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The Temporal Relationship Between Self-Acceptance and Generativity over Two Decades

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Abstract

Generativity is defined as a concern for the well-being of future generations, which involves both caring and a will to extend the self into the future. Extant research indicates that generativity plays an important role in successful aging. The present study sought to examine the temporal relationship between self-acceptance and generativity over about 2 decades. The data were drawn from the three waves of the Midlife in the United States (MIDUS) project, collected with intervals of about 10 years (N = 4,167). The random-intercept cross-lagged panel model was used for data analysis. It was found that self-acceptance prospectively predicted generativity, whereas generativity did not predict self-acceptance. Thus, coming to terms with various aspects of one's personality and past life contributes to higher future levels of generativity.

Keywords

self-acceptance, generativity, longitudinal, random-intercept cross-lagged panel model, Midlife in the United States

Generativity is defined as "the concern in establishing and guiding the next generation" (Erikson, 1963, p. 240), which includes productivity, care, and creativity. Generativity "aims at the broader social good" (McAdams & de St. AubinAubin, 1992, p. 236) and is antithetical to a sense of stagnation, personal impoverishment, and self-preoccupation. This variable has evidenced positive associations with hedonic and eudaimonic well-being (e.g., An & Cooney, 2006; Grossman & Gruenewald, 2020; Rothrauff & Cooney, 2008). Generativity is also related to other desirable life and career outcomes, including various aspects of physical health (e.g., Doerwald et al., 2021; Moieni et al., 2020). Thus, generative actions not only benefit the person on the receiving end, but also the person who performs them. Based on these results, generativity is considered an important contributor to successful aging (e.g., Schoklitsch & Baumann, 2012).

Generativity involves externalizing various aspects of the self (e.g., values and beliefs) into the outer world (Wakefield, 1998; McAdams & de St. AubinAubin, 1992). Generative actions are meant to be reflective of the self, aimed at the perpetuation of oneself or an extension of the self beyond the boundaries of its temporal limitations (Wakefield, 1998). Indeed, variables capturing different features of self-perceptions are related to generative tendencies. For example, generativity is related to self-esteem, self-efficacy, and self-clarity (Blatný et al., 2019). However, the relationship between self-acceptance and generativity has not received much attention. Self-acceptance is defined as having positive self-regard, acknowledging both positive and negative aspects of the self, and feeling positive about the past life (Ryff & Singer, 2002). Given that generativity involves a will to expand the self, a sense of self-acceptance may play an important role in the development of generativity. Consistent with this prediction, existing cross-sectional evidence suggests that there is a positive relationship between self-acceptance and generativity (e.g., An & Cooney, 2006). Yet, little is known about the temporal relationship between self-acceptance and generativity. The present study sought to fill this gap. It was predicted that self-acceptance would be a positive predictor of future generativity.

Methods

Participants

The sample is from the Midlife in the United States (MIDUS; midus.wisc.edu) project. Data for Wave 1 (collected during 1995–1996), Wave 2 (2004–2006), and Wave 3 (2013–2014) were included in the present study. Wave 1 of MIDUS

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Table 1. Reliabilities and R-Square Values.

	Alpha	R^2
Generativity		
Wave 1	0.84	
Wave 2	0.85	0.036
Wave 3	0.85	0.048
Self-acceptance		
Wave 1	0.59	
Wave 2	0.66	0.047
Wave 3	0.67	0.086

Note. Alphas are from the MIDUS official documents.

consists of 7108 individuals. Given the longitudinal nature of the study, the present study included participants that participated in at least two waves (N = 4167, females = 54.90%, whites = 91.17%, mean age = 47.14 at Wave 1, SD = 12.36). Except for participants who participated in less than two waves, no other participant was excluded from the analysis.

Measures

Generativity. MIDUS uses a 6-item version of the Loyola Generativity Scale (McAdams & de St Aubin, 1992). The items are rated on a 4-point scale from *a lot* (1) to *not at all* (4).

Self-acceptance. The 3-item version of Ryff's self-acceptance scale was used (Ryff, 1989). The items are rated on a scale of *strongly agree* (1) to *strongly disagree* (7).

Demographic variables. The baseline age (i.e., age at Wave 1), gender (female = 1, male = 0), and race (white = 1, others = 0) were included as the time-invariant predictors of all observed variables.

The items were recoded such that higher scores reflect higher levels of self-acceptance and generativity. Internal consistencies are presented in Table 1.

Analytic Strategy

The present study sought to investigate the mutual relationships between self-acceptance and generativity over time. For this purpose, the random-intercept cross-lagged panel model (RI-CLPM) was used (Hamaker et al., 2015). The RI-CLPM is an extension of the cross-lagged panel model (CLPM), which is typically used to examine the associations between variables in panel data. In the CLPM, the between- and within-person influences are not separated. The main contribution of the RI-CLPM is a partitioning of the variance into between- and within-person components. In the RI-CLPM, the trait-like, time-invariant stability of the variables is accounted for by using random intercepts (trait components). Thus, the between-person variance in the variables is partialled out before the autoregressive and cross-lagged relationships are examined. In other words, in the RI-CLPM, autoregressive and cross-lagged parameters merely reflect the influences of the state-like time-varying parts of the variables. Whereas between-person linkages do not reflect temporal dynamics, within-person linkages reflect the temporal associations between the two variables. These two sources of variance are not distinguished in the conventional CLPM, confusing temporal relationships (Hamaker et al., 2015), and thus the RI-CLPM provides more clarity on within-person associations.

The model of the study (displayed in Figure 1) was estimated with observed variables and robust maximum likelihood (MLR) in *Mplus* 8.4. The model was estimated under missing data theory using all available data. A minimum cutoff of .95 for the comparative fit index (CFI), a maximum cutoff of .06 for the root mean square error of approximation (RMSEA), and a maximum cutoff of .08 for the standard root mean square residual (SRMR) were considered as indicative of good fit (Kline, 2015). The predictive paths between state variables were held equal over time. To control for age, gender, and race, all the observed variables across all time points were regressed on these three variables.

The study also included several auxiliary variables. These variables are not of substantive interest in the analysis. They are included to assist the missing data estimation process by reducing the uncertainty caused by the missing data and thereby improving the precision of the estimation (Asparouhov & Muthén, 2008; Kline, 2015). In this study, seven variables were used: income (square-root-transformed) at three time points, the highest educational level at three time points (from 1 = eighth grade/junior high school and below to 6 = Ph.D. and similar degrees), and a dummy variable indicating if the individual participated in three (n = 2654) or two (n = 1513) waves. The latter variable was included to account for the possibility that people with complete versus incomplete data might have different scores of self-acceptance and generativity.

Results

The model fit the data very well (X^2 = 43.200, df = 7, RMSEA = 0.035 [0.026–0.046], CFI = 0.994, SRMR = 0.026). The R^2 values for state variables are reported in Table 1. Parameter estimates are presented in Table 2. The variances for the two intercepts (7.918 and 6.252, for generativity and self-acceptance, respectively) were significant at p < .001, suggesting that there are individual differences in the person-level means of the variables. Autoregressive paths reflect the degree of within-person/cross-situation stability in variables. Significant autoregressive paths were found for both variables, showing that when an individual's score on a variable is above (or below) their average level of that variable, they are expected to score above (or below) their average level of that variable at the next time point as well. A significant cross-lagged effect shows that a score above (or below) the person-specific mean in one variable is associated with a score above (or below) the person-specific mean in the other variable at the subsequent time point. Whereas the cross-lagged effects from generativity to

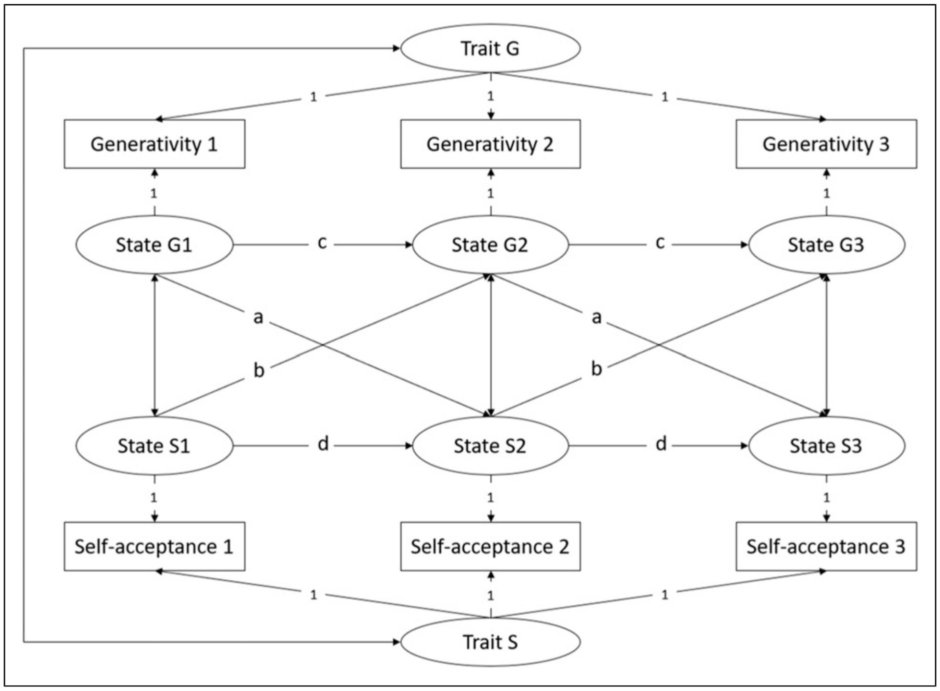

Figure 1. The random-intercept cross-lagged panel model. G = generativity. S = self-acceptance. Labels on lagged effects indicate equality constraints. For simplification, time-invariant covariates and residual terms are not shown.

Table 2. Random-Intercept Cross-Lagged Model Results.

				Confidence Interval		
Predictor	Outcome	Unstandardized Coefficient	*p*	Low	Up	Standardized Coefficient
Autoregressive						
Gen1	Gen2	0.184	0.000	0.112	0.256	0.172
Gen2	Gen3					0.185
SA1	SA2	0.257	0.000	0.191	0.323	0.210
SA2	SA3					0.279
Cross-lagged						
SA1	Gen2	0.073	0.005	0.022	0.124	0.066
SA2	Gen3					0.081
Gen1	SA2	0.044	0.116	−0.011	0.100	0.037
Gen2	SA3					0.043
Covariance between						
Gen1	SA1	0.492	0.008	0.131	0.854	0.083
Gen2	SA2	1.774	0.000	1.316	2.232	0.240
Gen3	SA3	1.212	0.000	0.827	1.597	0.184
Trait gen	Trait SA	3.254	0.000	2.804	3.704	0.463

Note. Gen = generativity. SA = self-acceptance.

self-acceptance were not significant, those from self-acceptance to generativity were. Thus, self-acceptance prospectively predicts generativity, but generativity does not predict future levels of self-acceptance. The between-person correlation between self-acceptance and generativity (i.e., the correlation between the stable components of the variables) was positive and significant ($r = .463$).

Discussion

Self-acceptance and generativity were moderately correlated at the between-person level. Hence, people with high levels of self-acceptance are also likely to be those who are more generative and vice versa, which is consistent with prior cross-sectional findings (e.g., An & Cooney, 2006). However, the between-person associations do not reflect temporal dynamics. For that information, the within-person associations should be inspected. Within-person cross-lagged estimates showed that whereas self-acceptance predicted future generativity, generativity did not predict future self-acceptance. Therefore, as predicted, self-acceptance preceded generativity, that is, fluctuations in self-acceptance are expected to predict future fluctuations in generativity over long periods. These results suggest that developing a sense of self-acceptance can increase generative tendencies in adulthood.

Prior research has shown that generativity enhances various aspects of well-being, and generative failure is linked to decreased well-being over time (Grossman & Gruenewald, 2020). The present results add the insight that self-acceptance is among the psychological variables that generativity depends on. This insight can be used in developing generativity interventions (Moieni et al., 2020). These interventions would benefit from considering the finding that acknowledging and accepting one's good and bad qualities could reinforce generative tendencies, and the lack of self-acceptance may hinder generative engagement.

It is noteworthy that the study had a very long lag length between measurement points, and thus the results only speak to long-term associations between self-acceptance and generativity. With shorter lag lengths (e.g., 1 week, month, or year), the sizes and/or directions of the within-person associations between self-acceptance and generativity could be different. Therefore, the influence of lag length needs to be investigated in future research on the relationship between self-acceptance and generativity. Another suggestion for future research is to use lengthier and more reliable measures. Finally, a fruitful avenue for future research is to examine the potential mediators of the relationship between self-acceptance and generativity. For example, are people high on self-acceptance more likely to be generative because of their fewer internal conflicts allowing them to invest more in the outer world? Are they more generative because they have a broader sense of self that is inclusive of others, even strangers? Are they more generative because they have a stronger need to have others' acceptance as well (with generativity serving as a means towards that end)? These and other possibilities remain to be tested in future studies.

In sum, this study investigated the long-term temporal relationships between self-acceptance and generativity and found that self-acceptance predicted generativity over time. Individuals who successfully come to terms with various aspects of their personality and past life are more likely to strive to care for future generations and to externalize and expand their selves over time. Thus, the findings are in keeping with prior research showing that self-perceptions play a nontrivial role in the development of generativity in adulthood (Blatný et al., 2019).

Declaration of Conflicting Interests

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Data Availability

The data that support the findings of this study are openly available in Inter-university Consortium for Political and Social Research.

Midlife in the United States 1 (MIDUS 1): https://doi.org/10.3886/ICPSR02760.v19

Midlife in the United States 2 (MIDUS 2): https://doi.org/10.3886/ICPSR04652.v7

Midlife in the United States 3 (MIDUS 3): https://doi.org/10.3886/ICPSR36346.v7

IRB and Informed Consent

This study presents a secondary analysis of de-identified and publicly available data set. All participants provided written informed consent. More information on the data and study procedures can be found at https://www.midus.wisc.edu.

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