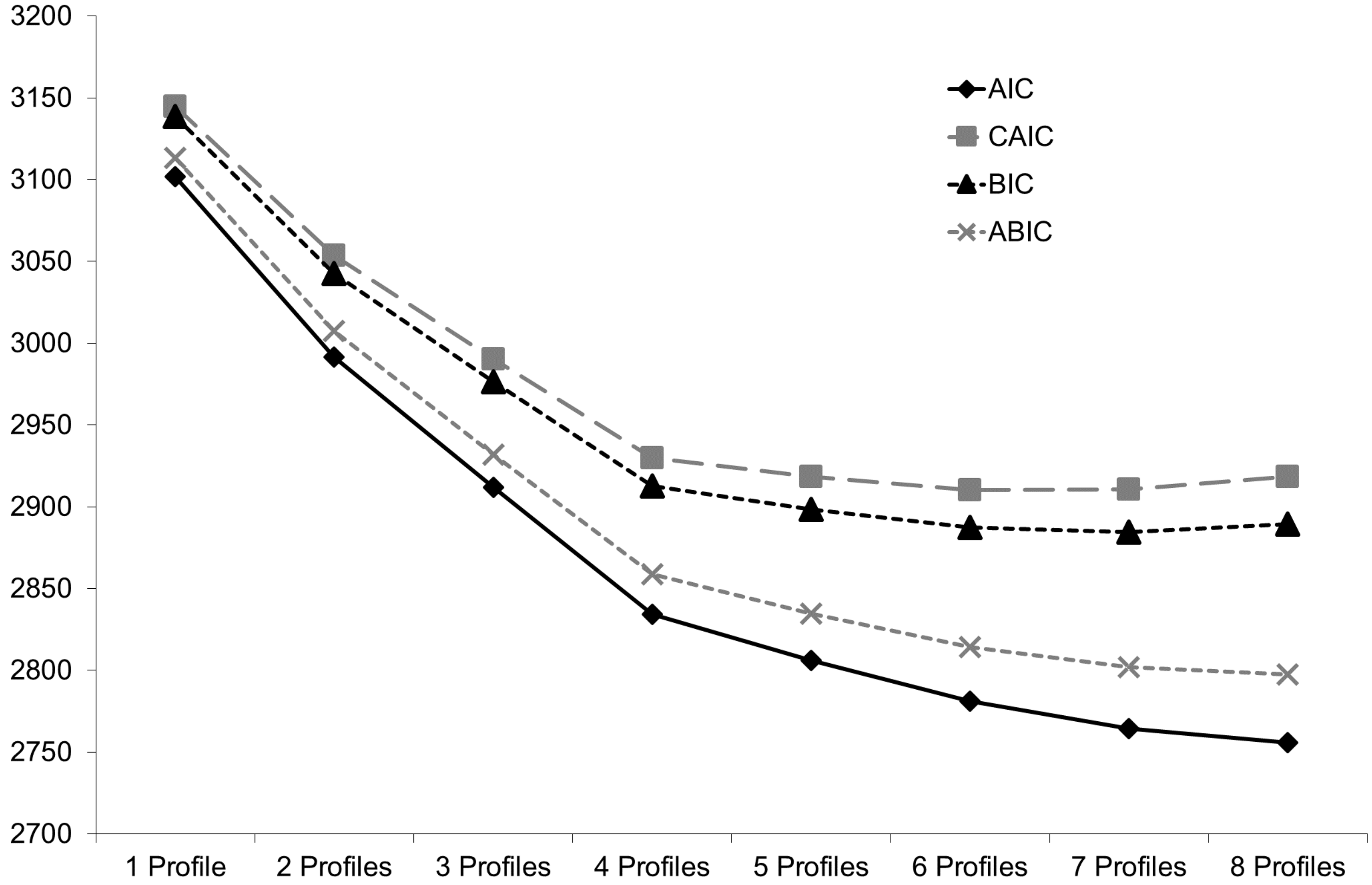

Figure S2. Elbow Plot of the Value of the Information Criteria for Solutions Including Different Number of Latent Profiles

Table S6

Parameters Estimates from the final Unconditional Growth Mixture Analysis Model

Parameter	Profile 1 (High) Estimate (*t*)	Profile 2 (Low) Estimate (*t*)	Profile 3 (Decreasing) Estimate (*t*)	Profile 4 (Increasing) Estimate (*t*)
Intercept Mean	.508 (12.525)**	-1.125 (-16.564)**	.156 (.699)	-1.269 (-4.175)**
Slope Mean	-.026 (-2.636)**	.032 (1.574)	-.624 (.102)**	.881 (.189)**
Intercept Variability ($SD = \sqrt{\sigma}$)	.564 (12.521)**	.564 (12.521)**	.564 (12.521)**	.564 (12.521)**
Slope Variability ($SD = \sqrt{\sigma}$)	.200 (3.906)**	.200 (3.906)**	.200 (3.906)**	.200 (3.906)**
Intercept-Slope Correlation	-.171 (-2.418)*	-.171 (-2.418)*	-.171 (-2.418)*	-.171 (-2.418)*
Time 1: SD(ε_{yi1})	.190 (.921)	.190 (.921)	.190 (.921)	.190 (.921)
Time 2: SD(ε_{yi2})	.259 (5.127)**	.259 (5.127)**	.259 (5.127)**	.259 (5.127)**
Time 3: SD(ε_{yi3})	.217 (2.778)**	.217 (2.778)**	.217 (2.778)**	.217 (2.778)**

Note. *t* = Estimate / standard error of the estimate (*t* value are computed from original variance estimate and not from their square roots); SD(ε_{yi}) = Standard deviations of the time-specific residuals; We present the square roots of the estimates of variability (trajectory factors, time-specific residuals) so that these results can be interpreted in the same units as the constructs used in these models (here, factor scores saved in standardized units from preliminary measurement models); * $p \leq .05$; ** $p \leq .01$

Table S7

Classification Accuracy: Classification Probability for Most Likely Profile Membership (Column) as a Function of the Profile Membership (Row).

	Profile 1 (High)	Profile 2 (Low)	Profile 3 (Decreasing)	Profile 4 (Increasing)
Profile 1 (High)	.951	.045	.003	.001
Profile 2 (Low)	.140	.850	.005	.004
Profile 3 (Decreasing)	.121	.082	.797	0
Profile 4 (Increasing)	.023	.033	0	.944