Abstract

Research on the effects of within-person personality variability has mainly focused on the consequences for subjective well-being. Drawing on a resource-based approach, we extend this field to the work domain, expecting that since deviating from one’s average trait level is resource intensive, it should relate negatively to behaviors that require the investment of additional resources, such as organizational citizenship behavior (OCB), while it should relate positively to behaviors that replenish one’s resources, such as counterproductive work behavior. Using two personality dimensions that are predictive for work-performance (conscientiousness and core self-evaluations), and a new variability index that is not confounded by the mean, we find an effect of personality variability on negative performance outcomes (counterproductive work behavior), while no relation is found with positive forms of extra-role performance (organizational citizenship behavior). These results were replicated across three separate experience sampling studies, confirming that, while within-person personality variability is related to performance, those relationships are relatively weak and they do not hold for every performance facet.
Driven by the awareness that people not only differ in how they behave, feel and think on average, but also in the extent to which these behaviors, thoughts and feelings fluctuate across time and situations, scientific interest in the role of within-person personality variability has increased during the last two decades. The large majority of these studies have focused on examining the relevance of within-person personality variability—or the extent to which one’s personality states fluctuate within the individual across time and situations—for wellbeing, typically suggesting that higher levels of within-person personality variability relate to psychological maladjustment (e.g., Bleidorn & Ködding, 2013).

Whereas these findings are instrumental in the sense that they provide a proof of concept for the importance of within-person personality variability in everyday life, our knowledge on the relevance of within-person personality variability for outcomes other than wellbeing is still limited at best. This is an important lacuna because such knowledge is needed to determine whether and to what extent within-person personality variability can be placed at the same level of average trait levels as a predictor of a broad range of human behaviors, feelings and outcomes. A second limitation of previous research on within-person personality variability is of a methodological nature. Typical measures of within-person personality variability (such as the within-person standard deviation) tend to be confounded with the average state level. That is, with a high (respectively low) average state level, people cannot increase (respectively decrease) their scores much, implying that measures of within-person personality variability are likely to be lower for people with high and low mean state levels than for people with more moderate mean state levels (Baird, Le & Lucas, 2006). The consequence is that, unless this methodological issue is resolved, it is hard to make strong claims about the unique relationships between within-person personality variability and real-life outcomes.
In the present study, we address both issues, thereby contributing to research on within-person personality variability in two important ways. First, we broaden our knowledge on the predictive validity of within-person personality variability for outcomes beyond wellbeing by extending the study of within-person personality variability to the work domain. In particular, we study the predictive validity of within-person personality variability in conscientiousness and core self-evaluations for two important work outcomes: Organizational Citizenship Behaviors (OCB)—or behaviors that exceed one’s formal tasks and promote organizational functioning (Lee & Allen, 2002)—and Counterproductive Work Behaviors (CWB)—or intentional behaviors viewed by the organization as contrary to its legitimate interests (Sackett, 2002)—. Second, we contribute to the research on within-person personality variability by adopting a novel measure of within-person personality variability that is not confounded by the trait level, thereby examining the unique predictive effect of within-person personality variability for OCB and CWB (Mestdagh, Pe, Pestman, Verdonck, Kuppens, & Tuerlinckx, 2018).

Within-person personality variability: State of the Art

For decades, personality psychologists have conceptualized personality as individual differences in people’s consistent patterns of thoughts, feelings, and actions (Eysenck & Eysenck, 1985; McCrae & Costa, 1995). Adhering to this idea, personality has typically been seen as one’s average behavioral, cognitive and affective tendencies across a wide variety of situations. However, with the rise of daily diary and experience sampling studies (Hofmans, De Clercq, Kuppens, Verbeke, & Widiger, 2019), an increasing number of studies demonstrated that people regularly engage in behaviors, feelings, and thoughts that are not in line with these average tendencies (e.g., Eid & Diener, 1999; Fleeson, 2001; Pickett, Hofmans, & De Fruyt, 2019; Pickett, Hofmans, Feldt & De Fruyt, 2020; Sosnowska, Kuppens, De Fruyt, & Hofmans, 2019). What’s more, such studies consistently show that the
amount of within-person variation in trait-relevant behaviors, feelings and thoughts is about as large as the amount of between-person variation (e.g., Fleeson, 2001).

Studying such moment-to-moment fluctuations in people’s personality states, Fleeson (2001) demonstrated that not only the average level of one’s personality states, but also other characteristics of their personality state distributions show remarkable regularities within individuals over time. For example, shape parameters of the personality state distributions, such as kurtosis and skew, show moderate week to week correlations, while the week-to-week correlations for size parameters (i.e., within-person personality variability) and location parameters (i.e., the average level) are even higher (Fleeson & Jayawickreme, 2015). Thus, not only one’s average state level is relatively stable from one week to another, this also holds true for the variability of one’s personality states. Going beyond week-to-week stability, Hardy and Segerstrom (2017) revealed that variability in negative affectivity showed relatively high test-retest correlations over a 10-year interval (i.e., $r = .39$). Given such remarkable stability in variability, Fleeson—in his density distribution approach (Fleeson, 2001), and later also in his more elaborate Whole Trait Theory (Fleeson & Jayawickreme, 2015)—suggested that within-person personality variability is as key to the understanding of personality as the average state level is. Acknowledging the crucial role of within-person personality variability, other scholars have referred to it as ‘consistency in inconsistency' (Roberts, 2009), and more recently also as “personality strength” (Dalal et al., 2015), with people who are less variable in their personality states being assumed to be less susceptible to external and internal forces, suggesting that they have a “stronger personality”.

Empirical studies on the correlates of within-person personality variability have shown that within-person personality variability is mildly positively associated across personality dimensions, suggesting that people who vary a lot on one dimension also tend to vary a lot on other dimensions (Beckmann et al., 2020; Dalal et al., 2015; Fleeson, 2001). Moreover,
research has also looked into mechanisms that underlie within-person personality variability. For example, Fleeson (2001) demonstrated that within-person personality variability reflects individual differences in the reactivity to situational cues, with higher levels of within-person personality variability on a specific personality dimension suggesting that the person is more sensitive to situational cues relevant to that dimension.

In terms of the predictive validity of within-person personality variability, a recent multi-study paper of Dejonckheere et al. (2019) looked into time series data from 15 different studies (total sample size of $n = 1,777$), testing whether dynamic measures of affect—among which within-person affect variability—demonstrated unique relations with wellbeing above and beyond mean levels of positive and negative affect. They showed that, although the unique predictive validity of most measures above and beyond the mean level is limited, within-person affect variability was the best predictor of wellbeing after accounting for mean levels of affect. Despite the fact that their focus was on affect dynamics rather than personality dynamics, their findings suggest that, among those measures that capture dynamics, within-person variability is a very promising one.

Theoretically speaking, there exist two different—and competing—perspectives on the meaning and role of within-person personality variability (Beckmann et al., 2020). According to the first perspective, within-person personality variability is indicative of a lack of an integrated inner core identity (Donnahue et al, 1993). Such weak sense of self implies that within-person personality variability concerns a vulnerability or risk factor and is therefore negatively related to health and wellbeing outcomes. Supportive of this perspective, Bleidorn and Köddings (2013) in their meta-analysis found that adults with greater self-concept differentiation—representing the extent to which the individual’s self-representation of personality varies across roles and situations—tend to have lower self-esteem, experience less positive and more negative affect, and experience increased feelings of depression and
anxiety. Similarly, Hardy and Segerstrom (2017) found within-person personality variability in negative affectivity to be positively related to psychological distress and physical ill health, both concurrently and prospectively.

According to the second perspective, within-person personality variability results from adaptive reactions to environmental changes. In other words, within-person personality variability is indicative of adaptive flexibility, rather than a vulnerability resulting from a weak sense of self. Whereas this perspective has received less support, a small number of studies have revealed positive correlations between within-person personality variability and health and wellbeing outcomes. For example, Magee, Buchtel, Human, Murray, and Biesanz (2018) showed that, in some very specific cases, within-person personality variability in openness, extraversion, and neuroticism was weakly related to psychological adjustment indicators.

Finally, there are also a couple of papers that reported null findings. For example, Baird et al. (2006; 2017) demonstrated that within-person personality variability was not systematically related to wellbeing when controlling for average trait levels, while Magee et al. (2018) showed that there is no consistent relation between within-person personality variability and adjustment.

**The Current Study**

As we have argued above, there is an increasing number of studies on within-person personality variability. However, much of this research is (1) limited to associations with wellbeing, and (2) plagued by an important methodological shortcoming.

Regarding the methodological issue, because of the bounded nature of our measurement tools (e.g., “describe how energetic you feel on a scale from 1 to 9”), estimates of within-person personality variability are typically confounded with the average state levels. In other words, someone with a very high (or low) average state level tends to show less
variability than somebody with a more moderate average state level as it is impossible to increase (or decrease) beyond the scale. The consequence of this is that measures of within-person personality variability are typically lower for people with high and low average state levels than for people with more moderate average state levels (Baird et al., 2006). Such methodological confound between the average state level and within-person personality variability is problematic because it might artificially inflate the predictive validity of within-person personality variability. A strong example of this is that current research on neuroticism indicates that the tried-and-true belief that neuroticism is characterized by greater emotional variability may be partially caused by the confound between emotional variability and the average level of negative emotions experienced. That is, when accounting for the confound between variability and average level, neuroticism turns out to be primarily associated with a higher average levels of negative emotions, rather than with greater emotional variability (Kalokerinos et al., 2020, Wendt et al., 2020).

There currently exist a couple of “solutions” aimed at disentangling the confound between the mean level and within-person variability, but each of those solutions suffers from their own shortcomings. For example, the most common attempt at resolving the issue is to control for the average state level as well as the squared average state level in a regression analysis (Baird et al., 2006). Aside from potential problems with multicollinearity, the issue with this method is that, regardless of how the dependency between the average state level and within-person personality variability takes form, such an approach makes it very difficult to interpret the relationship between within-person personality variability and the variable of interest. A regression analysis is commonly interpreted as the increase in the outcome variable when one of the predictor variables increases by one, while keeping the other variable constant. Provided that the average state score and within-person personality variability are intrinsically related to each other, it makes no sense to assume that the variability will
increase while the average state level remains constant, making interpretation problematic (Mestdagh et al., 2018).

In the present study, we adopt an alternative solution that directly resolves the issues with previous solutions. Based on the work by Mestdagh et al. (2018), we adopt a variability index that provides an unbiased measure of within-person personality variability in the sense that it directly rectifies the dependency between the average state level and within-person personality variability (see also Beckmann et al., 2020). This relative variability index calculates for each average state level the maximum possible variation provided the boundedness of the scale, and then rescales each raw variability score using this maximum possible variation. Specifically, the relative variability index \( V_i^* \) is calculated by dividing the variability \( V_i \) by its upper bound, which is the maximum variability given a mean \( M_i \) for individual \( i \).

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V_i^* = \frac{V_i}{\text{max}(V_i|M_i)}
\]

Using this novel measure of variability, we test associations between within-person personality variability and two important work outcomes: Organizational Citizenship Behaviors (OCB), and Counterproductive Work Behaviors (CWB). OCB pertains to behaviors that exceed one’s formal tasks and promote organizational functioning (e.g., helping a colleague, working overtime, Lee & Allen, 2002). CWB, in turn, refers to intentional behaviors viewed by the organization as contrary to its legitimate interests, such as arriving late or working slowly (Sackett, 2002).

Together with task performance, OCB and CWB cover the major components of job performance (Dalal, 2005). Although research on the relationship between within-person personality variability and performance is scarce, there are a handful of studies on the topic. Reddock et al. (2011) demonstrated that personality variability—as measured by the variability across the different items of a personality dimension rather than the variability of
the dimension across situations—was negatively related to academic performance and cognitive ability, supporting the idea that within-person personality variability is a vulnerability. Lievens et al. (2018), instead, found within-person personality variability in sociability and dutifulness to positively predict performance in a student sample, while within-person personality variability in personal initiative predicted supervisory-rated job performance in a sample of employees. Based on these findings, they suggested that within-person personality variability might tap into adaptive flexibility, a conclusion that was also tentatively drawn by Magee et al. (2018). Finally, the study of Beckmann et al. (2020) reported mixed findings, with within-person personality variability in Neuroticism being negatively related to job performance, while within-person personality variability in Agreeableness positively predicted supervisor evaluations of performance. Importantly, this study also measured within-person personality variability by looking at the variability across the different items of a personality dimension rather than the variability across situations.

In the present study, we move away from the vulnerability versus adaptive flexibility discussion. Instead, and drawing on the idea that engaging in behaviors that deviate from the trait level exhausts self-regulatory resources (Gallagher, Fleeson & Hoyle, 2011), we expect a negative relationship between within-person personality variability and OCB, and a positive one between within-person personality variability and CWB. The rationale is that the trait level serves as a baseline towards one’s behaviors, feelings and cognitions are attracted (Sosnowska et al., 2019). Hence, trait-consistent behaviors feel natural and automatic, which is why engagement in those behaviors requires little attention and energy. Deviating from the trait level, on the contrary, requires active monitoring, modification and maintenance of one’s behavior, which all exhaust people’s self-regulatory resources (Gallagher et al., 2011; Pickett et al., 2019). Importantly, research on OCB and CWB has shown such resources to play an important role in the elicitation of OCB and CWB (Spanouli & Hofmans, 2020). Whereas
OCBs might lead to the acquirement of valuable resources on the long term (e.g., Podsakoff & Mackenzie, 1997; Podsakoff, Whiting, Podsakoff, & Blume, 2009), engaging in these behaviors exhausts self-regulatory resources on the short term, with research showing that engagement in OCBs is associated with feelings of tiredness, being worn out or being on edge (Bolino, Hsiung, Harvey, & Lepin, 2015). For example, helping a colleague or working overtime both imply the investment of energy and resources, and those investments might only later on result in the generation of other resources, such as help from that colleague with your own work, or a promotion to a higher function. Because OCBs require the investment of self-regulatory resources, people with high levels of those resources are better able and more inclined to engage in such behaviors, which is supported by a positive relationship between vitality and OCB (Spanouli & Hofmans, 2020). Thus, because on average, people who deviate less from their trait level (i.e., low within-person personality variability) need to tax their self-regulatory resources less, we expect them to engage more in OCBs than people who deviate more from their trait level (i.e., high within-person personality variability).

Hypothesis 1: Within-person personality variability is negatively related to organizational citizenship behavior

CWBs, in turn, typically result in short-term gains, and therefore such behaviors can be seen as an effort to protect one’s resources from further resource depletion (Krischer, Penney and Hunter, 2010; Spanouli & Hofmans, 2020). For example, intentionally arriving late, working slowly or surfing on the internet during workhours are behaviors that allow one to replenish one’s resources. This perspective has been supported by empirical studies, showing that CWBs are sometimes used in response to emotional exhaustion (Bolton, Harvey, Grawitch, & Barber, 2012) and that when people are low in vitality they tend to engage more in CWBs than when they are high in vitality (Spanouli & Hofmans, 2020). Drawing on the idea that deviating from one’s trait level depletes self-regulatory resources, and that CWBs
can be used to regain such resources, we expect a positive relationship between within-person personality variability and CWB.

Hypothesis 2: Within-person personality variability is positively related to counterproductive work behavior

To test these hypotheses, we test the effect of within-person personality variability on OCB and CWB using two personality traits whose average trait levels are known to be predictive for work performance: conscientiousness and core self-evaluations. Among the Big Five personality dimensions, conscientiousness—being “the propensity to follow socially prescribed norms for impulse control, to be goal directed, to plan, and to be able to delay gratification” (Roberts, Jackson, Fayard, Edmonds & Meints, 2009, p. 369)—has been shown to be the best predictor of general job performance (Barrick & Mount, 1991) and OCB (Organ & Ryan, 1995), while it is also a consistent predictor of CWB (Berry, Ones, & Sackett, 2007). Core self-evaluations (CSE) is defined as “fundamental premises that individuals hold about themselves and their functioning in the world” (Judge, Erez, & Bono, 1998, p. 168). CSE has also been shown to be a good predictor of job performance (Judge & Bono, 2001), with Debusscher, Hofmans and De Fruyt (2016) showing that state CSE not only predicts task performance, but also OCB and CWB towards the organization. In the context of the present study, it is important to note that both conscientiousness and CSE have been shown to positively relate to OCB, whereas the relation with CWB is consistently negative. Hence, we expect the effects of within-person personality variability in conscientiousness and CSE not only to be additive to those of the average state level, but to be opposite in sign.

Method

We tested our hypotheses in three existing experience sampling datasets. The usage of existing datasets has two important implications. First, because the data were not collected for the research questions of the present paper, we did not pre-register the studies and our hypotheses. Second, we did not perform an a priori power analysis with sample size planning.
Instead, we report observed power for all of our study findings using the method proposed by Bliese and Wang (2020). This method calculates the cumulative probability of finding statistically significant effects, trying to address the pivotal question whether an independent study using similar measures and a similar design would also find statistically significant results. To provide an (approximate) answer to this question, the method by Bliese and Wang (2020) relies on nonparametric bootstrapping, drawing samples with replacement from the original dataset. The same analysis is then performed on each bootstrap sample, with the cumulative probability of finding statistical significant effects being defined as the proportion of bootstrap samples for which the effect was statistically significant. By reporting observed power for our study findings, we hope to help readers get an idea about the level of (un)certainty associated with our findings (Bliese & Wang, 2020).

In terms of ethical approval, the general guidelines of our institution at the time of data collection were applied. According to these guidelines, formal permission from an ethical committee was not required. Nevertheless, we followed the American Psychological Association Codes of Ethics. In particular, in all studies, we informed participants about the purpose and expected duration of the study, we informed them that they could withdraw from the study at any point without any consequences, they were reassured that their answers would be anonymized and kept confidential, and they were encouraged to reach out to us in case of issues and/or problems.

The data and R script used to run the analyses can be found on https://osf.io/zka9w/?view_only=a58294e913c24a1ab53aee2ab4db4df2.

Procedure and Participants

Study 1. In the first study, 49 employees reported on their state conscientiousness and OCB four times a day over a period of 10 consecutive workdays, resulting in 1,132 repeated

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1 We would like to thank an anonymous reviewer for this suggestion
observations. The final sample consisted of 31 (63.3%) female, and 18 (36.7%) male Dutch speaking, full-time employees, working in the profit sector in a wide variety of jobs. The sample was predominately highly educated, with 87.8% holding a Bachelors’ degree or higher. 57.1% of the sample was aged between 18 and 30 years old, and both organizational seniority and function seniority were rather low, with less than two years of seniority for 57.1% and 61.2%, respectively. Only 16.3% had an organizational seniority over 15 years.

Study 2. In the second study, state conscientiousness, OCB, and CWB were measured in 88 employees twice a day over a period of 10 consecutive workdays. Eight respondents were removed from this sample for not having filled out more than one daily survey, resulting in a final sample of 80 respondents with 728 repeated observations. This sample consisted of 48 (54.4%) female, and 39 (44.3%) male full-time employees, employed in various sectors including education (17%), finance (13.6%), government (10.2%), non-profit (10.2%) and health (9.1%). The average age was 27 years old ($SD = 6.68$), ranging from 21 till 57 years old.

Study 3. In the third study, 112 employees reported on their state Core Self-Evaluations (CSE) five times a day over a period of 10 consecutive workdays. OCB and CWB were measured once at the end of the study. Three respondents were removed from the sample for not having filled out more than one daily survey, and an additional 29 respondents were removed for not having filled out the OCB and CWB measures at the end of the study, resulting in a final sample of 78 respondents with 2,982 repeated observations. This sample consisted of 29 (37.2%) female and 56 (71.8%) male participants from a variety of different nationalities, being Belgian (43.5%), Indian (23.5%), Dutch (12.9%), Hungarian (11.8%), and German (5.9%). 43.5% of the sample worked in the same company in the industrial electronic sector. The other 46.5% worked in different sectors. The average age was 40 years old ($SD = 11.70$), ranging from 22 to 65 years old.
Measures

In studies 1 and 2, state conscientiousness was measured using the Dutch translation of Goldberg’s eight unipolar adjective Markers (Saucier, 1994). To capture momentary levels of conscientiousness, participants were asked to rate how each of the adjectives (e.g., organized, practical, efficient) applied to them at that particular moment using a nine-point Likert scale ranging from extremely inapplicable to extremely applicable. Because of the multilevel nature of the data, internal consistency was computed using multilevel confirmatory factor analysis, yielding an internal consistency index at the between- and one at the within-person level\(^2\) (Geldhof, Preacher, & Zyphur, 2014). Between-person omega reliability was .93 and .87, while within-person omega reliability equaled .85 and .68 for studies 1 and 2, respectively.

Momentary OCB and CWB were measured in studies 1 and 2 using the short eight-item OCB and CWB scales by Dalal, Lam, Weiss, Welch and Hulin (2009). These scales are specifically designed for measuring OCB and CWB in experience sampling studies (Dalal, Lam, Weiss, Welch & Hulin, 2009) because of their length and the fact that they only measure behavior that occurs in short timeframes (e.g, “Volunteered to do something that was not required” for OCB, and “Did not work to the best of my ability” for CWB). For each item, the respondent answered whether he/she had engaged in this behavior since the last measurement moment (Study 1), or during that day (Study 2). This resulted in a scale score from 0 (none of these behaviors did occur) to 8 (all behaviors did occur). Between-person omega reliability was .88 and .82 for OCB in studies 1 and 2 respectively, and .74 for CWB in study 2.

In Study 3, State CSE was measured using a four-item scale developed by Doci and Hofmans (2015). In this scale, each item pertains to one of the four sub-components of core

\(^2\) In Study 1, within-person variability coincides with between-day variability, while in Study 2 within-person variability is comprised of both within-day as well as between-day variability.
self-evaluations, being self-efficacy (‘To what degree did you feel confident about your abilities today?’), locus of control (‘To what degree did you feel in control of the situation today?’), neuroticism (‘To what degree did you experience negative emotions today?’), and self-esteem (‘To what degree did you feel good about yourself today?’). Each item was rated on a nine-point Likert scale ranging from ‘not at all’ to ‘absolutely’. Between-person omega reliability was .91 and within-person (being a blend of within-day and between-day variability) omega reliability equaled .81.

General OCB was measured in Study 3 using the original English 20-item scale by Fox et al. (2012), as well as a Dutch translation of the scale. In contrast to the scale used in Study 2, this scale also contains questions on less frequent behavior (e.g., “Said good things about your employer to others”, or “Decorated, straightened up, or otherwise beautified common workspace”). Each statement was rated on a 7-point Likert scale ranging from ‘never’ to ‘always’. Omega reliability equaled .93 for the English version, and .93 for the Dutch version. Regarding the OCB subdimensions, omega reliability equaled .86 for the English and .79 for the Dutch OCB-O dimension (i.e., OCB directed towards the organization) items, and .78 for the English and .82 for the Dutch OCB-P dimension (i.e., OCB directed towards the people inside the organization).

General CWB was measured in Study 3 using the original English 45-item CWB-C scale by Spector et al. (2006), as well as Dutch translation of the scale. Similar to the difference in OCB measures, this scale consists of a more exhaustive list of less frequent behavior in comparison to the scale used in Study 2 (e.g., “Hid something so someone at work couldn’t find it”, or “Hit or pushed someone at work”). Each statement was rated on a 7-point Likert scale ranging from ‘never’ to ‘always’. Omega reliability equaled .96 for the English
version, and .90 for the Dutch version\(^3\). Regarding the CWB subdimensions, omega reliability equaled .94 for the English and .77 for the Dutch CWB-O dimension (i.e., CWB directed towards the organization) items, and .92 for the English and .89 for the Dutch CWB-P dimension (i.e., CWB directed towards the people inside the organization).

**Analytic plan**

In the present paper, all findings are obtained using methods that are robust to the effect of outliers. The reason for using robust methods is that within-person personality variability indices are not directly rated by the respondents but derived from a series of repeated self-ratings. In particular, and in line with the density distribution approach (Fleeson, 2001), within-person personality variability is calculated as the (relative) variability across all (lowest-level) momentary states of the individual, which was done using the relativeVariability package (Mestdagh et al., 2018) in R. In such situation, outlying within-person personality variability values cannot simply be considered to be “erroneous”, and can therefore not be removed from the analyses. By the same token, we needed to make sure that such outlying values did not exert a disproportional influence on the findings, which robust methods resolve by downweighing the influence of outlying observations.

As a first step, and as an alternative to the well-known Pearson correlation coefficient, we computed the percentage bend correlation (Wilcox, 1994) using the WRS2 package (Mair & Wilcox, 2020) in R. The percentage bend correlation uses an M-estimator to downweigh a specific percentage of marginal observations that deviate from the median, after which a Pearson correlation coefficient is computed on the transformed data (Pernet, Wilcox & Rousselet, 2013). In line with Wilcox (2011), we set the beta (i.e., the breakdown point, or the

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\(^3\) Three items were dropped from the omega reliability test, as they were scored the same by all participants, and therefore contained no variability.
maximum proportion of data that can be arbitrarily changed without biasing the estimator) for
the percentage bend to the default of 0.2.

In a next step, we regressed the outcome variable(s) (i.e., CWB and OCB) on the
relative variability index. This was done using robust linear regression analyses using Huber’s
M-Estimation weighing method, which is a regression method in which influential
observations are downweighed, using the MASS package (Venables & Ripley, 2002) in R. To
test the regression parameters for statistical significance, bootstrapped confidence intervals
were computed for each regression parameter using non-parametric bootstrapping (50,000
bootstrap samples along with bias-corrected and accelerated [BCa] 95% confidence intervals)
using the boot package in R. Because robust regression models do not yield effect size
measures, those were obtained by re-running the analysis in a weighted least squares
regression using the weights from the Huber M- Estimation weighing method. In a second
step, we re-ran the regression models, adding the average state level as a predictor. Note that
inclusion of the average state level should not affect the predictive validity of within-person
personality variability because the relative variability index $V_r$ is specifically designed to
factor out the impact of the average state level on the variability estimate. These analyses are
mainly done to allow comparing the effects of the mean state level and within-person
personality variability.

Additionally, we performed a post-hoc analysis in which we tested whether the effects
of within-person personality variability on OCB and CWB held across different OCB and
CWB subdimensions$^4$ (see Table 5 for an overview). Note that this analysis was only possible
in Study 3, as this is the only study in which we used multi-dimensional OCB and CWB
measures.

$^4$ We would like to thank an anonymous reviewer for this suggestion.
As mentioned earlier, for each analysis we additionally report the cumulative probability of finding statistically significant effects (CPFS). For the percentage bend correlations, this was done by drawing 10,000 nonparametric bootstrap samples from the original data, calculating the percentage bend correlation on each bootstrap sample, and computing the proportion of bootstrap draws for which the percentage bend correlation was statistically significant using a p-value of .05. For the robust regression analyses, the approach was slightly different because we already used bootstrapping for constructing the confidence intervals. Therefore, CPFS was calculated by drawing 1,000 nonparametric bootstrap samples from the original data, performing the robust regression analysis on each bootstrap sample (which includes another nonparametric bootstrap from the bootstrap sample to construct the bias-corrected and accelerated [BCa] 95% CI), and counting the proportion of (initial) bootstrap samples for which 0 was not included in the 95% BCa CI. Due to the heavy processing load required to perform such a nested bootstrap analysis, we used 1,000 bootstraps for calculation of the CPFS and 1,000 bootstraps to construct the 95% BCa CI within each CPFS bootstrap sample. Also note that we did not bootstrap from the raw multilevel data, but rather from the (aggregated) person-level data (i.e., from the dataset including the relative variability indices). Doing so circumvents the issue that there is no widely accepted way to perform nonparametric bootstrapping on multilevel data (Bliese & Wang, 2020).

Results

Descriptive statistics and correlations

Descriptive statistics of our study variables are shown in Table 1, and within- and between-person percentage bend correlations are shown in Table 2. At the within-person level, deviations from one’s average level of conscientiousness were moderately positively related to deviations from one’s average level of OCB in Study 1 \(r(1130) = .21, p < .01\),
CPFS = 1; Study 1), although this relationship was not replicated in Study 2 \((r(702) = .06, p = .107, CPFS = .380)\). No significant relationship with CWB was found \((r(702) = -.07, p = .078, CPFS = .424; Study 2)\). In Study 3, the outcome variables (i.e., OCB and CWB) were measured only once, so no within-person correlations were computed.

Between-person percentage bend correlations revealed that the average level of state conscientiousness is positively related to the average level of state OCB, both in Study 1 \((r(47) = .39, p = .002, CPFS = .818)\) and Study 2 \((r(78) = .36, p < .001, CPFS = .910)\). No significant relationship was found between average state conscientiousness and average CWB \((r(78) = -.19, p = .094, CPFS = .390; Study 2)\). Finally, the average level of state CSE was unrelated to OCB \((r(76) = -.03, p = .821, CPFS = .077; Study 3)\) and CWB \((r(76) = -.16, p = .172, CPFS = 323; Study 3)\).

Turning to the relationships with our focal variables, we found no significant relationship between OCB and within-person variability in conscientiousness \((r(47) = -.14, p = .348, CPFS = .157; r(78) = .01, p = .915, CPFS = .043; Study 1 and 2 respectively)\) and CSE \((r(76) = .00, p = .975, CPFS = .077; Study 3)\). For CWB, a moderate positive relationship with within-person variability in conscientiousness \((r(76) = .30, p < .01, CPFS = .796; Study 2)\), and CSE \((r(76) = .33, p < .01, CPFS = .809; Study 3)\) was found. Lastly, both for conscientiousness \((r(47) = -.13, p = .390, CPFS = .129; r(78) = -.04, p = .708, CPFS = .055; Study 1 and 2 respectively)\) and CSE \((r(76) = -.09, p = .335, CPFS = .192; Study 3)\), no significant relationship was found between within-person personality variability and the average state level. Note that this makes sense because the relative variability index is specifically designed to correct the dependency between the average state level and within-person personality variability.

**Regression analyses**
When regressing the outcome variables on within-person personality variability, within-person personality variability in both CSE ($\beta_1 = .28$; 95% BCa CI [.04, .48]; $f^2 = .48$; $CPFS = 1$; Study 3), and conscientiousness ($\beta_1 = .18$; 95% BCa CI [.04, .41]; $f^2 = .24$; $CPFS = 1$; Study 2) related to higher levels of CWB. Figure 1 shows a graphical representation of the regression lines along with the raw data for each study.

For OCB, we found no relationship with within-person personality variability in CSE ($\beta_1 = -.13$; 95% BCa CI [-.48, .25]; $f^2 = .14$; $CPFS = 0$; Study 3) nor with within-person personality variability in conscientiousness ($\beta_1 = .02$; 95% BCa CI [-.33, .32]; $f^2 = .02$; $CPFS = 0$ for Study 1 and $\beta_1 = .00$; 95% BCa CI [-.13, .33]; $f^2 = .00$; $CPFS = 0$ for Study 2).

Again, the raw data along with the regression lines are shown in Figure 2.

In the second step, we added the average state level to our regression models (see Table 3 & 4 for an overview). Also in those models, within-person personality variability in both CSE ($\beta_1 = .28$; 95% BCa CI [.02, 0.48]; $f^2 = .48$; $CPFS = .872$; Study 3), and conscientiousness ($\beta_1 = .18$; 95% BCa CI [.04, .40]; $f^2 = .24$; $CPFS = 1$; Study 2) was related to higher levels of CWB.

For OCB, the relationship with within-person personality variability in CSE ($\beta_1 = -.13$; 95% BCa CI [-.49, .28]; $f^2 = 0.13$; $CPFS = 0$; Study 3) as well as the relationship with within-person personality variability in conscientiousness ($\beta_1 = .06$; 95% BCa CI [-.31, .36]; $f^2 = .05$; $CPFS = 0$ for Study 1 and $\beta_1 = .03$; 95% BCa CI [-.14, .19]; $f^2 = .03$; $CPFS = 0$ for Study 2) remained statistically nonsignificant.

The post-hoc analysis revealed that the findings for the subdimensions were in line with the overall pattern of findings. Within-person personality variability in CSE was unrelated to both OCB directed towards the organization ($\beta_1 = -.24$; 95% BCa CI [-.51, .19]; $f^2 = .21$; $CPFS = 0$), and OCB directed towards people ($\beta_1 = -.23$; 95% BCa CI [-.52, .19]; $f^2 = .21$; $CPFS = 0$). For CWB, a positive relationship was found with CWB directed towards
the organization ($\beta_1 = .35; 95\% \text{ BCa CI}. [.06, .51]; f^2 = .51; CPFS = .999$), while CWB directed towards people ($\beta_1 = .25; 95\% \text{ BCa CI}. [-.00, .41]; f^2 = .32; CPFS = .267$) approached conventional levels of significance.

**Discussion**

Up until now research on the predictive validity of within-person personality variability has mainly focused on its predictive role for subjective well-being. In the present study, we go beyond this focus on subjective feeling states and examine whether within-person personality variability in conscientiousness and core-self evaluations (CSE) relate to concrete, work-related behaviors. Drawing on a resource-based approach to within-person personality variability, we hypothesized that, because within-person personality variability taps into the extent to which one deviates from one’s average state level, and because such deviations have been shown to tax one’s self-regulatory resources (Gallagher et al., 2011), within-person personality variability in conscientiousness and core-self evaluations should negatively relate to behaviors that require the investment of additional resources, such as organizational citizenship behavior (OCB), while it should be positively related to behaviors that replenish one’s resources, such as counterproductive work behavior (CWB).

In line with the few existing studies on the predictive validity of within-person personality variability for performance, we obtained mixed findings. While within-person personality variability was indeed predictive of negative performance outcomes (CWB), no association was found with positive forms of extra-role performance (OCB). Generally speaking, this mixed pattern of findings is consistent with previous research, which has shown that, although within-person personality variability relates to work performance, “overall predictive effects were small in number and size” (Beckmann et al., 2020, p. 1). In other words, our study findings confirm that, although within-person personality variability is
related to performance, those relationships are relatively weak, and they do not hold for each and every performance facet.

In terms of theorizing, the mixed findings challenge our theorizing and specifically the theorized mediational role of self-regulatory resources. Although the exact mechanisms underlying our findings are not known because we did not explicitly include mediating variables in our studies, one possibility might be that personality variability may not tax self-regulatory resources but instead be associated with another construct that is only relevant to CWB. One example of such mediating variable is negative affect. According to the emotion-centered model of voluntary work behavior of Spector and Fox (2002) CWB is primarily affected by negative emotions, while OCB is primarily associated with positive emotions. Provided that the positive association between self-concept differentiation and negative affect is stronger than that negative one between self-concept differentiation and positive affect (Bleidorn & Köddig, 2013), the negative affective feelings associated with higher levels of personality variability might explain the stronger association with CWB. On the other hand, the finding that personality variability was primarily linked to CWB towards the organization aligns with the resources perspective in the sense that one typically replenishes resources by engaging in behaviors such as intentionally arriving late, taking longer breaks, or working slowly (all being examples of CWB towards the organization) rather than by engaging in for example bullying (being an example of CWB towards other people). Hence, an alternative explanation for the asymmetry between OCB and CWB might be that personality variability does deplete self-regulatory resources, but that such depletion only affects CWB (towards the organization) and not OCB. Thus, although our study showed that personality variability relates to CWB, future research is needed to test the exact mechanisms underlying their relationship.
Notwithstanding the mixed findings, there are several reasons why the present study makes an important contribution to the accumulation of knowledge in this young research domain. First, using different personality dimensions and using different measures of OCB and CWB, we found a consistent pattern of findings. There was a null relationship between personality variability and OCB across three studies and a positive one with CWB in two studies. Moreover, by studying within-person personality variability not only in conscientiousness but also in CSE, we not only found consistent results across studies, but also across personality dimensions, suggesting that the effects might generalize across personality dimensions.

Second, by using the relative variability index of Mestdagh et al. (2018), our measure of within-person personality variability corrected for the problematic confounding of within-person personality variability with the average state score. Finally, we made use of an analytical technique that is robust to outliers when testing the relation between within-person personality variability and OCB and CWB. Such robust methods are important because traditional least squares regression models are highly sensitive to outliers, and the presence of such outliers tends to inflate the type two error rate.

Combined with findings of previous research, our study results suggest that the relation between within-person personality variability and performance is a complex tangle. When specifically looking at the findings for CWB, the fact that within-person personality variability related positively to CWB is quite interesting, particularly because trait conscientiousness and trait CSE are known to be negatively—and thus inversely—related to CWB (Berry et al., 2007; Debusscher et al., 2016). The reversal in sign when switching from average trait levels to within-person personality variability provides convincing evidence for the fact that within-person personality variability can be a liability when it comes to work performance. Whereas this conclusion is in line with studies that have also found negative
effects on (academic) performance (Reddock et al., 2011), it is important to note that other studies found within-person personality variability to positively predict (work) performance (Lievens et al., 2018; Magee et al., 2018), while still other studies found mixed evidence in the form of revealing both positive and negative relations (Beckmann et al., 2020). Collectively, such inconsistent pattern of findings calls for a deeper understanding of the factors affecting the relationship between within-person personality variability and different facets of performance. Studying the reasons why within-person personality variability is sometimes advantageous, at other times a liability, and on still other times it just does not matter is clearly is an avenue for future research. It is important to note that several scholars have already proposed several mechanisms through which within-person personality variability is believed to relate to performance outcomes: functional flexibility (e.g., Lievens et al., 2018), mere inconsistency because of a weak sense of self (e.g., Donnahue et al, 1993), and resource depletion (our study). It would be interesting for future research to explicitly study those mechanisms, perhaps even simultaneously in a competing mediation framework.

In studying those factors, context most probably also plays an important role. In the present study, we examined within-person personality variability in conscientiousness and CSE in one specific context: work. However, people might not only fluctuate within this single context but also across contexts. For example, one might behave, feel and think differently at work than at home. Differences in how one behaves on average in those different contexts also indexes within-person personality variability. Importantly, differing between within- and between-context fluctuations is key to studying (the effects of) within-person personality variability because, according to the Within and Across Context Variability Framework (WAC; Geukes, Nestler, Hutteman, Küfner, & Back, 2017) such differentiation directly maps onto the processes one is studying. For example, responsiveness—or the extent to which one responds to unique situational characteristics—
will most likely be observed in cross-context, rather than in within-context fluctuations. Inconsistency, in turn, being an internal source of variation free from systematic external causes, should particularly enhance within-context variability because people who are inconsistent should fluctuate despite being in a similar context. Finally, rigidity—or the extent to which one follows strict behavioral, cognitive and affective rules—should be observed both within and across contexts.

According to the WAC framework, our measure of within-person personality variability, being a measure of within-context variability, primarily tapped into inconsistency, which is known to be detrimental to performance (Dudley, Orvis, Lebiécki, & Cortina, 2006). Hence, the positive relationship between within-person personality variability and CWB—a negative form of performance—is consistent with the WAC framework. Of course, defining where one context ends and another one starts is a difficult matter. For example, jobs are typically composed of a series of different tasks, and sometimes these tasks require different levels of conscientiousness. Moreover, an employee might have a different level of mastery of the different tasks, which might explain why their level of CSE is different for each of these tasks. In such case the different tasks constituting one’s job should probably be considered different contexts, which would—according to the WAC framework—imply that within-person personality variability within the job across the tasks will be an indicator of responsiveness or functional flexibility rather than of inconsistency.

**Practical implications**

By showing that within-person personality variability has unique predictive validity for CWB above and beyond the trait level, our findings suggest that it might be interesting to expand the assessment of personality when selecting personnel. The difficulty, however, is that our conceptualization of within-person personality variability necessitates repeated measurements of the same individual, which can be challenging in a selection setting. Viable
ways to collect such data is through a multiple speed assessment procedure, in which candidates go through a large number of short AC exercises and their personality states are rated, or through situational judgement tests, in which candidates are confronted with different situations and are asked to report how they would react in those situations (see Sosnowska, Hofmans, & Lievens, 2021). A third alternative is to assess personality using a frequency-based response format (Edwards & Woehr, 2007) instead of a traditional Likert-type response format. In a frequency-based response format, respondents are asked to indicate for each item the relative frequency with which each response category (e.g., very inaccurate, neither accurate nor inaccurate, and very accurate) reflects their behavior in the past six months. Although such self-reports of one’s within-person personality have obvious disadvantages (such as recall biases), this approach is less expensive and less time-consuming than the other alternatives, and research has shown that it correlates highly with actual frequency counts in everyday life (Kane & Woehr, 2006).

Limitations

A first limitation of our study pertains to sample size. In the context of our study, sample size is important at two levels. First, enough repeated observations per individual are needed to obtain stable within-person personality variability estimates. In terms of repeated measurements, we had on average 23.10, 9.10, and 38.23 repeated observations per participant for studies one, two, and three, respectively. Second, sample size also matters at the participant level, because the individual participants are the units of interest in our regression analyses. In our studies these numbers were 49, 80, and 78, respectively. Whereas such low to moderate numbers of participants are fairly common in experience sampling research, it might compromise the statistical power of our analyses. To get an idea of the severity of this issue, we calculated the cumulative probability of finding statistically significant effects. This analysis revealed that the statistically significant findings—the effect
of personality variability in conscientiousness and CSE on the average level of CWB—had an observed power of 87.5% and 100% respectively, while the statistically non-significant findings—the effect of personality variability in conscientiousness and CSE on average level of OCB—had an observed power of 15.7%, 4.3%, and 7.7%. We believe that reporting these numbers gives an idea about the level of (un)certainty that is associated with these findings, showing that our findings are fairly robust. Finally, the moderate number of participants per individual study is to some extent compensated by the fact that the patterns of results were tested in three separate studies.

A second limitation is that all of our data were self-rated. Although it is not uncommon to collect observer ratings of personality, this is a highly complex matter when individuals are repeatedly measured as they go through everyday life. Moreover, traditional concerns with self-rated data, such as common method bias, are less of an issue in our study because the predictor variables (and in two of the three studies also the outcomes) are derived from the repeated measures data, rather than directly rated by the participants themselves. Nevertheless, it is important to acknowledge that our findings cannot readily be generalized to personality ratings from other sources. This point is clearly illustrated by the findings of Beckmann et al. (2020), who found that the predictive validity of within-person personality variability—as measured by the variability across the different items of a personality dimension rather than the variability of the dimension across situations—for performance was different for self-ratings than for observer ratings.

Third, because our measures only focused on the individual’s personality states and performance, and not on the situation, we cannot test the extent to which within-person personality variability was unrelated to situational cues (i.e., inconsistency) or rather in response to those cues (i.e., adaptive flexibility). This implies that we cannot tell which mechanisms drove the (non-)effects that were observed. Although the mixed findings in the
literature suggest that different mechanisms might co-exist, further research is needed to clarify this issue.

Fourth, whereas using the relative variability index rectifies the confound of the uncorrected variability index with the average state score, within-person personality variability indices can be distorted by other factors as well. Among those factors are the separation of true, meaningful variability from measurement error and the presence of high person misfit (being an indicator of careless responding or cheating). To address these additional challenges, Lang et al. (2019) suggest studying within-person personality variability by applying item response theory (IRT) tree models to responses to the items of a traditional personality measure (see also Lievens et al., 2018). The assumption underlying IRT tree models is that responding to a Likert scale is a multi-stage process in which one first decides whether to give a directed answer or not (i.e., whether they select the middle category), in case of a directed answer then decide on the direction of the answer, and finally on the extremity of one’s answer. Variability is then captured by the tendency to prefer a directional over a neutral response and the tendency to prefer extreme responses over more moderate responses. Lang et al. (2019) show that this form of variability generalizes across traits, correlates well with within-person $SD$s from personality inventories, and with within-person $SD$s gathered from daily diary data. Hence, future research might want to try to replicate our findings using an IRT tree variability index. This would allow to not only account for floor or ceiling effects in the data, but also to separate meaningful variability from measurement error and to account for the presence of high person misfit.

Finally, although our findings generalized across two personality dimensions, generalizability to other personality dimensions remains to be tested. Also, generalizability to other types of within-person personality variability is still an open issue, particularly because all of these different types of within-person personality variability tap into slightly different
constructs (see Debusscher et al., 2016). In particular, within-person personality variability as measured by the variability across the items of a personality dimension taps into the extent to which the individual has a strong internal representation of the personality dimension. Our measure of within-person personality variability, in turn, captures the extent to which one’s personality states are (dis)similar across different situations, implying that it taps into the extent to which one is (in)sensitive to situational cues. Because those two types of within-person personality variability are not only measured in a different way but also differ conceptually, it is unclear whether similar results can be expected to hold for these different types of within-person personality variability.

Conclusions

The current study adds to a growing number of studies on the relation between within-person personality variability and performance by studying the predictive validity of within-person personality variability in conscientiousness and core self-evaluations (CSE) for organizational citizenship behavior (OCB) and counterproductive work behavior (CWB). Using a variability index that rectifies the confound between variability and the average state level, and using robust analyses in three experience sampling datasets, we found that within-person personality variability in conscientiousness and core CSE related positively to CWB but was unrelated to OCB, suggesting that within-person personality variability in conscientiousness and core self-evaluations can be a liability when it comes to work performance.

References


https://doi.org/10.1037/pas0000600


Table 1: Descriptive statistics of the study variables

<table>
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<th>Study 1</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
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<td>5.73</td>
<td>1.93</td>
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<tr>
<td>State Conscientiousness</td>
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<td>1.16</td>
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<tr>
<td>RSD State Conscientiousness</td>
<td>49</td>
<td>.24</td>
<td>.10</td>
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<table>
<thead>
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<th>Study 2</th>
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<tbody>
<tr>
<td></td>
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<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>State OCB</td>
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<td>1.56</td>
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<tr>
<td>State CWB</td>
<td>707</td>
<td>1.69</td>
<td>1.44</td>
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<td>RSD State Conscientiousness</td>
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<td>.07</td>
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<th>Study 3</th>
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<tr>
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<td>Mean</td>
<td>SD</td>
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<tr>
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<td>CWB</td>
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<td>.30</td>
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<td>.77</td>
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<tr>
<td>RSD State CSE</td>
<td>110</td>
<td>.12</td>
<td>.07</td>
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</table>

*Note: OCB = organizational citizenship behavior, CWB = counterproductive work behavior, CSE = core self-evaluations, RSD = relative standard deviation*
Table 2: Percentage bend Within- and Between-person Correlations (beta = .2)

<table>
<thead>
<tr>
<th>Between-Person Correlations</th>
<th>Within-Person Correlations</th>
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<tr>
<td>State C</td>
<td>State OCB</td>
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<td>Study 1</td>
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<td>State C</td>
<td>—</td>
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<tr>
<td>State OCB</td>
<td>.39***</td>
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<tr>
<td>RSD C</td>
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<td>State C</td>
<td>—</td>
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<tr>
<td>State OCB</td>
<td>.36***</td>
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<tr>
<td>RSD C</td>
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<tr>
<td>State CWB</td>
<td>-.19*</td>
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<td>Study 3</td>
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<td>State CSE</td>
<td>—</td>
</tr>
<tr>
<td>OCB</td>
<td>—</td>
</tr>
<tr>
<td>CWB</td>
<td>-.16</td>
</tr>
<tr>
<td>RSD CSE</td>
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</tr>
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</table>

Note: OCB = organizational citizenship behavior, CWB = counterproductive work behavior, CSE = core self-evaluations, C = conscientiousness, RSD = Relative standard deviation, *p<0.1; **p<0.05; ***p<0.01
Table 3: Robust linear regression results when regressing CWB on the relative variability index and the average state level

<table>
<thead>
<tr>
<th></th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
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<tbody>
<tr>
<td></td>
<td>Mean CWB Study 2</td>
<td>Mean CWB Study 3</td>
</tr>
<tr>
<td>RSD state Conscientiousness Study 2</td>
<td>2.324</td>
<td>[.518,.224]</td>
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<tr>
<td>Mean state Conscientiousness Study 2</td>
<td>-.175</td>
<td>[-.3477,-.013]</td>
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<tr>
<td>RSD state Core Self-Evaluations Study 3</td>
<td>1.497</td>
<td>[.095,2.125]</td>
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<tr>
<td>Mean state Core Self-Evaluations Study 3</td>
<td>-.026</td>
<td>[-.125,.056]</td>
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<tr>
<td>Intercept</td>
<td>1.571</td>
<td>[1.399,1.788]</td>
</tr>
<tr>
<td>Residual Std. Error</td>
<td>.601 (df = 77)</td>
<td>.175 (df = 75)</td>
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</table>

Note: CWB = counterproductive work behavior, RSD = relative standard deviation, confidence intervals are bias-corrected and accelerated [BCa] bootstrapped 95% confidence intervals
Table 4: Robust linear regression results when regressing OCB on the relative variability index and the average state level

<table>
<thead>
<tr>
<th></th>
<th>Mean OCB Study 1</th>
<th>Mean OCB Study 2</th>
<th>Mean OCB Study 3</th>
<th>Mean OCB Study 1</th>
<th>Mean OCB Study 2</th>
<th>Mean OCB Study 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>RSD state Conscientiousness Study 1</td>
<td>.858</td>
<td>-.065</td>
<td>.065</td>
<td>[-4.023,4.798]</td>
<td>[.305,.363]</td>
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<tr>
<td>Mean state Conscientiousness Study 1</td>
<td>.715</td>
<td>.415</td>
<td>[.255,1.120]</td>
<td>[-2.223,2.998]</td>
<td>[.161,.707]</td>
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<tr>
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<td>.454</td>
<td>.030</td>
<td>.030</td>
<td>[-2.223,2.998]</td>
<td>[.141,.190]</td>
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<tr>
<td>RSD state Core Self-Evaluations Study 3</td>
<td>-2.214</td>
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<td>-1.129</td>
<td>[-6.756,3.882]</td>
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<tr>
<td>Mean state Core Self-Evaluations Study 3</td>
<td>.040</td>
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<td>.023</td>
<td>[-.555,.516]</td>
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<td></td>
<td>4.339</td>
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<td></td>
<td>-.219,.248</td>
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<tr>
<td>Residual Std. Error</td>
<td>1.233 (df = 46)</td>
<td>.845 (df = 77)</td>
<td>.987 (df = 75)</td>
<td>.929 (df = 46)</td>
<td>.743 (df = 77)</td>
<td>.909 (df = 75)</td>
</tr>
</tbody>
</table>

Note: OCB = organizational citizenship behavior, RSD = relative standard deviation, confidence intervals are bias-corrected and accelerated [BCa] bootstrapped 95% confidence intervals
Table 5: Robust linear regression results when regressing OCB and CWB dimensions on the relative variability index and the average state level CSE

<table>
<thead>
<tr>
<th>Unstandardized Coefficients</th>
<th>Study 3</th>
<th>Study 3</th>
<th>Study 3</th>
<th>Study 3</th>
<th>Study 3</th>
<th>Study 3</th>
<th>Study 3</th>
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</thead>
<tbody>
<tr>
<td>RSD state CSE</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean OCB-P</td>
<td>-3.569</td>
<td>-3.558</td>
<td>1.059</td>
<td>1.870</td>
<td>-.231</td>
<td>-.235</td>
<td>.247</td>
<td>.348</td>
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<tr>
<td>Mean OCB-O</td>
<td></td>
<td></td>
<td></td>
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<tr>
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<tr>
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<td>Mean OCB-P</td>
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<td>.322</td>
<td>.010</td>
<td>-.009</td>
<td>.031</td>
<td>.023</td>
<td>.021</td>
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<tr>
<td>Intercept</td>
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<td>4.524</td>
<td>1.233</td>
<td>1.327</td>
<td>.027</td>
<td>.010</td>
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<tr>
<td>Residual Std. Error</td>
<td>1.230 (df = 75)</td>
<td>1.151 (df = 75)</td>
<td>.193 (df=74)</td>
<td>.205 (df = 75)</td>
<td>1.020 (df=75)</td>
<td>.488 (df =75)</td>
<td>.5767 (df =74)</td>
<td>.488 (df =75)</td>
</tr>
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</table>

Note: OCB = Organizational citizenship behavior, CWB = Counterproductive work behavior, RSD = Relative standard deviation, P = Person focused, O = Organization focused, CSE = Core self-evaluations, confidence intervals are bias-corrected and accelerated [BCa] bootstrapped 95% confidence intervals
Effect of within-person personality variability on average level of Organizational Citizenship Behavior

Figure 1

Note: Figure 1 shows the relationship between the average level of organizational citizenship behavior and relative variability in state conscientiousness in Study 1 (a) and Study 2 (b), and relative variability in state Core Self-Evaluations in Study 3 (c). Triangles indicate influential observations that have a Cook’s distance that is greater than 3 times the average distance. The black line represents the robust linear regression line along with the 95% confidence interval in gray.
Figure 2

Effect of within-person personality variability on average level of Counterproductive Work Behavior

Note: Figure 2 shows the relationship between the average level of counterproductive work behavior and relative variability in state conscientiousness in Study 2 (a), and relative variability in state Core Self-Evaluations in Study 3 (b). Triangles indicate influential observations that have a Cook’s distance that is greater than 3 times the average distance. The black line represents the robust linear regression line along with the 95% confidence interval in gray.