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Testing mediation via indirect effects in PLS-SEM: A social networking site illustration

Murad Moqbel
The University of Texas Rio Grande Valley

Rakesh Guduru
The University of Texas Rio Grande Valley

Ahasan Harun
The University of Texas Rio Grande Valley

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Murad Moqbel
University of Texas Rio Grande Valley, USA

Rakesh Guduru
University of Texas Rio Grande Valley, USA

Ahasan Harun
University of Texas Rio Grande Valley, USA

Abstract

Mediation analysis, in the context of structural equation modeling via partial least squares (PLS-SEM), affords a better understanding of the relationships among independent and dependent variables, when the variables seem to not have a definite connection. In this paper, we demonstrate such an analysis in the context of social networking sites, using WarpPLS, a leading PLS-SEM software tool.

Keywords: Mediation; Indirect Effects; Structural Equation Modeling; Nonlinear Relationship; Partial Least Squares; WarpPLS.

Introduction

Researchers prefer structural equation modeling (SEM) over conventional analyses that ignore the interrelationships among latent constructs that are measured indirectly by multiple measurement items and paths (Bollen, 2014; Chin, 1998a). Among the two main SEM methods in use today, namely covariance-based and partial least squares (PLS)-based, the latter is more suitable over other analytical methods for several reasons. First, the PLS-SEM method makes the modeling of formative and reflective constructs simpler (Chin, 1995, 1998b) as it facilitates handling second-order constructs (Wetzels et al., 2009). Second, it simultaneously examines both the measurement and structural models (Wixom & Watson, 2001). Third, the PLS-SEM method is commonly recommended when the condition of multivariate normality is not met in a dataset (Kock, 2020c).

Despite increased use and awareness of mediation effects, studies employing PLS-SEM often do not consider and analyze mediating effects in their path models (Hair et al., 2010). To facilitate mediation analysis, we use the WarpPLS software in this paper. WarpPLS is popular PLS-SEM software with advanced features (e.g., Kock, 2020a, 2020b), such as outputs enabling multivariate normality, multicollinearity, common-method bias, and predictive validity tests. The software also allows the assessment of direct and indirect effects. We employ WarpPLS version

7.0 to illustrate our analyses in this paper. Our objective in this paper is to test mediation via indirect effects in PLS-SEM.

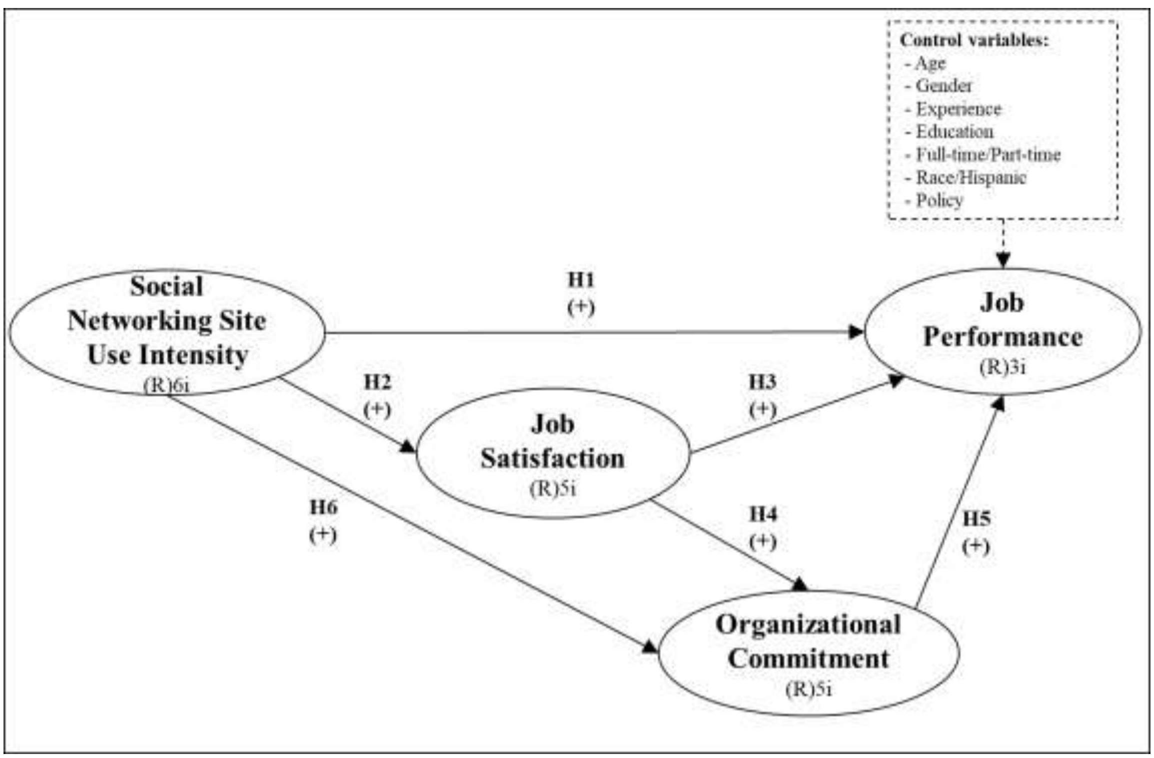
What is Mediation?

Mediation refers to examining how a third variable intervenes, or impacts, the relation between two other variables (Hayes, 2009). For example, in an intervening model, a variable X is postulated to affect an outcome variable Y via one or more intervening variables, sometimes called mediators (Hayes 2009). The total effect of X on Y may come through various forces, both direct and indirect. We focus on the indirect force in this paper.

Illustrative model and data

Figure 1 depicts the model used as a basis for our paper. It contains four latent variables – 1) the degree of social networking site use intensity by employees, 2) the degree of job satisfaction, 3) the degree to which employees feel committed to their organization, and 4) the degree of job performance.

Figure 1: Illustrative model used

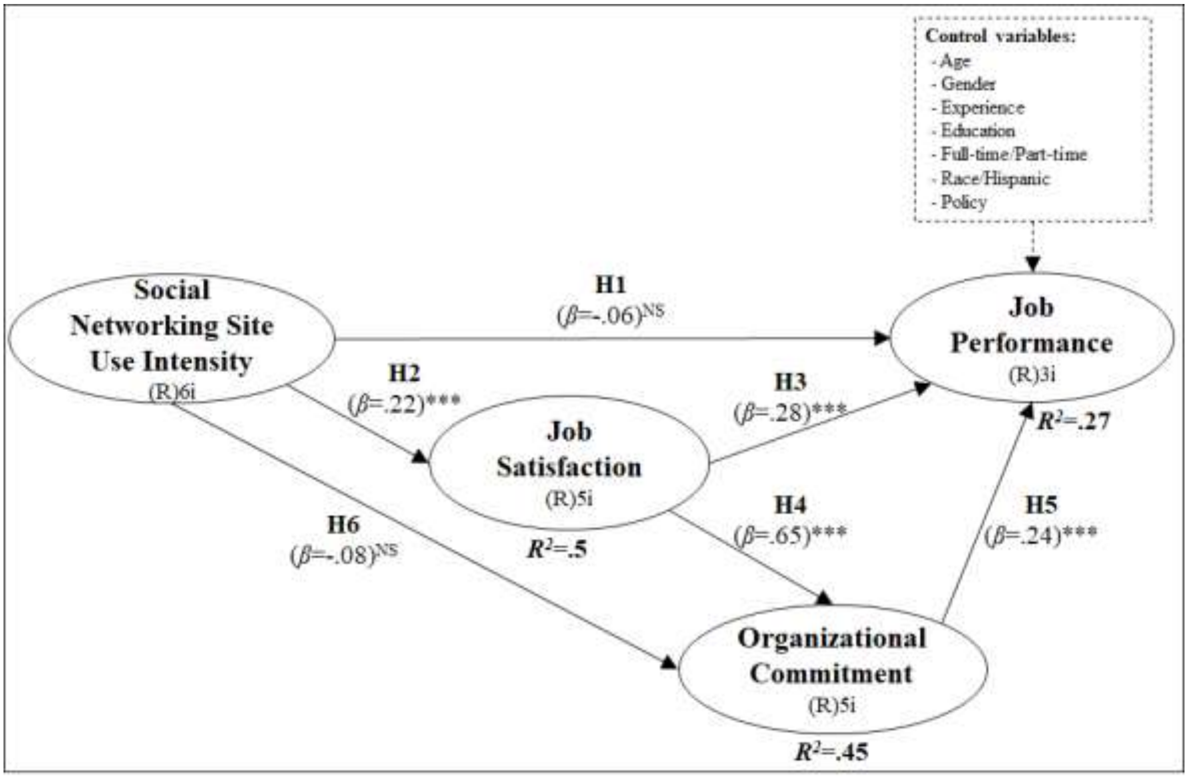


Notes: notation under the latent variable describes the measurement approach and number of indicators, e.g., (R)6i = reflective measurement with six indicators.

We used data collected from online and mail surveys, completed by knowledge workers from different states across the USA. The data consisted of 193 individual observations.

The model, which was published in Moqbel et al. (2013), theorizes the following hypotheses – *social networking site use intensity leads to higher job performance directly as well as indirectly* *through the intervention (mediation) of job satisfaction and organizational commitment due to the mechanism of work-life balance.* It was found that social networking site use intensity enhanced job satisfaction and organizational commitment; job satisfaction augmented organizational commitment; both job satisfaction and organizational commitment increased job performance. The main results of the SEM analysis are presented in Figure 2 below.

Figure 2: Model results



Notes: NS = P>0.05; *** P<0.001.

Using Indirect effects to test mediation

Unlike the classic approach for assessing mediation presented by Baron and Kenny (1986), which does not rely on standard errors, the new approach for testing mediation introduced by Kock (2014), which builds on Preacher and Hayes (2004) and Hayes and Preacher (2010), is more efficient and less fallible. This approach relies on the estimation of indirect effects, which are automatically calculated by WarpPLS. The approach also enables testing of multiple mediating effects simultaneously and effects with more than one mediating variable (Kock, 2014). Using the menu option "View indirect and total effects," WarpPLS saves users from the multi-step and lengthy classic approach for mediation assessment. This menu option allows users to view outputs for an independent latent variable's indirect effects on a latent dependent variable with one or more mediating effects (i.e., nested mediations) by calculating the sum of indirect effects regardless of the number of path segments.

Figures 3, 4, 5, 6, and 7 present the sum of indirect effects, the number of path segments associated with the effects, respective P values, the standard errors associated with the effects, and the effect sizes as indicated by f^2 (Cohen, 1988). As can be seen, the total sum of indirect effects of SNS on performance, which consists of three paths (i.e., (1) SNS→SAT→ PERF, (2) SNS → COM → PERF, (3) SNS → SAT → COM → PERF), is marginally significant (β = 0.115, $P < 0.10$, $f^2 = .02$) with a small effect size. Additionally, the indirect effect path coefficient between SNS and COM through the SAT mediation was significant (β = 0.142, $P < 0.01$, $f^2 = .03$), indicating that SAT fully mediated the relationship between SNS and COM. The indirect effect path coefficient of the relationship between SAT and PERF was also significant (β = 0.157, $P < 0.001$, $f^2 = .07$) which represents a nested mediation (i.e., mediation within a mediation). In sum, one can conclude that this model's indirect effects suggest that the relationship between SNS and PERF was indirect and fully mediated by SAT and COM.

Figure 3: Sums of indirect effect coefficients

---------------- Indirect and total effects (table view) ----------------				
Sums of indirect effects				

	PERF	SNS	SAT	COM
PERF		0.115	0.157	
SNS				
SAT				
COM		0.143		

Notes: PERF = job performance; SNS = social networking site use intensity; SAT = job satisfaction; COM = organizational commitment

Figure 4: Number of paths for indirect effects

---------------- Indirect and total effects (table view) ----------------				
Number of paths for indirect effects				

	PERF	SNS	SAT	COM
PERF		3	1	
SNS				
SAT				
COM		1		

Figure 5: P values for sums of indirect effect coefficients

---------------- Indirect and total effects (table view) ----------------				
P values for sums of indirect effects				

	PERF	SNS	SAT	COM
PERF		0.051	<0.001	
SNS				
SAT				
COM		0.002		

Figure 6: Standard errors for sums of indirect effect coefficients

---------------- Indirect and total effects (table view) ----------------				
Standard errors for sums of indirect effects				

	PERF	SNS	SAT	COM
PERF		0.070	0.049	
SNS				
SAT				
COM		0.049		

Figure 7: Effect sizes for sums of indirect effect coefficients

---------------- Indirect and total effects (table view) ----------------				
Effect sizes for sums of indirect effects				

	PERF	SNS	SAT	COM
PERF		0.019	0.072	
SNS				
SAT				
COM		0.031		

Conclusion

Mediation analysis, in the context of structural equation modeling via partial least squares (PLS-SEM), affords a better understanding of the relationship between independent and dependent variables when the variables seem not to have a definite connection. In this paper, we illustrated an alternative approach for such an analysis by applying multiple mediation effects (i.e., indirect effects), in the context of social networking sites, using WarpPLS, a leading PLS-SEM software tool.

References

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173-1182.

Bollen, K. (2014). *Structural equations with latent variables*. New Jersey, USA: John Wiley & Sons.

Chin, W. W. (1995). Partial least squares is to LISREL as principal components analysis is to common factor analysis. *Technology Studies, 2*(2), 315-319.

Chin, W. W. (1998a). Commentary: Issues and opinion on structural equation modeling. *MIS Quarterly, 22*(1), vii-xvi.

Chin, W. W. (1998b). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research, 295*(2), 295-336.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences (revised ed.)* (2 ed.). Hillsdale, NJ: Lawrence Erlbaum.

Hair, J., Black, W., Babin, B., & Anderson, R. (2010). *Multivariate data analysis*. Upper Saddle River, N.J.; London: Pearson.

Hayes, A. F. (2009). Beyond Baron and Kenny: Statistical mediation analysis in the new millennium. *Communication Monographs, 76*(4), 408-420.

Hayes, A. F., & Preacher, K. J. (2010). Quantifying and testing indirect effects in simple mediation models when the constituent paths are nonlinear. *Multivariate Behavioral Research, 45*(4), 627-660.

Kock, N. (2014). Advanced mediating effects tests, multi-group analyses, and measurement model assessments in PLS-based SEM. *International Journal of e-Collaboration (IJeC), 10*(1), 1-13.

Kock, N. (2020a). Full latent growth and its use in PLS-SEM: Testing moderating relationships. *Data Analysis Perspectives Journal*, *1*(1), 1-5.

Kock, N. (2020b). Multilevel analyses in PLS-SEM: An anchor-factorial with variation diffusion approach. *Data Analysis Perspectives Journal*, *1*(2), 1-6.

Kock, N. (2020c). *WarpPLS User Manual: Version 7.0*. Laredo, TX: ScriptWarp Systems.

Moqbel, M., Nevo, S., & Kock, N. (2013). Organizational members’ use of social networking sites and job performance: An exploratory study. *Information Technology & People, 26*(3), 240-264.

Preacher, K., & Hayes, A. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, 36*(4), 717-731.

Wetzels, M., Odekerken-Schröder, G., & Van Oppen, C. (2009). Using PLS path modeling for assessing hierarchical construct models: Guidelines and empirical illustration. *MIS Quarterly, 3*(1), 177-195.

Wixom, B. H., & Watson, H. J. (2001). An empirical investigation of the factors affecting data warehousing success. *MIS Quarterly, 25*(1), 17-41.