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Assessing reciprocal relationships in PLS-SEM: An illustration based on a job crafting study

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Abstract

Over the last 25 years two types of job crafting have emerged with similar quantitative measurement scales. This paper describes the process used in determining the presence of reciprocal relationships between the two job crafting constructs using WarpPLS.

Keywords: Reciprocal Analysis; Structural Equation Modeling; Partial Least Squares; WarpPLS.

Introduction

Statistical reciprocal relationship analysis was used to investigate the extent to which two constructs simultaneously influence each other. In our study, the main research question was: To what extent was job crafting based on job-demand resources (JD-R) a reciprocal of job crafting techniques (JCT), the two most commonly used job crafting measures (Slemp & Vella Broderick, 2013; Tims et al, 2012). We used WarpPLS (Kock, 2020a; Moqbel et al., 2020) version 6.0 to illustrate the analyses in this paper.

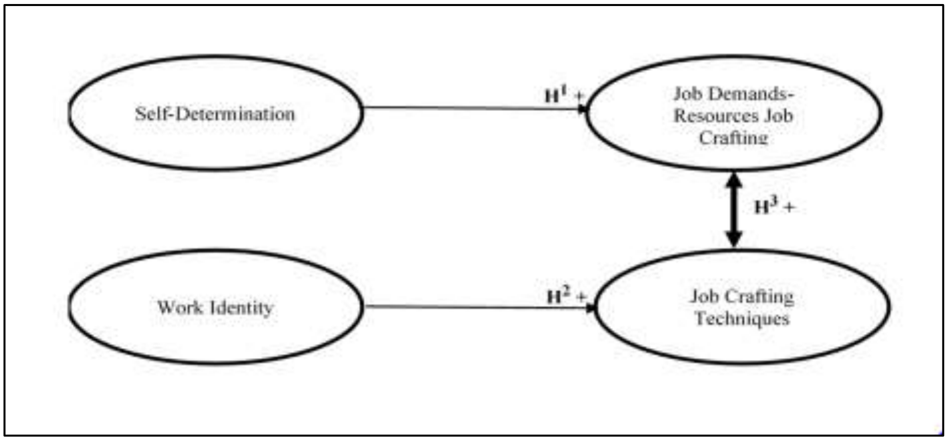
What is a reciprocal?

In statistics, a reciprocal is two constructs that simultaneously influence each other; therefore, we measured the extent to which the two types of job crafting were correlated and share co-variance. The bi-directional relationships could be shown within a single model; however, statistical packages do not support such relationships. WarpPLS allows for the direct testing of reciprocity, among other useful features (Kock, 2020b).

Illustrative model and data

The model in Figure 1 served as the basis for the research. To test if two constructs have a reciprocal relationship, the constructs being tested must be endogenous and be correlated. In addition, each endogenous construct must have an exogenous construct, which is not the same, pointing at it (Kock, 2017). Based on theory and the requirement to use different predictor constructs to test for reciprocity, the structural model was defined with self-determination (eSDT) and work identity (eWRKID) as the exogenous constructs and exhibited positive relationships with JD-R (eJDRJC) and JCT (eJCTEQ) (See Figure 2). These defined a fully-specified model, as required to perform the analysis.

Figure 1: Illustrative model



Notes: Hypothesis 1: Self-determination will have a positive relationship with job demands-resources job crafting. Hypothesis 2: Work identity will have a positive relationship with job crafting techniques. Hypothesis 3: Job demands-resources job crafting, and job crafting techniques will have reciprocal relationships.
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A total of 293 cases were analyzed. The dataset was split to create an exploratory dataset of 146 cases and a confirmatory dataset of 147 cases. Power for both datasets was .80 ($p<.001$) for the smallest absolute path coefficients of .473 and .333, for exploratory and confirmatory datasets, respectively. Demographics were similar in both datasets, including nationality: 98% US and European, and 2% Australasian; gender: about a 50-50 split male-female; job role: including entrepreneur, blue collar, white collar, pink collar, and service staff; age: from 18 to 60; number of years of work, from one to 30+; and education: from high school to doctorates, MDs, and JDs.

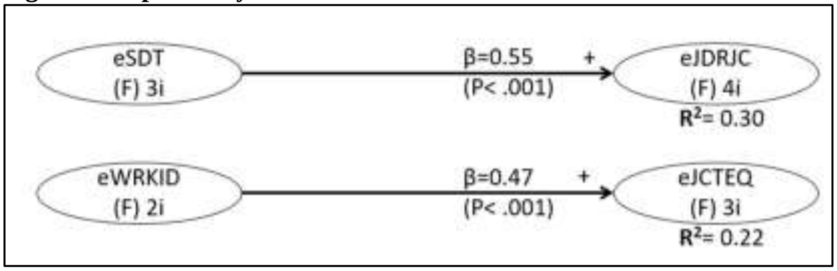
Measuring reciprocal relationships

Analysis of the reciprocal relationships was accomplished using WarpPLS with default settings. The first-order reflective model was assessed and accepted. The second-order formative model passed all evaluations, which allowed for the structural model to be evaluated.

The relationships among the exogenous and endogenous constructs were strong as eSDT to eJDRJC had a $\beta = 0.55$ and eWRKID to eJCTEQ had a $\beta = 0.47$ (see Figure 2). The results of this study indicated, based on adjusted R^2 coefficients, that: eSDT explained 30% of the variance in eJDRJC, and eWRKID explained 22% of the variance in eJCTEQ. The model's predictive validity was demonstrated for eJDRJC, $Q^2 = 0.30$; and for eJCTEQ, $Q^2 = 0.23$ (Kock, 2017). Further, because the variance added for reciprocal assessment was likely to be collinear with other variables in the model, collinearity assessment was considered (Kock & Lynn, 2012) before any instrumental variables were added and was found to be satisfactory with variance inflation factors (VIFs) all under 5.0.

The relationship between the two types of job crafting was checked by evaluating the Pearson correlation to verify that they were related. If strongly correlated, they were more likely to have a reciprocal relationship. The eJDRJC to eJCTEQ Pearson correlation of 0.546 showed that the two job crafting types were likely to be part of a reciprocal relationship.

Figure 2. Exploratory structural model



Stochastic variables were added to the model using the option in the Explore tab option 'Explore analytic composites and instrumental variables→ Instrumental variable → Single stochastic variation sharing.' The stochastic instrumental variables were created to account for independent effects, i.e., covariance between the exogenous and endogenous constructs to which they are not directly related, e.g., eWRKID's relationship to eJDRJC.

Instrumental variables to define the reciprocal relationship were then defined through the same process, except that the 'Stochastic variation sharing' option was selected instead of the 'Single stochastic' option. The two reciprocals were selected then the option to create two new variables (eJDTJDR and eJCRJCT) was selected to allow testing of the reciprocal relationship (Kock, 2017). Next, the reciprocal relationships were added to the model (see Figure 3); then the model was created and analyzed. Notice there is no direct relationship between the two job crafting constructs; the bi-directionality from Figure 1 is developed through the two reciprocal stochastic variables and their relationships. The model was defined, with the reciprocal stochastic variables relating to the two endogenous constructs eJDRJC and eJCTEQ. This approach, with stochastic variables, "avoids questionable results such as incorrectly computed values and out-of range values for coefficients" (Bentler and Raykov, 2000, p 128).

The exploratory reciprocal structural model showed acceptable goodness of fit through the standardized chi squared (SChS) with 65 degrees of freedom, and the standardized threshold difference count ratio (STDCR) of .925 (see Table 2). The standardized mean absolute residual (SRMR) at 0.111 was slightly over the threshold for acceptable fit of 0.1 (Kock, 2017). As this research is exploratory with the intent to test reciprocal relationships, the small amount over the acceptable limit of SRMR was deemed acceptable to continue the analysis.

Table 2. Structural model exploratory fit indices

Exploratory Fit Indices	Result	Acceptability
Standardized root mean squared residual (SRMR)	0.111	Good if < .1
Standardized chi-squared with 65 degrees of freedom (SChS)	6.067, $p < 0.001$	$p < 0.05$
Standardized threshold difference count ratio (STDCR)	0.925	Good if > 0.70, ideally = 1

The path coefficients reflected positive, strong relationships between eJCTEQ and eJDRJC (eJCTJDR, $\beta = 0.53$) and between eJDRJC and eJCTEQ (eJDRJCT, $\beta = 0.45$). The adjusted R^2 of each of the reciprocal path coefficients, R^2=.46 (eJDRJCT) and R^2=.49 (eJCTEQ), was significant with low standard errors and acceptable t-statistics (see Figure 3 and Table 3). The confirmatory dataset had almost identical results. Stochastic reciprocal variables demonstrated the reciprocal relationships between the two types of job crafting; they in fact demonstrated fairly strong relationships. As a result of this analysis, we conclude that further investigation of job crafting integration is warranted.

Figure 3. Exploratory structural model – reciprocal relationship

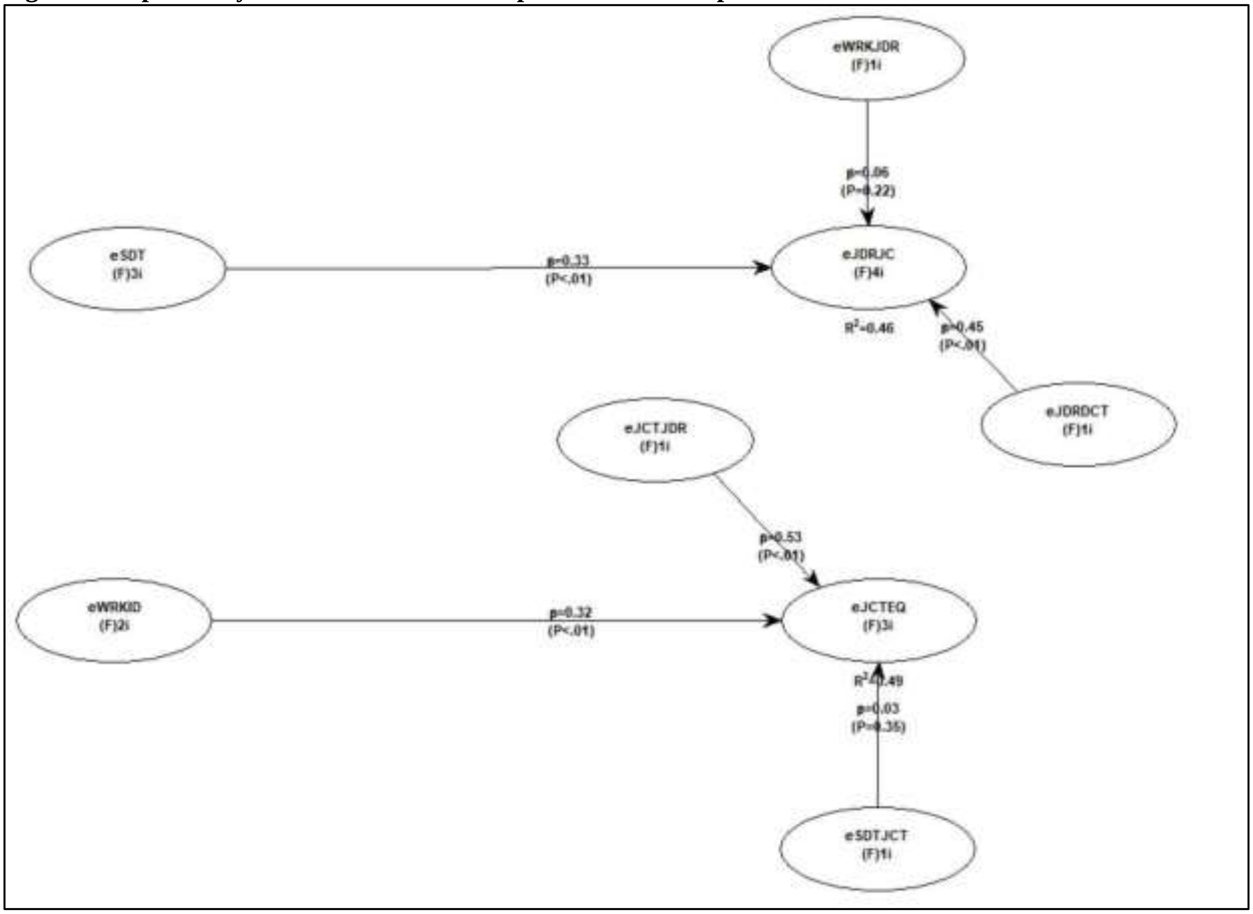


Table 3. Summary of support for the exploratory reciprocal structural model

Hypothesis	Support	Reciprocal Variables	Path Coefficient	p < .05	SE	R^2	t-statistic > 1.96	95% CI	
								Lower	Upper
H^3	Yes	eJDRJCT	0.45	p < 0.001	0.075	0.46	5.989	0.301	0.595
H^3	Yes	eJCTJDR	0.53	p < 0.001	0.073	0.49	7.268	0.390	0.677

Conclusion

Reciprocal analysis is a multi-step process, including exogenous constructs that relate independently and significantly to the constructs of interest. The two linear relationships must first be supported followed by the reciprocal relationship analysis. This is followed by introduction of stochastic instrumental variables to account for indirect variance from those separate relationships, and introduction of stochastic instrumental reciprocal variables to measure the reciprocal relationships. At the time of this writing, WarpPLS is the only known software able to easily accommodate reciprocal analysis.

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