

Using data labels to discover moderating effects in PLS-based structural equation modeling

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Abstract

Two main types of exploratory analyses are frequently employed in the context of PLS-based structural equation modeling: covariance (or correlation) analyses, where the covariances (or correlations) among all variables are inspected; and model-driven exploratory analyses, where one or more variations of theory-supported models are built and associations among variables are inspected. These analyses, while useful, provide limited insights about the possible presence of moderating effects. We discuss a general approach through which researchers can employ data labels, implemented as symbols that are displayed together with legends on graphs, to uncover moderating relationships among variables. The discussion is illustrated with the software WarpPLS version 4.0. While the approach is illustrated in the context of e-collaboration research, it arguably applies to any field where PLS-based structural equation modeling can be used.

Keywords: WarpPLS, E-Collaboration, Path Analysis, Partial Least Squares, Structural Equation Modeling, Statistical Moderation

Introduction

The method of path analysis (Wright, 1934; 1960) provides the foundation for structural equation modeling (SEM). Both path analysis and SEM rely on the development of models where causal assumptions are expressed through links among variables. In SEM variables that are measured indirectly through other variables are known as latent variables; the directly measured variables used to measure latent variables are known as indicators (Maruyama, 1998; Mueller, 1996). Often directly measured variables are obtained from questionnaires where answers are provided on numeric scales, such as Likert-type scales (Cohen et al., 2003).

Two main approaches to SEM exist today (Kock & Lynn, 2012; Schumacker & Lomax, 2004). In both of them researchers define a measurement model by linking indicators to their respective latent variables, and define a structural model by linking latent variables among themselves; both based on causal assumptions supported by theory. The classic approach is known as covariance-based SEM (Schumacker & Lomax, 2004). This approach estimates model coefficients (e.g., path coefficients) based on the minimization of differences between covariance matrices, and makes parametric assumptions in the calculation of coefficients that serve as a basis for calculation of significance levels (often expressed as P values). The more modern SEM approach is known as variance-based SEM or PLS-based SEM (Kock & Lynn, 2012), where “PLS” stands for “partial least squares”. This approach estimates model coefficients by creating latent variable scores through weighted aggregations of indicators. It makes no parametric assumptions in the calculation of P values; for example, it does not assume that latent variable or indicator scores are normally distributed.

PLS-based SEM is extensively used in e-collaboration research and in related fields, such as management information systems (Guo et al., 2011; Kock, 2013a; Kock & Lynn, 2012; Schmiedel et al., 2014). These are fields where the topic of statistical moderation is given a central role in empirical research (Carte & Russel, 2003). In a linear model, a variable X is said to moderate a linear relationship between two other variables Y and Z if a variation in X leads to a variation in the slope of the best-fitting line for the relationship between Y and Z . Frequently X represents elements of the physical and social contexts in which Y affects Z . Generally speaking, those contexts play key roles in how e-collaboration phenomena unfold (Kock, 2005).

In this paper we discuss how researchers can employ data labels, implemented as symbolic elements that are displayed together with legends on a graph, to identify moderating relationships among variables. Our discussion focuses primarily on linear models, but can be extended to models that include nonlinear relationships. The software WarpPLS version 4.0 (Kock, 2013b) is used in this discussion. The extensive set of results produced by this software allows us to illustrate the several steps involved in using data labels to uncover the existence of statistical moderation in an exploratory analysis and subsequently model the moderation explicitly in a confirmatory analysis.

Data used in the analysis

We created 300 rows of data, equivalent to 300 returned questionnaires, for several latent variables and indicators based on a Monte Carlo simulation (Robert & Casella, 2005; Paxton et al., 2001). Using this method we departed from a “true” model, which is a model for which we know the nature and magnitude of all of the relationships among variables beforehand. The true model was based on an actual study of the effects of e-collaboration technology use on team-based project success, which was previously used by Kock & Lynn (2012) to illustrate their discussion of vertical and lateral collinearity. At the time of this writing this data set was publicly available from the WarpPLS web site:

<http://warppls.com>

The following variables were included in this analysis: e-collaboration technology use (ECollab), project management (Projmgt), job satisfaction (JSat), and project success (Success). E-collaboration technology use (ECollab), the main technology-related variable in the model, measures the extent to which a team that is tasked with the development of a new product (e.g., a new toothpaste or airplane part) uses an e-collaboration technology that integrates several synchronous and asynchronous features (e.g., e-mail, text-based chat, video-conferencing, discussion board).

Project management (Projmgt) measures the degree to which the team uses project management techniques that allow them to monitor and control the progress of their work. Job satisfaction (JSat) measures the degree to which team members are satisfied with their current

jobs. Project success (Success) measures the degree to which the new product developed by the team is successful in the marketplace (i.e., has a high volume of sales, with a good profit margin).

In our true model, e-collaboration technology use (ECollab) directly influences project management (Projmgt), and also moderates the relationship between project management (Projmgt) and project success (Success). Job satisfaction (JSat), while directly influencing project success (Success), is unrelated to any of the other variables in the model. Each of these variables is measured indirectly through three indicators, which in turn refer to questionnaire answers provided on Likert-type scales going from 1 to 7 (see Figure 1).

Figure 1: Indicator data used in the analysis

A	B	C	D	E	F	G	H	I	J	K	L	
JSat1	JSat2	JSat3	ECollab1	ECollab2	ECollab3	Projmgt1	Projmgt2	Projmgt3	Success1	Success2	Success3	
6	6	5	4	4	4	5	4	6	5	5	4	
4	4	4	4	3	5	5	5	4	3	4	4	
4	5	3	4	3	3	3	4	4	4	4	4	
4	3	4	3	4	4	3	4	4	4	2	4	
5	4	4	4	4	4	3	3	5	5	5	4	
4	3	3	4	4	4	4	4	5	4	4	4	
3	4	3	4	4	5	4	4	5	3	5	5	
4	4	3	4	3	4	5	5	5	3	3	3	
3	3	5	5	5	5	5	6	5	5	5	4	
4	5	3	2	3	2	5	4	4	3	4	4	
5	4	5	5	5	4	5	5	4	5	5	6	
3	4	3	5	5	5	5	5	4	5	5	5	

In our analyses we employed the “PLS regression” algorithm for measurement model estimation and the “stable” method for P value calculation (Kock, 2013b). We also set all of the structural model paths as linear. The composite reliability coefficients, also known as Dillon–Goldstein coefficients (Tenenhaus et al., 2005), ranged from 0.811 to 0.821, suggesting good reliability. Full collinearity variance inflation factors ranged from 1.098 to 1.243, suggesting no multicollinearity (Kock & Lynn, 2012). Loadings, cross-loadings, correlations among latent variables, and average variances extracted were used as a basis for validity tests (Kock, 2013b). Those tests suggested good convergent and discriminant validity.

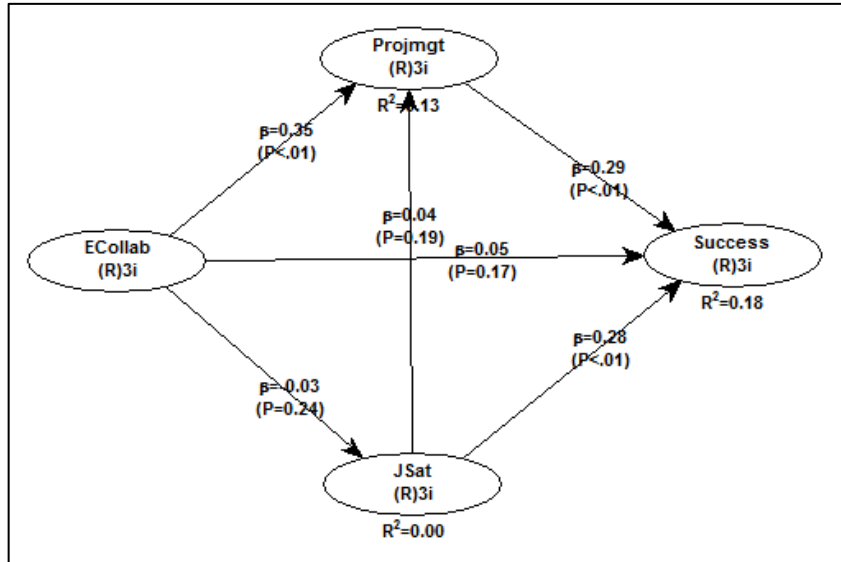
Exploratory analysis

Because we departed from a true model, we knew beforehand the nature and magnitude of all of the relationships among the variables in our model. The “nature” of the relationships includes

the true direction of causality of the links in the model, the presence or absence of true moderating effects, and the presence or absence of true nonlinearity. Researchers analyzing empirical data do not have this information. If they did, there would be no point in analyzing empirical data. Researchers analyzing empirical data try to uncover the true nature of the relationships among variables and their magnitudes with incomplete information.

Given a data set in connection with several variables, and limited additional information about how the variables are related, a researcher can conduct several types of exploratory analyses, of which two are frequently employed: (a) a covariance (or correlation) analysis, where the covariances (or correlations) among all variables are calculated; and (b) a model-driven exploratory analysis, where one or more variations of theory-supported models are built and associations among variables are inspected. Figure 2 shows one such model. A table with correlations among all variables was generated automatically by the software (Kock, 2013b). When the “PLS regression” algorithm is used, such a table is independent from the structural model.

Figure 2: Exploratory analysis model with results



As we can see, e-collaboration technology use (ECollab) is positively and significantly associated with project management (Projmgt) in a direct way, but not significantly associated with project success (Success) in a direct way. Project management (Projmgt) is positively and significantly associated with project success (Success) in a direct way. Job satisfaction (JSat) is

positively and significantly associated with project success (Success) in a direct way, but not significantly associated with any other variable in the model.

This model's fit with the data is not particularly good. For example, the average adjusted R-squared (AARS) for the model is 0.095 (P=0.014). This is to be expected, as the goal of this exploratory analysis is to better understand the nature of the relationships among the variables so that we can build a better model. This better model is expected to be supported by theory and also have a better fit with the data.

While the exploratory analysis provides us with some insights about the nature of the relationships among the variables in the model, it does not tell us almost anything about the presence of moderating effects. This is where data labels can be useful, as they add new dimensions to our understanding of linear models.

Creating data labels

Data labels are text elements that are displayed as legends or as text next to data points on a graph. When the number of data points is small (e.g., 50 or less) showing data labels as text next to data points is feasible. However, when the number of data points is significantly greater than 50, showing data labels as text can give a graph a cluttered look. In this case displaying data labels as legends is preferable, with different symbols being used for data points that refer to different data labels.

Before data labels are used in graphs they must be created and imported. In version 4.0 of WarpPLS each column of labels so created must be imported individually. Figure 3 shows how a column of data labels can be created using Microsoft Excel. The column is titled "JSatGroup", and contains in its cells one of two data labels, either "HighJSat" or "LowJSat", depending on the average value of the indicators JSat1 ... JSat3 for the variable job satisfaction (JSat). If that value is greater than 4, the "JSatGroup" column shows "HighJSat"; otherwise it shows "LowJSat".

Figure 3: Creating data labels with Microsoft Excel

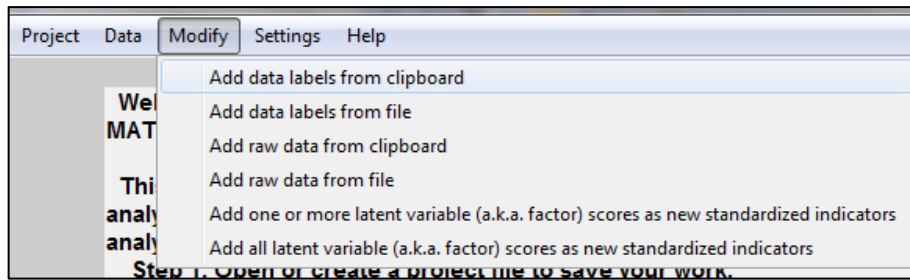
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	JSat1	JSat2	JSat3	ECollab1	ECollab2	ECollab3	Prjmgmt1	Prjmgmt2	Prjmgmt3	Success1	Success2	Success3		JSatGroup	ECollabGroup
2	6	6	5	4	4	4	5	4	6	5	5	4		HighJSat	LowECollab
3	4	4	4	4	3	5	5	5	4	3	4	4		LowJSat	LowECollab
4	4	5	3	4	3	3	3	4	4	4	4	4		LowJSat	LowECollab
5	4	3	4	3	4	4	3	4	4	4	2	4		LowJSat	LowECollab

The formula used to fill in cells in the column as either “HighJSat” or “LowJSat” is shown below. Similar formulas are used for three other columns: “ECollabGroup”, “PrjmgmtGroup” and “SuccessGroup”. Together, the four columns with data labels can be used to add different dimensions to two-dimensional graphs, essentially supporting a multi-dimensional analysis. Each new data label column adds a new dimension to a graph.

`IF(AVERAGE(A2:C2)>4,"HighJSat","LowJSat")`

The number of rows in a data label column must be exactly the same as the number of rows of numeric data, since each data label cell refers to a data point. Figure 4 shows the menu option used for importing data labels in WarpPLS 4.0. Data labels can be imported one column at a time either via the clipboard or a file. The clipboard option is more convenient for data sets with a relatively small number of rows, such as 300 or less. For significantly larger numbers of rows, reading from a file would arguably be more convenient. However, only one column of data labels can be read at a time, which means that single-column files would have to be used, one for each data label column.

Figure 4: Menu option for importing data labels



Data labels cannot be read together with numeric data; they must be read separately, even though they may be created based on formulas in the same sheet as the numeric data. Figure 5 shows a column of data labels immediately after reading it into WarpPLS 4.0.

Figure 5: Column of imported data labels



Once they have been read into the software, data labels can be viewed or saved using the “View or save data labels” menu option, which is available under the “Modify” menu option on the main window of WarpPLS 4.0.

Figure 6 shows the four data label columns titled “JSatGroup” “ECollabGroup”, “PrjmgmtGroup” and “SuccessGroup”. These labels allow users to visualize high and low values of the four latent variables in graphs, essentially grouping data points based on whether they refer to high or low values of the latent variables.

Figure 6: Four imported data label columns

	JSatGroup	ECollabGroup	PrjmgmtGroup	SuccessGroup
1	HighJSat	LowECollab	HighProjmgt	HighSuccess
2	LowJSat	LowECollab	HighProjmgt	LowSuccess
3	LowJSat	LowECollab	LowProjmgt	LowSuccess
4	LowJSat	LowECollab	LowProjmgt	LowSuccess
5	HighJSat	LowECollab	LowProjmgt	HighSuccess
6	LowJSat	LowECollab	HighProjmgt	LowSuccess
7	LowJSat	HighECollab	HighProjmgt	HighSuccess
8	LowJSat	LowECollab	HighProjmgt	LowSuccess
9	LowJSat	HighECollab	HighProjmgt	HighSuccess
10	LowJSat	LowECollab	HighProjmgt	LowSuccess
11	HighJSat	HighECollab	HighProjmgt	HighSuccess
12	LowJSat	HighECollab	HighProjmgt	HighSuccess
13	LowJSat	LowECollab	LowProjmgt	LowSuccess
14	HighJSat	LowECollab	LowProjmgt	HighSuccess
15	LowJSat	LowECollab	LowProjmgt	LowSuccess

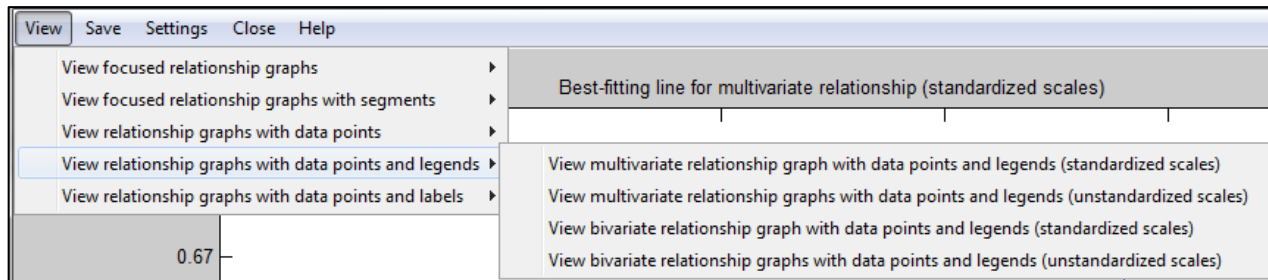
Each of these data label columns can be used in two-dimensional graphs that show relationships between pairs of latent variables. The reason why visualizing high and low values of the four latent variables in graphs can be useful in the identification of moderating effects is that moderating variables lead to different patterns of distributions of data points for high and low values of the moderating variables. This will be illustrated in the next section.

Identifying moderation based on data labels

Data labels are text elements that can be used in two types of displays involving data points. One of these involves showing the data labels as legends, which is preferable when the number of data points is significantly greater than 50, and especially so when the number of different data labels is small (e.g., two, referring to high and low values of a variable, as illustrated here). The other involves showing the data labels next to the data points on a graph.

Figure 7 shows how these display options and related variations can be selected in WarpPLS 4.0. As soon as an SEM analysis is completed, the software shows the results in graphical format on a window, which also contains several menu options. One of these is the menu option “View/plot linear and nonlinear relationships among latent variables”. This option takes the user to a table with the types of relationships, referred to as “warped” or “linear” (or nonlinear and linear; in our case only the latter are used), between the latent variable pairs that are linked in the structural model. The options shown are accessed by clicking on a cell of this table.

Figure 7: Menu options for viewing graphs with data points and legends



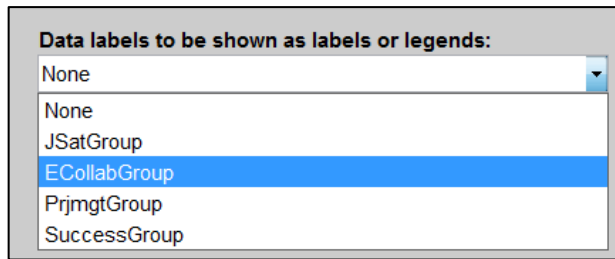
The options available combine variations in terms of two main aspects: whether the scales are standardized or unstandardized, and whether the graphs refer to multivariate or bivariate relationships.

By definition, latent variable scores are standardized aggregations of indicators. The latter, namely the indicators, are originally in unstandardized format. Therefore, to obtain the unstandardized equivalents of the latent variable scores, some decisions must be made and extra calculations performed.

Multivariate and bivariate relationship graphs usually differ only when two or more predictor latent variables point at one criterion latent variable in a latent variable block. The addition of predictors will normally reduce the path coefficients in a latent variable block. Because of this, typically a multivariate relationship graph will have a lower overall inclination (or steepness) than its corresponding bivariate relationship graph. In cases when statistical suppression occurs (Kock, 2013b; MacKinnon et al., 2000), the opposite will happen.

The “View relationship graphs with data points and legends” options allow users to view graphs with the best-fitting lines or curves, the data points used to produce the best-fitting lines or curves, and legends associated with data labels. When these graphs are shown, a “Settings” menu option becomes available. Through this option users can select what specific data label will be used in the graph (see Figure 8).

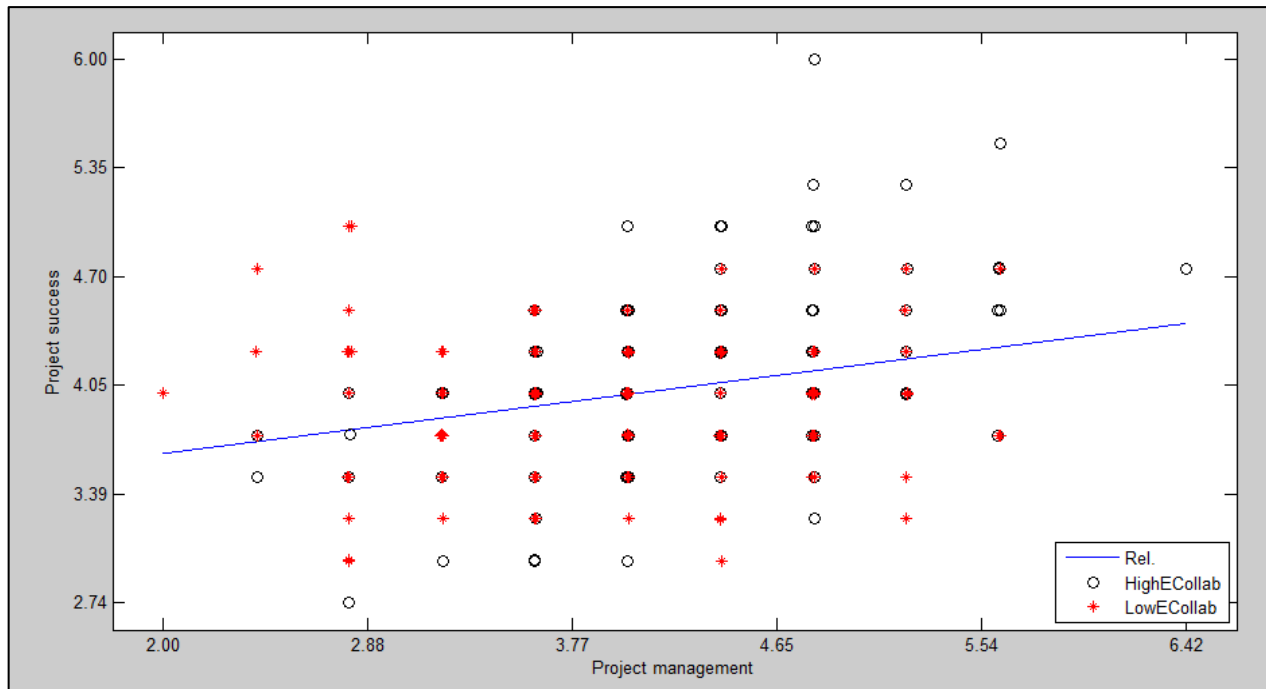
Figure 8: Specifying data labels to be shown



Through the “Settings” menu option users can also set the X axis label, the Y axis label, and the position of the legend box in the graph. The X axis label is the text shown next to the X axis, or the horizontal axis. The Y axis label is the text shown next to the Y axis, or the vertical axis. The position of the legend box in the graph is set based on text elements that refer to several of the cardinal directions; for example, “SouthEast”. These settings allow users to customize the graph.

Figure 9 shows one such graph where the data label used is “ECollabGroup”. This is one of the four previously created data labels, whose column contained the values “HighECollab” or “LowECollab” depending on the average value of the indicators ECollab1 ... ECollab 3 for the variable e-collaboration technology use (ECollab). If that value is greater than 4 the “ECollabGroup” column shows “HighECollab”, otherwise it shows “LowECollab”. The graph differentiates data points that refer to each of these values by using different symbols to plot the data points on the graph. The symbols used are indicated in the legend box located in the bottom-right corner of the graph (the “SouthEast” position). The graph also shows the best-fitting line for the overall relationship between the project management (Projmgt) and project success (Success) variables.

Figure 9: Graph suggesting the presence of moderation



The telltale sign of a moderating effect is the presence of different patterns of distributions of data points for high and low values of a variable – which is then identified as a moderating variable. In this illustration we can see that the distribution of data points for high values of the e-collaboration technology use (ECollab) variable has a slope that is tilted upwards when compared with the slope of the best-fitting line for the overall relationship between the project management (Projmgt) and project success (Success) variables. We can also see that the distribution of points for low values of the e-collaboration technology use (ECollab) variable has a slope that is either flat or tilted slightly downwards.

These different patterns of distributions of data points for high and low values of the e-collaboration technology use (ECollab) variable suggest that e-collaboration technology use (ECollab) moderates the relationship between project management (Projmgt) and project success (Success). This can be further tested through a confirmatory analysis, which is discussed in the next section.

At this point one could ask whether it would have been easier to test the existence of moderating relationships directly, by including them in exploratory models. There are a few reasons why the answer to this question might be negative, with the data labels approach

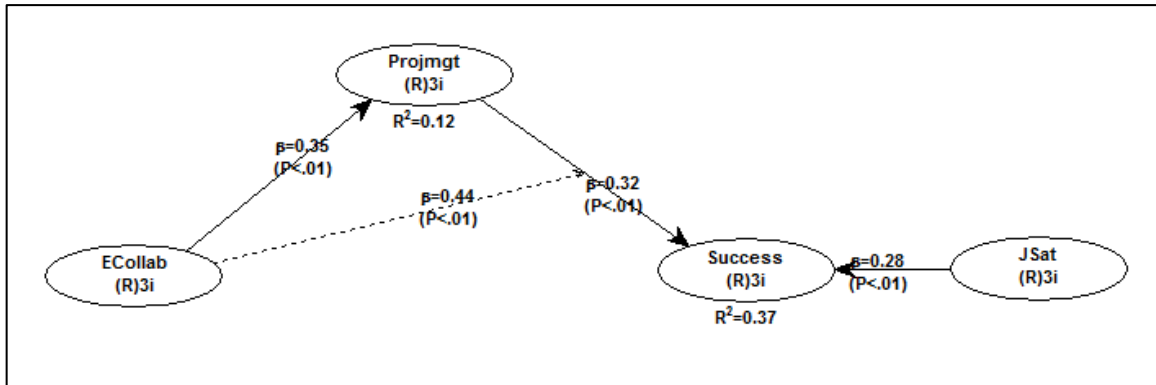
discussed here being seen as preferable. Once a researcher creates labels for a variable, he or she can check the variable's likely moderating influence in connection with all links in a model – plus any other links the researcher may create in the future – without having to create new models. Arguably it would be significantly more time-consuming to create one model at a time, with each moderating link, and test it. Creating all moderating links at once, on the other hand, could easily lead to multicollinearity, which might in turn significantly distort the results of the analysis.

Confirmatory analysis

Our exploratory analyses provided us with a wealth of information that would arguably be very useful in helping us uncover the true nature and magnitude of each of the relationships among the variables in our data (assuming we did not know them beforehand). In our case, the exploratory analysis involved building one variation of theory-supported model where associations among variables were inspected, calculating the correlations among all variables, conducting various structural and measurement model tests (reliability, validity, and multicollinearity), and conducting an exploratory analysis of moderating effects based on data labels.

Armed with the results of these exploratory analysis, we can build what we believe is a theory-supported model that best fits the data. This model is shown in Figure 10, along with the results of an SEM analysis employing the same settings as in the exploratory model analysis. E-collaboration technology use (ECollab) is associated with a significant increase ($\beta=0.35$, $P<0.01$) in project management (Projmgt), and also significantly moderates ($\beta=0.44$, $P<0.01$) the relationship between project management (Projmgt) and project success (Success). Project management (Projmgt), or the degree to which a team uses project management techniques, is associated with a significant increase ($\beta=0.32$, $P<0.01$) in project success (Success).

Figure 10: Confirmatory analysis model with results



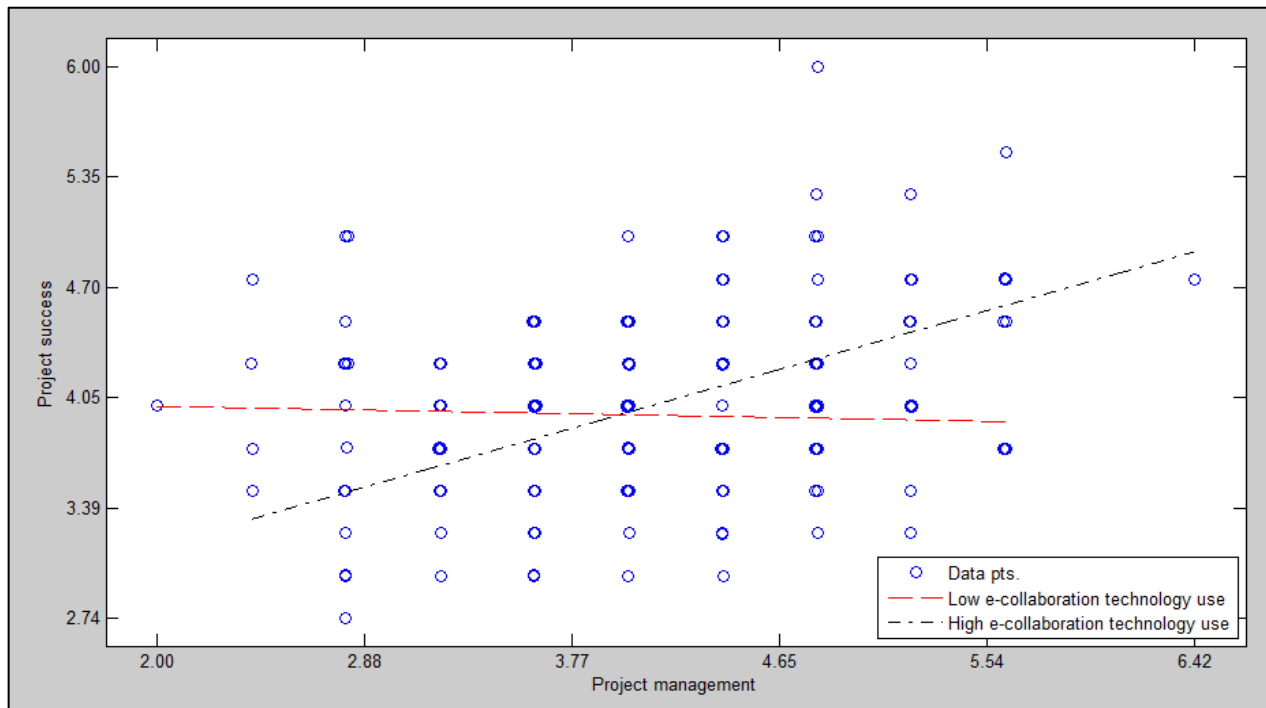
Job satisfaction (JSat) is included in the model as a control variable. It is associated with a significant increase ($\beta=0.28$, $P<0.01$) in project success (Success). The inclusion of job satisfaction (JSat) as a control variable allows us to conclude that the results that refer to the part of the model to the left of the control variable (the “main” model) hold regardless of job satisfaction (JSat). In other words, even though job satisfaction (JSat) is significantly associated with project success (Success), this significant association is not part of the associations in which we are particularly interested from a theoretical perspective in a confirmatory analysis. This is particularly the case here because job satisfaction (JSat) is not significantly associated with any other variable in the model, which makes its inclusion as a direct or indirect predictor of project success (Success) in the model inadvisable.

This model’s fit with the data is much better than that of the exploratory model we built earlier. This model’s average adjusted R-squared (AARS) is 0.240 ($P<0.001$), which is significantly higher than the AARS of 0.095 ($P=0.014$) obtained for the exploratory model. As mentioned before, this is to be expected since the goal of the exploratory analysis was not to confirm a theory-supported model, but rather to better understand the nature of the relationships among the variables so that we could build a theory-supported model and conduct a confirmatory analysis.

Figure 11 shows a graph with the best-fitting lines for high and low values of the e-collaboration technology use (ECollab) variable, together with the data points for the relationship between the project management (Projmgt) and project success (Success) variables. Here we can see that the slopes of the relationship between the project management (Projmgt) and project

success (Success) variables vary based on the level of e-collaboration technology use (ECollab). This graph can be viewed in WarpPLS 4.0 by choosing the menu option “View moderating relationship in one graph with data points”.

Figure 11: Two-dimensional graph showing moderating effect

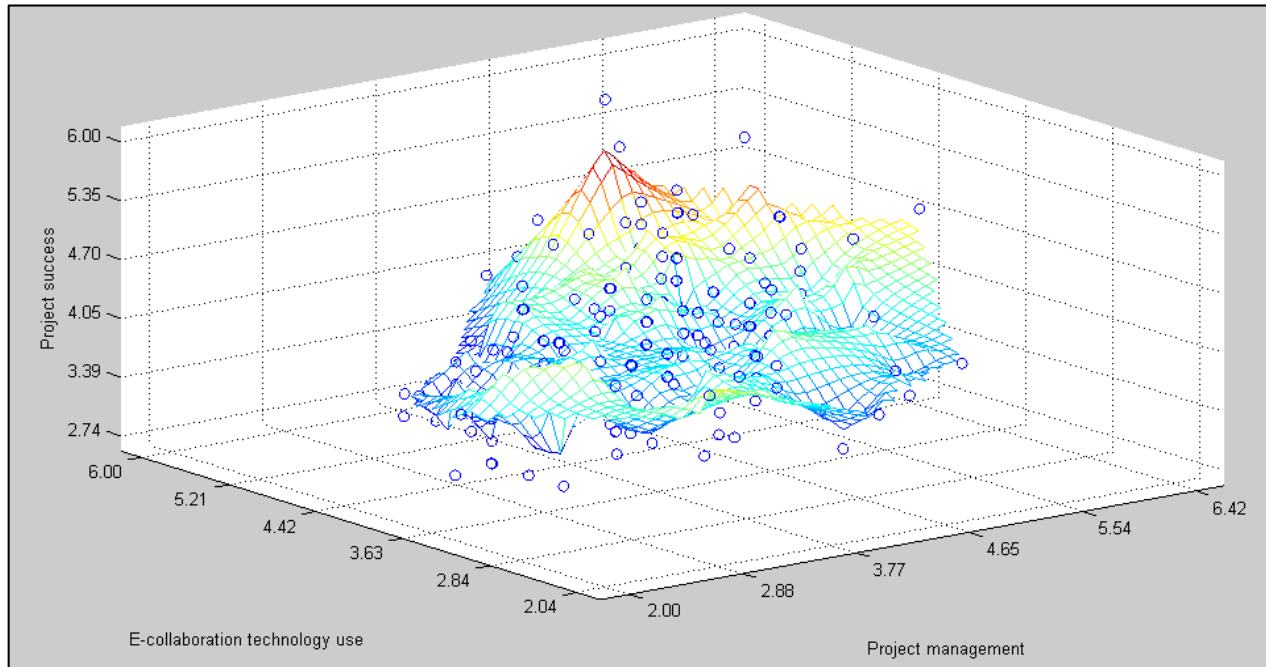


Some researchers argue that a moderating relationship should be represented as a three-dimensional graph, since a moderating relationship is in fact a relationship involving three variables. That is, two-dimensional graphs are seen by some researchers as incomplete and inaccurate representations of relationships involving three variables. It should be noted, however, that the addition of two best-fitting lines to a two-dimensional graph, where the slopes of the lines reflect the effect of a third variable, incorporates elements that characterize a three-dimensional representation. This is so even though the representation may look like it is two-dimensional.

Figure 12 shows the moderating relationship involving the e-collaboration technology use (ECollab), project management (Projmgt), and project success (Success) variables; this time represented as a three-dimensional graph, with three clearly defined axes. We can see in this graph that the slope of the relationship between project management (Projmgt) and project

success (Success) progressively increases as e-collaboration technology use (ECollab) increases. This progression shows several “bumps”, which give the graph a “rocky” configuration.

Figure 12: Three-dimensional graph showing moderating effect



Whether this type of representation is better at conveying information about a moderating effect than the previously shown two-dimensional representation with the two best-fitting lines is a matter of debate. While the three-dimensional representation provides more information, and may be appreciated by technical reviewers and a subset of the readers of a research report, it may also be somewhat confusing for less technical readers.

The User Manual of WarpPLS version 4.0 (Kock, 2013b) notes that no moderating relationship graph currently available from the software accurately represents the true nature of a moderating relationship. This is why various graphs are provided so that users can choose the one that in their view best illustrates the relationship. An accurate representation of a moderating relationship would be that of a multivariate distortion in the surface representing the relationship. The distortion refers to a “twisting” of the surface around the moderating variable axis, with a multivariate adjustment, and with corresponding changes in the overall inclinations of the sections of the surface representing the direct effect being moderated.

This “twisting” of the surface around the moderating variable axis can be seen, at least partially, in the three-dimensional graph presented here. The moderating variable axis is the one on the left, for the e-collaboration technology use (ECollab) variable. If we think of the surface as a sheet, the graph can be seen as showing the sheet being twisted counterclockwise.

The “bumps” throughout the surface are a reflection of measurement error. This brings to the forefront a problem with representations that provide very detailed visual information about a relationship, particularly one involving three variables. Most representations of variables, even when the variables are strongly associated, incorporate disturbances. These disturbances can be seen as “noise”, and usually have nothing to do with the underlying relationship. A three-dimensional graph, such as the one presented here, may represent disturbances with such a great degree of detail that it will give the impression that the disturbances are importance elements of the true underlying relationship.

Conclusion

The use of PLS-based SEM is widespread in the field of e-collaboration, as well as in related fields such as management information systems. These are also fields where statistical moderation studies play a central role, providing an important foundation for theory development. A key reason for this is that in these fields the context in which technologies are used frequently influences outcomes in a significant way.

When faced with a data set related to several variables, and little information about how the variables are related, two main types of exploratory analyses are likely to yield relevant insights: (a) a covariance (or correlation) analysis, where the covariances (or correlations) among all variables are calculated; and (b) a model-driven exploratory analysis, where one or more variations of theory-supported models are built and associations among variables are inspected. While certainly very useful, these two main types of exploratory analyses tell us very little about the possible presence of moderating effects.

In this paper we discussed a practical approach through which researchers can employ data labels to uncover moderating relationships among variables. The discussion focused chiefly on linear models, and was illustrated with the software WarpPLS version 4.0 (Kock, 2013b). While the approach discussed in this article was illustrated in the context of e-collaboration research, it arguably applies to any field where PLS-based SEM can be used.

Acknowledgments

The author is the developer of the software WarpPLS, which has over 5,000 users in 33 different countries at the time of this writing, and moderator of the PLS-SEM e-mail distribution list. He is grateful to those users, and to the members of the PLS-SEM e-mail distribution list, for questions, comments, and discussions on topics related to the use of WarpPLS.

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