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Short Communication

Longitudinal associations between subjective and psychological well-being in Japan: A four-year cross-lagged panel study

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ABSTRACT

The purpose of the present study was to explore the temporal associations between subjective well-being (SWB) and psychological well-being (PWB) across 4 years. A cross-lagged analysis of 2 waves of data was conducted using a Japanese sample ($N = 657$). The results concerning the auto-regressive effects indicated high stability over time for both of the variables. The cross-lagged effect of PWB on SWB was significant, suggesting that PWB predicts increases in SWB over time. However, SWB did not predict subsequent levels of PWB.

1. Introduction

Mental well-being has hedonic and eudaimonic aspects (Keyes, Shmotkin, & Ryff, 2002). Hedonic happiness consists of facets relating to subjective well-being (SWB), including life satisfaction, positive affect, and the absence of negative affect (Diener, Suh, Lucas, & Smith, 1999). Eudaimonic well-being consists of facets relating to psychological well-being (PWB), including psychological skills and competencies that facilitate optimal functioning (such as autonomy and self-acceptance, Ryff, 1989). The hedonic and eudaimonic dimensions are correlated yet empirically distinct (Joshanloo, 2016). Research has documented concurrent and longitudinal benefits for both SWB and PWB (e.g., Hill & Turiano, 2014; Keyes, Dhingra, & Simoes, 2010; Lyubomirsky, King, & Diener, 2005). However, research on the prospective associations between the two concepts is virtually nonexistent. An exception is Joshanloo's (in press) investigation of the temporal relationships between the two variables in an American sample collected over two decades. He found that PWB positively predicted future levels of SWB, whereas the prospective effects of SWB on PWB were weaker and ranged from negative to positive.

The present study sought to look at the longitudinal associations between the two variables in a different culture. The data were extracted from the Survey of Midlife Development in Japan (MIDJA), which includes scales of PWB and SWB. MIDJA has collected two waves of data with an interval of 4 years. Cross-lagged panel analysis (Little, 2013) was performed to estimate auto-regressive 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 auto-regressive effects provide insights on the stability of the concepts over time. The cross-lagged effects provide a test of the directionality of relationship between the two concepts (Newsom, 2015). Based on the results of Joshanloo (in press), PWB was expected to have a stronger prospective effect on SWB than the reverse.

2. Methods

2.1. Participants

Data were extracted from the first (collected in 2008) and second (collected in 2012) waves of the MIDJA (Ryff et al., 2012). The final sample of the study consisted of individuals who completed the survey at both time points, $N = 657$, 47% males. The average age was 54.92 years ($SD = 13.578$) at Time 1. Among the 657 participants, 634 (96.5%) had complete data on all of the 18 variables of the study, whereas 23 participants had 1 to 7 missing values. A detailed description of data collection procedures can be found at http://midus.wisc.edu.

2.2. Measures

2.2.1. SWB

The 12-item negative and positive affect scale was used to measure affect (Joshanloo, 2017; Mroczek & Kolarz, 1998). Respondents indicated how often (from 1 = *none of the time* to 5 = *all*), during the past 30 days, they felt six positive and six negative affective states. The scale has shown satisfactory psychometric properties (Joshanloo, 2017). Life satisfaction was measured using the satisfaction with life scale (Diener, Emmons, Larsen, & Griffin, 1985). This scale consists of five items that are rated on a 7-point scale (from 1 = *strongly disagree* to 7 = *strongly agree*).

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Table 1
Descriptive statistics and alphas.

Wave	Variable	*M*	*SD*	*α*	Skewness	Kurtosis
1	Autonomy	30.678	5.500	0.701	0.196	0.734
	Mastery	32.018	5.534	0.732	0.086	0.387
	Growth	34.031	5.691	0.744	0.092	0.150
	Relations	33.709	5.816	0.762	−0.219	0.740
	Purpose	31.816	5.165	0.561	0.111	0.164
	Acceptance	31.142	5.802	0.780	−0.153	0.931
	Negative affect	1.663	0.642	0.860	1.162	1.474
	Positive affect	3.276	0.765	0.927	−0.021	−0.100
	Life satisfaction	4.114	1.234	0.888	−0.318	−0.116
2	Autonomy	30.775	5.143	0.734	0.208	0.394
	Mastery	31.866	5.195	0.755	0.167	0.618
	Growth	33.372	5.673	0.796	0.171	0.078
	Relations	33.538	5.575	0.785	−0.270	0.850
	Purpose	31.396	4.853	0.577	0.411	0.477
	Acceptance	30.902	5.392	0.787	−0.169	0.940
	Negative affect	1.704	0.643	0.864	1.027	1.224
	Positive affect	3.261	0.721	0.934	−0.097	0.124
	Life satisfaction	4.078	1.184	0.901	−0.373	0.235

Note. The alphas are obtained from the MIDJA documentations of the constructs. All other values are based on the samples used in the present studies.

2.2.2. PWB

The 42-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). The six dimensions are autonomy, environmental mastery, personal growth, positive relations, purpose in life, and self-acceptance, each measured with seven items. The scale has shown satisfactory psychometric properties across various studies (e.g., Ryff & Singer, 2006).

The scales of the study were translated into Japanese using the method of back-translation. Descriptive statistics and Cronbach's alphas are reported in Table 1.

2.3. Statistical analysis

Longitudinal confirmatory factor analyses and bidirectional cross-lagged panel analyses were conducted in Mplus 8, with Robust Maximum Likelihood (MLR). Full information maximum likelihood (FIML) was used to handle missing data. FIML is among the most efficient and highly recommended methods to handle missing data in structural equation modeling (Graham & Coffman, 2012). The six PWB variables at each time point were used as the indicators of the PWB factors (labeled as PWB1 and PWB2). The latent variables of SWB (labeled as SWB1 and SWB2) were indicated by life satisfaction, positive affect, and reverse-coded negative affect. A minimum cutoff of 0.90 for Comparative Fit Index (CFI), a maximum cutoff of 0.08 for Root Mean Square Error of Approximation (RMSEA), and a maximum cutoff of 0.08 for Standardized Root Mean Square Residual (SRMR) were considered as indicative of acceptable fit (e.g., Brown, 2015). Smaller values of Akaike information criterion (AIC) and Bayesian information criterion (BIC) indicate better fit.

The analysis started with establishing a confirmatory factor analysis (CFA) model and metric and scalar invariance across time (Selig & Little, 2012). Longitudinal metric and scalar invariance 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 CFI values less than 0.01 were considered as indicative of measurement invariance (Cheung & Rensvold, 2002). After establishing measurement invariance, a bidirectional cross-lagged panel model was tested to investigate the reciprocal relationships between PWB and SWB. Finally, in a separate cross-lagged model, gender, age, and age^2 were added to control for their effects.

3. Results

A CFA involving all of the PWB and SWB variables was first tested. All of the factors were specified to have non-directional covariance relationships. All autocorrelations among measurement residuals across time were also estimated. The model fitted the data well (M1 in Table 2). Next, the longitudinal measurement invariance of the model was examined. Whereas full metric invariance (M2) was supported (ΔCFI = 0.000), full scalar invariance (M3) was not supported (ΔCFI = −0.019). As suggested by the modification indices, the constraints on the intercepts of negative affect were relaxed. The modified model (M4) fitted the data well, providing support for partial scalar invariance (ΔCFI = −0.001). Cross-lagged analysis is fairly robust to violations of measurement invariance, provided that the majority of the indicators are established as invariant (Little, 2013). In the present study, full metric invariance was supported and only a single intercept was found to be non-invariant. This can be considered a tolerable level of bias (Little, 2013; Newsom, 2015).

Holding the equality constraints, all of the lagged relationships were converted into directional predictive paths (M5). Given that the structural portion of this model is saturated, model fit does not indicate the accuracy of the directional paths. To build a more parsimonious model, the non-significant path from SWB1 to PWB2 was dropped (Little, 2013; Newsom, 2015), which resulted in the final model of the study (M6). This model is shown in Fig. 1, and its parameter estimates are presented in Table 3. The two autoregressive paths were significant and strong. With regards to the cross-lagged relationships, the path from SWB1 to PWB2 was not significant (and was dropped). This suggests that, when the initial levels of the variables are controlled for, SWB does not prospectively predict PWB. The cross-lagged path from PWB1 to SWB2 was significant, showing that PWB predicts increases in SWB over time. Finally, in a separate model (M7), all of the four factors were regressed on the demographic variables. As can be seen in Table 3, adding the covariates had nearly no effect on the lagged effects. Therefore, the effects observed in M6 cannot be explained by participants' gender and age. Table 3 shows that the covariates are not strong predictors of well-being. Models 5–7 are shown in Fig. 1.

Table 2
Fit indices.

Model	χ^2	*df*	CFI	SRMR	AIC	BIC	RMSEA	90% CI for RMSEA Low	90% CI for RMSEA Up
1-CFA model	447.4	120	0.946	0.050	50,655.8	50,965.4	0.064	0.058	0.071
2-Metric invariance	449.8	127	0.946	0.051	50,644.4	50,922.6	0.062	0.056	0.068
3-Scalar invariance	572.6	134	0.927	0.056	50,778.7	51,025.6	0.071	0.065	0.077
4-Partial scalar invariance	466.4	133	0.945	0.052	50,647.5	50,898.9	0.062	0.056	0.068
5-Structurally saturated cross-lagged model	466.4	133	0.945	0.052	50,647.5	50,898.9	0.062	0.056	0.068
6-Final cross-lagged model	467.5	134	0.945	0.052	50,646.7	50,893.5	0.062	0.056	0.068
7-Final cross-lagged model with covariates	621.0	176	0.932	0.053	50,629.2	50,929.9	0.062	0.057	0.067

Note. All χ^2 values are significant at $p < .001$.

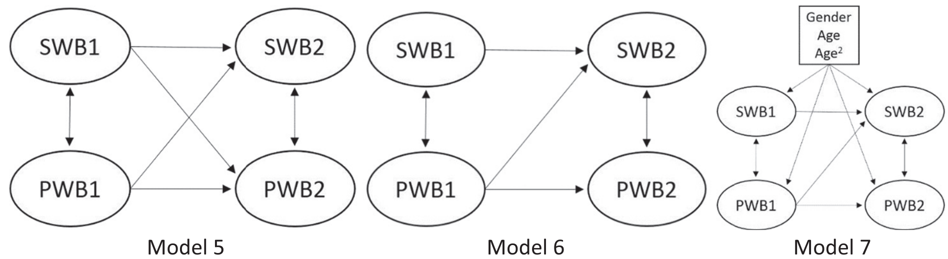

Fig. 1. Cross-lagged models.
Note. The factor indicators are not shown for brevity.

Table 3
Standardized estimates for models 6 and 7.

	Estimate	95% CI	
		Low	Up
Model 6 (no covariates)			
Regression paths			
PWB1 → PWB2	0.808***	0.768	0.847
SWB1 → SWB2	0.761***	0.667	0.856
PWB1 → SWB2	0.107*	0.000	0.213
Covariances			
PWB1 ↔ SWB1	0.729***	0.667	0.791
PWB2 ↔ SWB2	0.751***	0.654	0.848
R^2			
PWB2	0.652***		
SWB2	0.709***		
Model 7 (with covariates)			
Regression paths			
PWB1 → PWB2	0.808***	0.768	0.847
SWB1 → SWB2	0.739***	0.638	0.840
PWB1 → SWB2	0.115*	0.008	0.222
Covariances			
PWB1 ↔ SWB1	0.732***	0.670	0.794
PWB2 ↔ sSWB2	0.756***	0.659	0.852
R^2			
PWB1	0.011		
PWB2	0.653***		
SWB1	0.041*		
SWB2	0.714***		
Regression paths for demographic variables			
	Female	Age	Age^2
PWB1	0.081*	0.018	−0.059
PWB2	−0.005	0.001	−0.007
SWB1	0.148**	0.144**	−0.005
SWB2	0.049	0.062	−0.008

Note. PWB = psychological well-being. SWB = subjective well-being.
* $p < .05$.
** $p < .01$.
*** $p < .001$.

4. Discussion

The results showed that the auto-regressive paths were strong and almost equal for PWB and SWB (Table 3), indicating strong longitudinal stability for both dimensions over 4 years. Joshanloo (in press) found lower levels of stability over 20 years. He also found that PWB demonstrated generally more stability over time than did SWB, which may indicate that with longer lags, the stability of SWB decreases at a faster pace than PWB. Holding demographic variables constant in both studies hardly affected the autoregressive effects.

The initial levels of PWB predicted positive changes in the levels of SWB over time. This effect is not very strong (Table 3) but it is still impressive, considering that the effect holds when the initial level of SWB and the demographic variables are controlled for. This finding accords with Joshanloo's (in press) results showing that PWB was a positive prospective predictor of SWB over 10 and 20 years. In the present study, the cross-lagged path from SWB to PWB was not significant. This means that SWB does not predict changes in PWB over time. Similarly, Joshanloo (in press) found that the cross-lagged effects of SWB on PWB were mixed.

The broaden-and-build theory of positive emotions (Fredrickson, 2004) suggests that positive emotions broaden an individual's momentary thought-action repertoire, and thereby, promote discovery of novel and creative actions, ideas, and social bonds, which in turn build an individual's psychological resources. According to this theory, eudaimonia “appears to be one of the many resources that positive emotions serve to build” (Fredrickson, 2016, p. 186). Hence, from this perspective, SWB is expected to prospectively predict changes in PWB. However, the present results, as well as those of Joshanloo (in press), suggest that SWB does not robustly predict future PWB. It seems that SWB does not automatically lead to the development of psychological resources in the long run. In fact, empirical evidence shows that the experience of subjective happiness, particularly when it is excessive, extended, and immoderate, may have some negative effects, including compromised empathic performance (Devlin, Zaki, Ong, & Gruber, 2014), superficial information processing, increased stereotype effects, and reduced ability to detect deception (Forgas, 2013), and a short-term rather than long-term focus (Baumeister, Vohs, Aaker, & Garbinsky, 2013). The long-term positive effects of SWB on PWB may be canceled out by these potentially negative consequences.

Given that SWB and PWB positively and strongly predicted their own future levels, higher levels of both are beneficial and should be obtained, maintained, and promoted. However, PWB seems to have the extra advantage of boosting not only future levels of itself but also those of SWB. Hence, a general conclusion from the present study would be that eudaimonic well-being may be more beneficial in the long run than SWB. These results suggest that causality mostly runs from PWB to SWB, not the reverse. However, with panel models, causal inferences should be made with caution. Although panel models offer some benefits over purely cross-sectional studies (e.g., by controlling the initial levels of variables), they are not perfect tools for establishing causality, largely because they use passive observational data (Newsom, 2015). Supplementary evidence from experimental studies with random allocations, appropriate controls, and experimental manipulations would be necessary for a more conclusive reasoning about causal mechanisms (Little, 2013).

The results of an independent study with an American sample (Joshanloo, in press) were largely similar to those obtained with the present Japanese sample. Yet, given the dearth of cross-cultural studies on the temporal relationship between PWB and SWB, these findings cannot be generalized to other cultures, before additional investigations are undertaken. In addition, using other scales which are based on alternative conceptualizations of well-being may result in different conclusions. Therefore, future research will need to also apply other measures of the constructs. Common method bias is also a potential limitation of this study. Using measures from different sources (e.g., acquaintance reports) in future research can minimize such biases. Therefore, more research on this topic needs to be undertaken before the longitudinal association between PWB and SWB is fully understood.

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