the british psychological society
promoting excellence in psychology

Journal of Occupational and Organizational Psychology (2020), 93, 495–504

www.wileyonlinelibrary.com

Short research note

Revisiting the neuroticism – performance link: A dynamic approach to individual differences

Joanna Sosnowska[1]*, Joeri Hofmans[2] and Filip de Fruyt[3]

[1]Amsterdam Business School, University of Amsterdam, the Netherlands
[2]Vrije Universiteit Brussel, Belgium
[3]University of Gent, Belgium

In the present paper, the relationship between neuroticism and supervisory ratings of performance is examined using a dynamic approach to personality. This approach integrates both within- and between-person differences by looking at individual differences in baseline neuroticism, neuroticism variability and neuroticism attractor strength. Our findings showed that baseline neuroticism related to lower supervisory ratings of performance, and that a high level of baseline neuroticism is particularly detrimental for people who fail to return to their baseline swiftly. Altogether, these findings demonstrate that adopting a more integrative, dynamic approach to personality has the potential to contribute to a better understanding of the personality–performance relationship.

Practitioner points

- How employees' performance is perceived by their supervisors not only depends on between-person differences in employees' average level of neuroticism, but also on the extent to which their state neuroticism levels vary
- Assessing personality dynamics has the potential to contribute to a better understanding of the candidate's personality
- Managers should take into account that the impact of baseline personality on performance depends on how deviations from the baseline are regulated.

Traditionally, research on the personality–performance relation has focused on predicting between-person differences in job performance from between-person differences in personality traits. Despite the fact that meta-analytical research demonstrates that personality traits do indeed predict job performance, only looking at how people behave, feel and think *on average* is quite restrictive.

In response to this, personality scholars are increasingly adopting an integrative approach to personality. According to this approach, personality should not be equated with a set of scores on several trait dimensions, but attention should also be given to momentary expressions of those traits (Dalal *et al.*, 2015; DeYoung, 2015; Fleeson, 2001;

**Correspondence should be addressed to Joanna Sosnowska, Amsterdam Business School, University of Amsterdam, Plantage Muidergracht 12, 1018 TV Amsterdam, 15953 1001 NL Amsterdam (email: j.sosnowska@uva.nl).*

DOI:10.1111/joop.12298

Furr, 2009; Shoda, LeeTiernan, & Mischel, 2002; Vallacher, Nowak, Froehlich, & Rockloff, 2002).

In the present study, we study the relation between neuroticism and task performance using an integrative approach to neuroticism. To this end, we draw on the recently developed Personality Dynamics (PersDyn) model, a model that captures individual differences in the momentary expressions of personality traits using three building blocks: (1) one's baseline level on the personality dimension [trait baseline], (2) the extent to which one exhibits variability around this baseline [trait variability], and (3) the swiftness with which individuals return to their baseline once they deviated from it [trait attractor strength]. A more detailed account of the PersDyn model can be found in Table 1 and in Sosnowska, Kuppens, De Fruyt and Hofmans (2019).

Hypotheses

Our focus on neuroticism is motivated by previous studies showing that trait neuroticism, along with trait conscientiousness, is one of the best personality predictors of general job performance (Judge & Zapata, 2015). Moreover, also within

Table 1. The elements of the personality dynamics model

Trait baseline	Trait variability	Trait attractor strength
General description		
Central point around which behaviours, thoughts and emotions fluctuateBased on series of personality states; Represents how people act, think and feel on average, across time and situations	The extent to which behaviours, thoughts and emotions fluctuateDescribes deviations from the baseline (due to internal or external factors) Independent from the baseline	The regulatory force that pulls the fluctuations back to the baselineRepresents how fast a person returns to the baseline once they deviate from itBridges stability of the baseline and change (variation around the baseline) in personality
Examples		
High baseline neuroticism indicates that a person tends to act highly neurotic on average	High variability in neuroticism indicates that often shows neuroticism states that differ from his/her baseline neuroticism level	High attractor strength indicates that the person returns to their baseline fast, for example if their typical baseline behaviour is calm and relaxed, but due to external factors the person feels anxious and upset, people with a high attractor strength will return to their typical, calm behaviour swiftly
Links with previous research		
Central point of distribution in density distribution (Fleeson, 2001)Attractor (Shoda, LeeTiernan & Mischel, 2002) Psychological profile (Furr, 2009)	Personality strength (Dalal *et al.*, 2015)Traitedness (Baumeister & Tice, 1988)	Shape of basin of attraction (Nowak, Vallacher, & Zochowski, 2005) Self-regulation in Cybernetic Big Five theory (DeYoung, 2015)

individuals, state neuroticism has been shown to predict momentary levels of task performance (Debusscher, Hofmans, & De Fruyt, 2016). Finally, previous research demonstrated that people vary extensively in their momentary expressions of neuroticism, with the amount of within-person variability in state neuroticism being as large as or larger than the amount of between-person variability (e.g., Fleeson, 2007), which makes it a suitable trait for examining within-person fluctuations. In sum, when studying the dynamics of personality, neuroticism is a good starting point because of its dynamic nature.

Regarding the relation with performance, people who are generally high in neuroticism are more sensitive to negative stimuli (Elliot & Thrash, 2002). In addition, neuroticism relates to higher stress vulnerability and construing situations as threatening, which in turn triggers negative emotional responses, physiological stress and impaired task performance (Schneider, 2004). In line with this reasoning, research has shown that neuroticism relates negatively to performance on both the trait (Judge & Zapata, 2015) and the state level (Debusscher *et al.*, 2016). Because the first element of the PersDyn model, or the baseline around which one's neuroticism levels fluctuate, is akin to one's trait neuroticism level, our first hypothesis reads:

Hypothesis 1: Baseline neuroticism relates negatively to performance ratings

Research shows that people not only differ in their baseline, but also in the consistency of their trait-relevant behaviours (Dalal *et al.*, 2015). Moreover, individual differences in variability in trait-relevant behaviour appear to be stable over time and can therefore be used to characterize individuals (Jones, Brown, Serfass, & Sherman, 2017), whereas personality variability has generally been found to be independent from the baseline, neuroticism is an exception to this rule as it is intrinsically linked with behavioural, cognitive and affective consistency by definition. That is, people who are generally low on neuroticism tend to show less variability in their affect, self-esteem and neuroticism-related behaviours (Eid & Diener, 1999; Fleeson & Gallagher, 2009; Kuppens, Oravecz & Tuerlinckx, 2010). Hence, we hypothesize that:

Hypothesis 2: Neuroticism variability relates positively to baseline neuroticism

Regarding the relationship with performance, increases in state neuroticism are associated with a narrowing of one's attention. Such narrowing of the attention should allow the individual to exclude irrelevant task cues, thereby promoting performance (Le *et al.*, 2011). Importantly, these effects have been shown to be subject to boundary conditions, with increased levels of state neuroticism being beneficial when working on tasks low, but not on tasks high in complexity and work pressure (Debusscher, Hofmans, & De Fruyt, 2014). Arguably, such boundary conditions also exist at the person-level, with variation in state neuroticism potentially being more impactful for people low than for people high in baseline neuroticism. The reason is that people low in baseline neuroticism typically have a broad attentional focus and can therefore benefit from narrowing it down, while this is less the case for people high in baseline neuroticism, whose attentional focus is already narrow by default. Hence, we expect neuroticism variability to be particularly useful for people with a low neuroticism baseline:

Hypothesis 3: Baseline neuroticism moderates the link between neuroticism variability and performance, with the relation between variability and performance being more positive for people low than for people high on baseline neuroticism

Finally, and following the notion that people do not passively submit to what is happening to them but instead regulate their own behaviour, thinking and feelings (Baumeister & Vohs, 2004), we also look at the regulatory forces in neuroticism, represented by neuroticism attractor strength (see Table 1). Because attractor strength reflects how fast one returns to one's baseline after having deviated from it, it is responsible for the coherence in one's personality system (Nowak *et al.*, 2005). With low attractor strength, the person's behaviour, feelings and cognitions are at the whim of external influences. If, however, attractor strength of neuroticism is high, the person will return to their typical, baseline level of neuroticism swiftly after being pushed away from it. For example, if an individual tends to act in a very calm, relaxed manner (low baseline neuroticism) but situational factors (e.g., high workload) trigger temperamental and anxious behaviour, the time it takes to return to their typical, calm behaviour will be shorter for someone high than for someone low in attractor strength.

Such swift return to the baseline might be beneficial for performance as research shows that people perform better when their state and trait level converge (Tamir, 2005). The reason is that state-trait consistency leads to a synchronization of motivational cues, which in turn leads to higher task engagement and performance. Although it might seem counter-intuitive that high levels of state neuroticism are beneficial for performance, previous research has indeed shown that people high in trait neuroticism sometimes choose to experience negative affective states, despite their short-term hedonic costs (e.g., Tamir, 2005). In terms of the PersDyn model, state-trait consistency, and hence higher levels of performance, will be easier to achieve for people high than for people low on attractor strength. The reason is that people high on neuroticism attractor strength – due to their swift return to the baseline – can more easily bring their state neuroticism level in line with their trait (or baseline) level. Hence, we hypothesize that:

Hypothesis 4: Attractor strength relates positively to performance

Finally – and similar to our expectation for personality variability – the effect of synchronicity might be different for people with different levels of baseline neuroticism. In this respect, Tamir (2005; see Study 4) demonstrated that people with a high baseline level of neuroticism benefited from trait-congruent and suffered from trait-incongruent states, while this was less the case for people with low baseline neuroticism. Therefore, we also explore the moderating effect of baseline neuroticism on the relation between attractor strength and performance.

Method

Procedure

We conducted an experience sampling (ESM) study in which participants were asked to report their level of state neuroticism twice a day, for 10 consecutive days. The surveys were sent at a random moment before noon and at a random moment in the afternoon using an online survey system. Task performance ratings were provided by the direct supervisors at the start of the study.

Table 2. BHOUM estimates for state neuroticism – means of the posterior distributions, 95% posterior credibility intervals and posterior Standard Deviations (uncertainty)

Model parameter	Posterior mean	95% posterior credibility interval		Posterior *SD*
Baseline	2.52	2.36	2.67	0.08
Interindividual variation in baseline	0.48	0.33	0.67	0.09
Intraindividual variance	0.29	0.22	0.39	0.04
Attractor strength	0.89	0.40	2.15	0.48
Measurement error	0.02	0.01	0.03	0.01

Participants

We contacted 331 respondents, of whom 130 participated in the ESM study. We only retained participants with a response rate of at least 25 per cent, further reducing the sample size to 87, and for 50 of those 87 participants, we also collected supervisory task performance ratings. All participants were employees working for a large company in the financial sector, mainly administrative staff and their managers. Sixty per cent of the sample was female, the average age of the respondents was 39.3 years (SD = 10.8) and their average organization tenure was 14.4 years (SD = 12.7).

Measures

State neuroticism was measured using the eight adjective neuroticism subscale of Saucier's (1994) Mini Marker scale (see Table 2). People had to indicate to what extent these adjectives (e.g., relaxed, moody, temperamental) described them at the time of measurement, and they had to do so on a 7-point Likert scale ranging from 1 = extremely inaccurate to 7 = extremely accurate.

Supervisory ratings of task performance were collected using the 7-item task performance subscale of Williams and Anderson (1991). The items (e.g., 'Performs tasks that are expected of him/her') were rated using a 7-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree.

Analysis

Person-specific estimates for neuroticism baseline, variability and attractor strength were obtained using the Bayesian Hierarchical Ornstein-Uhlenbeck model (BHOUM; Oravecz, Tuerlinckx, & Vandekerckhove, 2016). The BHOUM model is based on stochastic differential equations and captures the trajectory of personality states over time through a measurement equation (Equation 1) and a transition equation (Equation 2):

$$Y(t) = \Theta(t) + \varepsilon(t) \tag{1}$$

$$d\Theta(t) = \beta(\mu - \Theta(t))\mathrm{d}t + \sigma \mathrm{d}W(t) \tag{2}$$

In the measurement equation, the manifest score $Y(t)$ is decomposed into the latent score $\Theta(t)$ and an error term $\varepsilon(t)$. In the transition equation, change in the latent score Θ

Table 3. Pearson's correlations between the PersDyn elements for state neuroticism and supervisory ratings of performance

		State neuroticism	
	Supervisory ratings of performance	Baseline	Variability
State neuroticism			
Baseline	−.29*		
Variability	.09	.30**	
Attractor strength	.20	−.05	.06

*$p < .05$, ** $p < .01$.

with respect to t (i.e., $d\Theta(t)$) results from the distance between the current state (i.e., $\Theta(t)$) and the baseline (i.e., μ). The extent to which this difference affects change in Θ depends on the regulatory force parameter β. Finally, the stochastic term $\sigma dW(t)$ adds random noise, with σ being the scale of the stochastic process and $dW(t)$ being the change in a Brownian motion process. In the BHOUM model, within-person variability is denoted as $\gamma = {}^{\sigma^2}/_{2\beta}$. The hierarchical character of the model allows for the estimation of person-specific parameters for baseline, variability and attractor strength.

In the present study, we modelled the repeated measures state neuroticism data from 87 participants (1,206 observations).[1] Inference in the BHOUM model is based on Markov chain sampling, using six chains with different starting values, consisting of 10,000 iterations each. The burn-in was set at 2,000 iterations. After obtaining person-specific baseline, variability and attractor strength BHOUM estimates, we related them to participants' supervisory ratings.

Results

Descriptive results

Table 2 provides an overview of the BHOUM estimates. First, the results show the existence of substantial individual differences in neuroticism baseline levels (posterior $M = .48$, posterior $SD = 0.09$). Furthermore, the amount of intraindividual variability (posterior $M = .29$, posterior $SD = 0.04$) was much higher than the average level of measurement error (posterior $M = .02$, posterior $SD = 0.01$), implying that the observed variability in state neuroticism is largely due to actual fluctuations in neuroticism, and not to random noise.

Hypothesis testing

Table 3 shows correlations between the elements of the PersDyn model and task performance. In line with Hypothesis 1, people with a high level of baseline neuroticism received lower performance ratings than those with low levels of baseline neuroticism ($r = -.29$; $p = .043$). Second, and in line with Hypothesis 2, we found that neuroticism baseline and neuroticism variability were positively correlated ($r = .30$; $p = .005$),

[1] *The BHOUM model was run on all 87 participants because – similar to multilevel regression analysis – the model borrows information from all available data when estimating the model parameters.*

Table 4. Interaction effect between baseline neuroticism and neuroticism variability (both grand-mean centred) predicting supervisory ratings of performance

					95% Confidence interval	
Parameter	*B*	*SE*	*T*	*Sig.*	Lower bound	Upper bound
Intercept	5.75	.10	58.61	.000	5.56	5.95
Baseline	−0.34	.13	−2.56	.013	−0.60	1.67
Variability	0.59	.53	1.11	.271	−0.48	−0.07
Interaction	.33	.55	0.59	.557	−0.78	1.44

Table 5. Interaction effect between baseline neuroticism and neuroticism attractor strength (both grand-mean centred) predicting supervisory ratings of performance

					95% Confidence interval	
Parameter	*B*	SE	*t*	*Sig.*	Lower bound	Upper bound
Intercept	5.91	.10	57.74	.000	5.71	6.12
Baseline	0.18	.21	0.84	.403	−0.24	0.59
Attractor strength	0.34	.18	1.89	.066	−0.02	−0.70
Interaction	.86	.37	2.31	.025	0.11	1.60

implying that people with high levels of baseline neuroticism fluctuate more in their neuroticism states. Third, we found no correlation between neuroticism variability and task performance (r = .09; p = .541), and the interaction between neuroticism baseline and variability was also not statistically significant (β = .32; p = .556, see Table 4). Finally, and in disagreement with Hypothesis 4, we found no relation between neuroticism attractor strength and task performance (r = .20; p = .164). However, the results did reveal a significant interaction effect between baseline neuroticism and neuroticism attractor strength (β = .86; p = .025, see Table 5), with people with high baseline neuroticism (+1 *SD*) receiving higher performance ratings when their attractor strength was high than when it was low (β = .91; p = .012) (see Figure 1). For those with low baseline neuroticism (−1 *SD*), neuroticism attractor strength was unrelated to their supervisory performance ratings (β = −.80; p = .235). This finding suggests that state-trait consistency benefits performance, but only for those high in trait neuroticism.

Discussion

The current study builds on and extends research on the neuroticism–performance relation in two important ways. First, our findings showed that, apart from the existence of individual differences in neuroticism baseline, also the amount of within-person variability in neuroticism is substantial. Hence, our study highlights the importance of integrating traits and states in personality research. However, neuroticism variability and attractor strength were not directly related to supervisory performance ratings.

Nevertheless, we demonstrated that self-regulatory forces do play an important role in the personality–performance link, as high baseline neuroticism was detrimental for task performance only for employees with a slow return to their baseline (i.e., low attractor

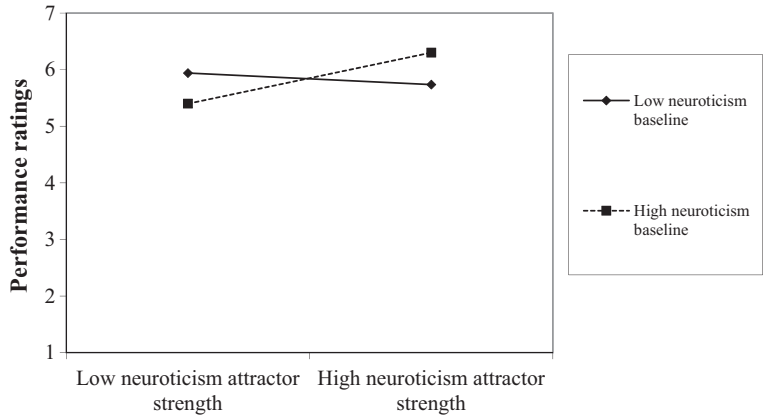

Figure 1. Interaction between attractor strength and neuroticism baseline in relation to supervisory ratings of performance.

strength). As attractor strength bridges stability and change, our results underline the importance of conceptualizing personality as incorporating both stability and change.

Limitations and future directions

The PersDyn model is likely to be trait-specific in the sense that the effects of its elements and the interactions between the elements might differ depending on the personality dimension under consideration. For example, conscientiousness pertains to being organized and rigid, and therefore it is likely that high levels of baseline conscientiousness are associated with low conscientiousness variability and high conscientiousness attractor strength. To explore such effects, further research is needed on the dynamics of other personality dimensions and on their effects on work performance. Finally, the model does not separate between internal and external triggers of changes in personality states, but instead captures the resulting trajectory. Further research is thus needed to look into the mechanisms that underlie these changes.

Practical implications

Our study demonstrates the importance of taking into account within-person fluctuations in personality when predicting work performance (Debusscher *et al.*, 2016). Given the key role of these personality fluctuations, adopting a more integrative, dynamic approach to personality assessment has the potential to contribute to a better understanding of the candidate's personality and therefore to strengthen the predictive validity of our selection procedures and decisions. Although such an integrative approach can be challenging to apply in a selection setting, Sosnowska, Hofmans and Lievens (2020) described how existing selection methods can be adjusted and expanded to measure more dynamic personality constructs.

Acknowledgements

This research was supported by Fonds Wetenschappelijk Onderzoek – Vlaanderen (FWO) (grant number G024615N). We would also like to thank Jonas Debusscher for the data collection.

References

Baumeister, R. F., & Tice, D. M. (1988). Metatraits. *Journal of Personality*, *56*, 571–598. https://doi.org/10.1111/j.1467-6494.1988.tb00903.x

Baumeister, R. F., & Vohs, K. D. (Eds.). (2004). *Handbook of self-regulation: Research, theory, and applications*. New York, NY: Guilford.

Dalal, R. S., Meyer, R. D., Bradshaw, R. P., Green, J. P., Kelly, E. D., & Zhu, M. (2015). Personality strength and situational influences on behavior: A conceptual review and research agenda. *Journal of Management*, *41*(1), 261–287. https://doi.org/10.1177/0149206314557524

Debusscher, J., Hofmans, J., & De Fruyt, F. (2014). The curvilinear relationship between state neuroticism and momentary task performance. *PLoS ONE*, *9*, e106989. https://doi.org/10.1371/journal.pone.0106989

Debusscher, J., Hofmans, J., & De Fruyt, F. (2016). Do personality states predict momentary task performance? The moderating role of personality variability. *Journal of Occupational and Organizational Psychology*, *89*, 330–351. https://doi.org/10.1111/joop.12126

DeYoung, C. G. (2015). Cybernetic big five theory. *Journal of Research in Personality*, *56*, 33–58. https://doi.org/10.1016/j.jrp.2014.07.004

Eid, M., & Diener, E. (1999). Intraindividual variability in affect: Reliability, validity, and personality correlates. *Journal of Personality and Social Psychology*, *76*, 662–676. https://doi.org/10.1037/0022-3514.76.4.662

Elliot, A. J., & Thrash, T. M. (2002). Approach-avoidance motivation in personality: Approach and avoidance temperaments and goals. *Journal of Personality and Social Psychology*, *82*, 804–818. https://doi.org/10.1037//0022-3514.82.5.804

Fleeson, W. (2001). Toward a structure- and process-integrated view of personality: Traits as density distributions of states. *Journal of Personality and Social Psychology*, *80*, 1011–1027. https://doi.org/10.1037//0022-3514.80.6.1011

Fleeson, W. (2007). Situation-based contingencies underlying trait-content manifestation in behavior. *Journal of Personality*, *75*, 825–862. https://doi.org/10.1111/j.1467-6494.2007.00458.x

Fleeson, W., & Gallagher, P. (2009). The implications of Big Five standing for the distribution of trait manifestation in behavior: Fifteen experience-sampling studies and a meta-analysis. *Journal of Personality and Social Psychology*, *97*(6), 1097–1114. https://doi.org/10.1037/a0016786.

Furr, R. M. (2009). Personality psychology as a truly behavioural science. *European Journal of Personality*, *23*, 369–401. https://doi.org/10.1002/per.724

Jones, A. B., Brown, N. A., Serfass, D. G., & Sherman, R. A. (2017). Personality and density distributions of behavior, emotions, and situations. *Journal of Research in Personality*, *69*, 225–236. https://doi.org/10.1016/j.jrp.2016.10.006

Judge, T. A., & Zapata, C. P. (2015). The person–situation debate revisited: Effect of situation strength and trait activation on the validity of the Big Five personality traits in predicting job performance. *Academy of Management Journal*, *58*, 1149–1179. https://doi.org/10.5465/amj.2010.0837

Kuppens, P., Oravecz, Z., & Tuerlinckx, F. (2010). Feelings change: Accounting for individual differences in the temporal dynamics of affect. *Journal of Personality and Social Psychology*, *99*(6), 1042–1060. https://doi.org/10.1037/a0020962.

Le, H., Oh, I.-S., Robbins, S. B., Ilies, R., Holland, E., & Westrick, P. (2011). Too much of a good thing: Curvilinear relationships between personality traits and job performance. *The Journal of Applied Psychology*, *96*(1), 113–133. https://doi.org/10.1037/a0021016

Nowak, A., Vallacher, R. R., & Zochowski, M. (2005). The emergence of personality: Dynamic foundations of individual variation☆. *Developmental Review*, *25*, 351–385. https://doi.org/10.1016/j.dr.2005.10.004

Oravecz, Z., Tuerlinckx, F., & Vandekerckhove, J. (2016). Bayesian data analysis with the bivariate hierarchical Ornstein-Uhlenbeck process model. *Multivariate Behavioral Research*, *51*(1), 106–119. https://doi.org/10.1080/00273171.2015.1110512

Saucier, G. (1994). Mini-markers: A brief version of Goldberg's unipolar Big-Five markers. *Journal of Personality Assessment*, *63*, 506–516. https://doi.org/10.1037/t07015-000

Schneider, T. R. (2004). The role of neuroticism on psychological and physiological stress responses. *Journal of Experimental Social Psychology*, *40*(6), 795–804. https://doi.org/10.1016/j.jesp.2004.04.005.

Shoda, Y., LeeTiernan, S., & Mischel, W. (2002). Personality as a dynamical system: Emergence of stability and distinctiveness from intra and interpersonal interactions. *Personality and Social Psychology Review*, *6*, 316–325. https://doi.org/10.1207/S15327957PSPR0604_06

Sosnowska, J., Hofmans, J., & Lievens, F. (2020) Assessing personality dynamics in personnel selection. In J. Rauthmann (Eds.), *The Handbook of Personality Dynamics and Processes*. Elsevier.

Sosnowska, J., Kuppens, P., De Fruyt, F., & Hofmans, J. (2019). A dynamic systems approach to personality: The Personality Dynamics (PersDyn) model. *Personality and Individual Differences*, *144*, 11–18. https://doi.org/10.1016/j.paid.2019.02.013

Tamir, M. (2005). Don't worry, be happy? Neuroticism, trait-consistent affect regulation, and performance. *Journal of Personality and Social Psychology*, *89*, 449–461. https://doi.org/10.1037/0022-3514.89.3.449

Vallacher, R. R., Nowak, A., Froehlich, M., & Rockloff, M. (2002). The dynamics of self-evaluation. *Personality and Social Psychology Review*, *6*, 370–379. https://doi.org/10.1207/S15327957PSPR0604_11

Williams, L. J., & Anderson, S. E. (1991). Job satisfaction and organizational commitment as predictors of organizational citizenship and in-role behaviors. *Journal of Management*, *17*, 601–617. https://doi.org/10.1177/014920639101700305

Received 14 December 2018; revised version received 10 December 2018