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BRIEF REPORT

Investigating the Relationships Between Subjective Well-Being and Psychological Well-Being Over Two Decades

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Although much research has been conducted on the predictors and outcomes of both subjective well-being (SWB) and psychological well-being (PWB), the magnitude and direction of the causal relationship between these constructs remain unclear. The studies reported in this article were designed to assess the temporal relationship between SWB and PWB during a period of 20 years. The studies used 3 waves of survey data, with intervals of 10 years, from the Midlife in the United States project, a representative longitudinal panel study of American adults (N = 2,731). Cross-lagged panel analyses were conducted to examine directionality of the relationships. Results showed that the autoregressive effects were large, suggesting a high degree of stability in SWB and PWB over time. Yet the levels of stability were generally higher for PWB than SWB. Whereas PWB unequivocally predicted increases in SWB over time, the prospective effects of SWB on PWB were inconsistent (i.e., positive, negative, or nonsignificant) across various points in time. The study findings suggest that PWB represents a more robust and consistent antecedent of future well-being than SWB.

Keywords: psychological well-being, subjective well-being, hedonic, eudaimonic, cross-lagged panel model

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Mental well-being is a multidimensional construct, including hedonic and eudaimonic dimensions (Ryan & Deci, 2001). Hedonic well-being is often operationalized as subjective well-being (SWB), consisting of three dimensions of life satisfaction, positive affect, and low negative affect. Eudaimonic well-being embodies positive skills that facilitate optimal functioning. Ryff's (1989) model of psychological well-being (PWB) posits that eudaimonic well-being consists of six dimensions: autonomy, environmental mastery, personal growth, positive relations, purpose in life, and self-acceptance. Joshanloo (2016) has shown that, despite being correlated, SWB and PWB are empirically distinct concepts. Research has documented various synchronic and diachronic benefits for both SWB and PWB (e.g., Hill & Turiano, 2014; Keyes, Dhingra, & Simoes, 2010). These benefits include positive psychological and physical outcomes, such as effective coping and global health (Lyubomirsky, King, & Diener, 2005).

The primary purpose of the present studies is to provide an exploration of how PWB and SWB influence one another over time. There is evidence to suggest that each variable prospectively predicts higher levels of the other. For example, the self-determination theory predicts that "certain activities and lifestyles, particularly those associated with eudaimonic living, supply the most reliable paths to happiness and positive affect" (DeHaan & Ryan, 2014, p. 40). According to the broaden and build theory (Fredrickson, 2004), positive emotions build personal resources and fuel psychological resilience and well-being over time. Therefore, a bidirectional temporal association between the two variables was expected. In terms of the relative strength of the prospective effects, the self-determination theory would predict that PWB will have a stronger lagged effect on SWB, whereas the broaden and build theory would predict the opposite. Recent evidence suggests that experiencing positive emotions, particularly when the magnitude and duration of the emotions are incompatible with the context, is linked to clinical syndromes and poor health outcomes (Gruber & Bekoff, 2017; Gruber, Mauss, & Tamir, 2011). Research also suggests that extremely high levels of SWB are associated with suboptimal functioning in important life domains, such as education and income (e.g., Oishi, Diener, & Lucas, 2007). Therefore, the cross-lagged effects of PWB on SWB were predicted to be stronger and more consistent than those of SWB on PWB.

Cross-lagged panel analysis (Little, 2013) was used. This type of analysis allows looking at autoregressive effects (linking a variable at earlier time points to itself at later time points) and cross-lagged effects (linking two different variables across time). Estimates of the autoregressive effects provide insights regarding the long-term stability of the concepts. The cross-lagged compo-

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nent of the model provides a test of the directionality of relationship between the two concepts (Newsom, 2015). The data used in the present studies were from the Midlife in the United States (MIDUS) project. This project has collected three waves of data since 1995 with intervals of about 10 years. Study 1 included data from all three time points, whereas Study 2 used data from the last two time points. Study 2 included more reliable PWB scales that were not available in the first wave of the project.

Method

Participants

Study 1. Data were from the first (collected in 1995–1996), second (2004–2006), and third (2013–2014) waves of the MIDUS project (Ryff, 1989). The integrated data file includes 7,108 participants. However, only individuals who completed the survey three times were included. The final sample of the study consisted of 1,217 males (44.5%) and 1,500 females. The average age was 46.53 years (*SD* = 11.24) at Time 1. Among the 2,731 participants included, 2,451 (89.7%) had complete data on all of the 27 variables of the study, whereas 280 participants had 1–20 missing values.

Study 2. Individuals who completed the survey at Time 2 and Time 3 were included. The final sample consisted of 1,217 males (44.6%) and 1,500 females. The average age was 64.52 years (*SD* = 11.18) at Time 3. Among the 2,731 participants included, 2,512 (92%) had complete data on all of the 18 variables of the study, whereas 219 participants had 1–11 missing values. A detailed description of data collection procedures can be found at the MIDUS website (http://midus.wisc.edu/).

Measures

SWB. In both studies, life satisfaction was assessed using five items capturing satisfaction with overall life, work, health, relationship with spouse/partner, and relationship with children. Each item was coded from *the worst possible* (0) to *the best possible* (10). In both studies, the 12-item negative and positive affect scale was used to measure affect (Joshanloo, 2017; Mroczek & Kolarz, 1998). Using a recoded scale from *none of the time* (1) to *all of the time* (5), respondents indicated how often, during the past 30 days, they felt six positive and six negative affective states.

PWB. In Study 1, the 18-item version of Ryff's (1989) PWB scale was used. Items are rated on a 7-point scale ranging from *strongly disagree* (1) to *strongly agree* (7). In Study 2, a 42-item version of Ryff's (1989) PWB scale was used.

Descriptive statistics, alphas, and R^2 estimates are reported in the supplementary material. The 18-item PWB scale used in Study 1 yielded unacceptable alphas. Study 2 was conducted to replicate the findings from Study 1 with longer and more reliable PWB scales. As expected, the internal consistencies of the PWB scales were found to be acceptable in Study 2.

Statistical Analysis

The analyses were conducted in Mplus 8 with robust maximum likelihood estimation. To handle missing data, full information maximum likelihood was used. The six PWB variables at each time point were used as the indicators of PWB factors (labeled as PWB1, PWB2, and PWB3). The latent variables of SWB (labeled as SWB1, SWB2, and SWB3) were indicated by life satisfaction, positive affect, and (reverse-coded) negative affect. First, confirmatory factor analysis (CFA) models and metric and scalar invariance across time were tested (Selig & Little, 2012). Invariance in this context would indicate that the measurement properties of the latent variables are stable over time, and the changes in the latent variables are not due to the changing measurement properties (Newsom, 2015). Changes in the Comparative Fit Index (CFI) values less than .01 were considered as indicative of invariance (Cheung & Rensvold, 2002). Next, bidirectional cross-lagged panel models were tested without covariates. Finally, in separate models, gender, age, and age[2] were added to control for their effects.

Results

Study 1

A CFA involving all of the PWB and SWB variables was first tested. All of the factors were specified to have nondirectional covariance relationships. Additionally, all of the autocorrelations among measurement residuals across time were estimated. The model fitted the data very well (M1 in Table 1). Whereas full metric invariance (M2) was supported (ΔCFI = −.002), full scalar invariance (M3) was not supported (ΔCFI = −0.022). As suggested by the modification indices, the constraints on the intercepts of environmental mastery and positive relations were relaxed. The modified model (M4) fitted the data very well, providing support for partial scalar invariance (ΔCFI = −0.007).

Holding the equality constraints, a model was tested (M5) in which all of the cross-time covariance relationships were converted into directional predictive paths. Given that the structural portion of this model is saturated, model fit does not indicate the accuracy of the directional paths. The nonsignificant cross-time paths are usually dropped in cross-lagged models to build more parsimonious models (Little, 2013; Newsom, 2015). Accordingly, in a series of modified models, the paths from PWB2 and SWB1 to SWB3, and from SWB1 to PWB2 were eliminated one at a time, which resulted in the final model of the study (M6). This model is shown in Figure 1. The parameter estimates of the final model are presented in Table 2.

The synchronous correlation between PWB1 and SWB1 were significant. The concurrent associations between latent variable disturbances at Time 2 and Time 3 were also significant. All of the autoregressive paths were significant, with the exception of SWB1 to SWB3. With regard to the cross-lagged relationships, the paths from SWB1 and SWB2 to PWB3 were significant, but the former was surprisingly negative. This suggests that, when the prior levels of the variables are held constant, higher levels of SWB may even lead to lower levels of PWB over time. The cross-lagged paths from PWB1 to SWB2 and SWB3 were positive and significant, suggesting that the higher the levels of PWB, the higher the future levels of SWB. Finally, in a separate model (M7), all of the well-being factors were regressed on gender, age, and age.[2] Controlling for the demographic variables had no substantial effect on the autoregressive and cross-lagged effects, indicating that the demographic variables do not explain the relationships observed in

Table 1
Fit Indices

Model	χ^2	*df*	CFI	SRMR	AIC	BIC	RMSEA	90% CI for RMSEA Low	Up
Study 1									
1. CFA model	1346.9	282	.963	.040	273338.9	274066.2	.037	.035	.039
2. Metric invariance	1418.4	296	.961	.046	273397.7	274042.1	.037	.035	.039
3. Scalar invariance	2047.0	310	.939	.052	274092.6	274654.3	.045	.043	.047
4. Partial scalar invariance	1615.3	306	.954	.049	273600.2	274185.6	.040	.038	.041
5. Saturated cross-lagged model	1615.3	306	.954	.049	273600.2	274185.6	.040	.038	.041
6. Final cross-lagged model	1620.1	309	.954	.049	273601.7	274169.3	.039	.038	.041
7. Final cross-lagged model with age and gender	2110.9	372	.942	.049	273393.7	274067.7	.041	.040	.043
Study 2									
8. CFA model	1018.2	120	.967	.036	219478.1	219886.0	.052	.049	.055
9. Metric invariance	1041.8	127	.966	.040	219490.6	219857.2	.051	.048	.054
10. Scalar invariance	1127.1	134	.963	.042	219567.1	219892.3	.052	.049	.055
11. Saturated cross-lagged model	1127.1	134	.963	.042	219567.1	219892.3	.052	.049	.055
12. Final cross-lagged model	1128.5	135	.963	.042	219567.6	219886.8	.052	.049	.055
13. Final cross-lagged model with age and gender	1580.9	177	.950	.044	219414.0	219804.2	.054	.051	.056

Note. CFI = comparative fit index; SRMR = standardized root mean square residual; AIC = Akaike information criteria; BIC = Bayesian information criterion; RMSEA = root mean square error of approximation. All χ^2 values are significant at $p < .001$.

M6. The fit of the model with covariates is reported in Table 1, and its parameter estimates are reported in the supplementary material.

Study 2

The CFA model fitted the data well (M8 in Table 1). Full metric (M9, ΔCFI = −.001) and scalar (M10, ΔCFI = −.003) invariance was also supported. A model with autoregressive and cross-lagged directional paths (M11) was next tested. The results with the structurally saturated model showed that the path from SWB2 to PWB3 was not significant, and accordingly it was dropped from the final model (M12). The parameter estimates of the final model are shown in Table 2. The model is shown in Figure 1.

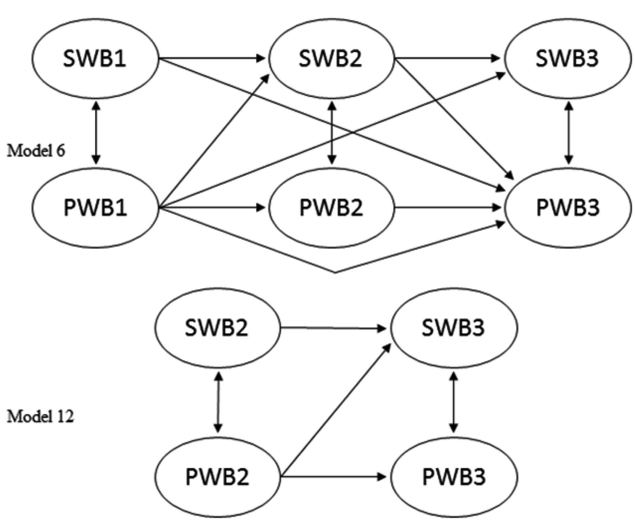

Figure 1. The final models of Study 1 (Model 6) and Study 2 (Model 12). The indicators and autocorrelations among indicator residuals are not shown in the figure.

The two autoregressive paths were significant. The cross-lagged path from PWB2 to SWB3 was also significant, indicating that the higher the levels of PWB at Time 2, the higher the levels of SWB at Time 3. The negative prospective effect of SWB on PWB was not replicated in Study 2, suggesting that the prospective effects of SWB may depend on lag length. For example, these effects may be more likely to be negative over longer periods of time and positive or nonsignificant over shorter periods. Finally, as reported in the supplementary material, the effects were nearly unchanged when controlling for the demographic variables (M13).

Discussion and Conclusion

It was found that SWB at a time predicted SWB 10 years later and PWB at a time predicted PWB both 10 and 20 years later. The autoregressive paths were generally stronger for PWB than for SWB (see Table 2), indicating more longitudinal stability for PWB. Compared with PWB, the levels of SWB are more strongly determined by emotional experiences, which can vary dramatically across time and context (Diener, 2014). In contrast, PWB is based on developing more stable skills and abilities, presumably leading to higher levels of stability (Steger, 2016). Therefore, these results suggest that PWB is more strongly predictive of its future values than SWB is. Along the same lines, Huta and Ryan (2010) found that participation in eudaimonic activities boosted well-being both immediately and 3 months afterwards, whereas participation in hedonic activities boosted well-being only immediately.

In both studies, the initial levels of PWB predicted positive changes in the levels of SWB over time. The sizes of the cross-lagged paths from PWB ranged from .162 to .372 (see Table 2). Yet the cross-lagged paths from SWB ranged from −.249 to .122, suggesting that higher initial levels of SWB may lead to increases or decreases in future PWB. The negative prospective effect of SWB observed here is consistent with evidence showing that intensive and/or extended positive states of mind can interfere with psychological functioning and the process of skill formation (Gru-

Table 2
Standardized Estimates for the Final Models

Study 1 Parameter	Estimate	95% CI Low	95% CI Up	Study 2 Parameter	Estimate	95% CI Low	95% CI Up
Regression paths				Regression paths			
PWB1 → PWB3	.551***	.446	.656	PWB2 → PWB3	.755***	.732	.778
PWB2 → PWB3	.398***	.309	.487	SWB2 → SWB3	.582***	.494	.670
SWB1 → PWB3	**−.249***	−.340	−.158	PWB2 → SWB3	**.162***	.076	.248
SWB2 → PWB3	**.122***	.029	.216				
PWB1 → SWB3	**.247***	.182	.313				
SWB2 → SWB3	.562***	.497	.626				
PWB1 → PWB2	.706***	.675	.737				
PWB1 → SWB2	**.372***	.268	.477				
SWB1 → SWB2	.327***	.220	.434				
Covariances				Covariances			
PWB3 ↔ SWB3	.733***	.682	.783	PWB3 ↔ SWB3	.734***	.694	.774
PWB2 ↔ SWB2	.717***	.671	.764	PWB2 ↔ SWB2	.833***	.808	.857
PWB1 ↔ SWB1	.853***	.826	.880				

Note. CI = confidence interval; PWB = psychological well-being; SWB = subjective well-being. Cross-lagged effects are shown in bold.
* $p < .05$. *** $p < .001$.

ber et al., 2011; Joshanloo & Jarden, 2016). This also is in accordance with evidence showing that moderate levels of cumulative lifetime adversity can be associated with optimal well-being in the long run (Seery, Leo, Lupien, Kondrak, & Almonte, 2013). That the cross-lagged paths from SWB were rather weaker or in the unexpected direction indicates that higher levels of SWB if not supplemented by higher levels of PWB may not be conducive to future PWB. Altogether, the results suggest that PWB may be more beneficial than SWB in the long run because it is more likely to boost future levels of both aspects of well-being.

Despite the clear advantages of cross-lagged panel models over cross-sectional studies for investigating causal precedence, it should be acknowledged that cross-lagged models of passive correlational data are in fact imperfect tools for determining causal directionality "with certainty" (Newsom, 2015, p. 147). Specifically designed experiments can lead to more certainty about directionality and causal precedence because of the fact that they are more efficient in minimizing potential confounding effects. Therefore, the present results should be considered preliminary until replicated in additional research with various methodologies, samples, and lag lengths.

References

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling, 9,* 233–255. http://dx.doi.org/10.1207/S15328007SEM0902_5

DeHaan, C., & Ryan, R. M. (2014). Symptoms of wellness: Happiness and eudaimonia from a self-determination perspective. In K. M. Sheldon & R. E. Lucus (Eds.), *Stability of happiness: Theories and evidence on whether happiness can change* (pp. 37–55). Amsterdam, the Netherlands: Elsevier. http://dx.doi.org/10.1016/B978-0-12-411478-4.00003-5

Diener, E. (2014). Stable happiness dies in middle-age: A guide to future research. In K. Sheldon & R. E. Lucas (Eds.), *Stability of happiness: Theories and evidence on whether happiness can change* (pp. 299–308). New York, NY: Springer. http://dx.doi.org/10.1016/B978-0-12-411478-4.00014-X

Fredrickson, B. L. (2004). The broaden-and-build theory of positive emotions. *Philosophical Transactions of the Royal Society of London Series B: Biological Sciences, 359,* 1367–1378. http://dx.doi.org/10.1098/rstb.2004.1512

Gruber, J., & Bekoff, M. (2017). A cross-species comparative approach to positive emotion disturbance. *Emotion Review, 9,* 72–78. http://dx.doi.org/10.1177/1754073915615430

Gruber, J., Mauss, I. B., & Tamir, M. (2011). A dark side of happiness? How, when, and why happiness is not always good. *Perspectives on Psychological Science, 6,* 222–233. http://dx.doi.org/10.1177/1745691611406927

Hill, P. L., & Turiano, N. A. (2014). Purpose in life as a predictor of mortality across adulthood. *Psychological Science, 25,* 1482–1486. http://dx.doi.org/10.1177/0956797614531799

Huta, V., & Ryan, R. M. (2010). Pursuing pleasure or virtue: The differential and overlapping well-being benefits of hedonic and eudaimonic motives. *Journal of Happiness Studies, 11,* 735–762. http://dx.doi.org/10.1007/s10902-009-9171-4

Joshanloo, M. (2016). Revisiting the empirical distinction between hedonic and eudaimonic aspects of well-being using exploratory structural equation modeling. *Journal of Happiness Studies, 17,* 2023–2036. http://dx.doi.org/10.1007/s10902-015-9683-z

Joshanloo, M. (2017). Factor structure and criterion validity of original and short versions of the Negative and Positive Affect Scale (NAPAS). *Personality and Individual Differences, 105,* 233–237. http://dx.doi.org/10.1016/j.paid.2016.09.060

Joshanloo, M., & Jarden, A. (2016). Individualism as the moderator of the relationship between hedonism and happiness: A study in 19 nations. *Personality and Individual Differences, 94,* 149–152. http://dx.doi.org/10.1016/j.paid.2016.01.025

Keyes, C. L., Dhingra, S. S., & Simoes, E. J. (2010). Change in level of positive mental health as a predictor of future risk of mental illness. *American Journal of Public Health, 100,* 2366–2371. http://dx.doi.org/10.2105/AJPH.2010.192245

Kline, R. B. (2015). *Principles and practice of structural equation modelling*. New York, NY: Guilford Press.

Little, T. D. (2013). *Longitudinal structural equation modeling*. New York, NY: Guilford Press.

Lyubomirsky, S., King, L., & Diener, E. (2005). The benefits of frequent positive affect: Does happiness lead to success? *Psychological Bulletin, 131,* 803–855. http://dx.doi.org/10.1037/0033-2909.131.6.803

Mroczek, D. K., & Kolarz, C. M. (1998). The effect of age on positive and negative affect: A developmental perspective on happiness. *Journal of Personality and Social Psychology, 75,* 1333–1349. http://dx.doi.org/10.1037/0022-3514.75.5.1333

Newsom, J. T. (2015). *Longitudinal structural equation modeling: A comprehensive introduction*. New York, NY: Routledge.

Oishi, S., Diener, E., & Lucas, R. E. (2007). The optimum level of well-being: Can people be too happy? *Perspectives on Psychological Science, 2,* 346–360. http://dx.doi.org/10.1111/j.1745-6916.2007.00048.x

Ryan, R. M., & Deci, E. L. (2001). On happiness and human potentials: A review of research on hedonic and eudaimonic well-being. *Annual Review of Psychology, 52,* 141–166. http://dx.doi.org/10.1146/annurev.psych.52.1.141

Ryff, C. D. (1989). Happiness is everything, or is it? Explorations on the meaning of psychological well-being. *Journal of Personality and Social Psychology, 57,* 1069–1081.

Seery, M. D., Leo, R. J., Lupien, S. P., Kondrak, C. L., & Almonte, J. L. (2013). An upside to adversity? Moderate cumulative lifetime adversity is associated with resilient responses in the face of controlled stressors. *Psychological Science, 24,* 1181–1189. http://dx.doi.org/10.1177/0956797612469210

Selig, J., & Little, T. (2012). Autoregressive and cross-lagged panel analysis for longitudinal data. In B. Laursen, T. D. Little, & N. A. Card (Eds.), *Handbook of developmental research methods* (pp. 265–278). New York, NY: Guilford Press.

Steger, M. F. (2016). Hedonia, eudaimonia, and meaning: Me versus us, fleeting versus enduring. In J. Vittersø (Ed.), *Handbook of eudaimonic well-being* (pp. 175–182). Switzerland, Cham: Springer International Publishing. http://dx.doi.org/10.1007/978-3-319-42445-3_11

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