Using the Partial Least Squares (PLS) Method to Establish Critical Success Factors Interdependence in ERP Implementation Projects

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Abstract

This technical research report proposes the usage of a statistical approach named Partial Least squares (PLS) to define the relationships between critical success factors for ERP implementation projects. In previous research work, we developed a unified model of critical success factors for ERP implementation projects. Some researchers have evidenced the relationships between these critical success factors, however no one has defined in a formal way these relationships. PLS is one of the techniques of structural equation modelling approach. Therefore, in this report is presented an overview of this approach. We provide an example of PLS method modelling application; in this case we use two critical success factors. However, our project will be extended to all the critical success factors of our unified model. To compute the data, we are going to use PLS-graph developed by Wynne Chin.

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1. Introduction

Over the past years, Enterprise Resource Planning (ERP) implementation projects success has been treated as one of the main issues in ERP research. Several studies have been published related with the Critical Success Factors (CSFs) in ERP implementation projects. In a previous stage of this research we unified these lists of CSFs and we created a unified model of CSFs in ERP implementation projects (Esteves and Pastor 2000). In this study we attempt to analyze how a set of CSFs lead to the success of an ERP implementation project and how these CSFs are interrelated between them.

The starting point for this present research is the assumption, that the different CSFs are interrelated. This assumption is supported by some studies (Baker et al. 1974, Pinto and Slevin 1989, Lechler and Gemünden 2000). However there is no study associated with ERP implementation projects. According to Lechler and Gemünden (2000) "the detailed analysis of interactions among the success factors is necessary and provides information for further inquiry concerning the series of effects that lead to project success or failure". This study is also important for manager predict the success of their ERP implementation projects through the control and monitorization of these CSFs. In order to model these relationships between CSFs, we explore the possibility of using a statistical approach named Partial Least Squares (PLS).

This technical research report is structured as follows. First we describe the background of this study. Next, we present the research methodology proposal to analyze the interdependence between CSFs. Then, we describe the structural equation modeling methods and we focus in a particular one, the partial least squares method, this method is described in detail. Finally we present some considerations.

2. Background

This section provides a brief description of the current research state of art. Until now, we made four phases:

- **Analysis of ERP research issues** –we made a literature review and we categorized all the publications we found through the ERP lifecycle. We also defined the main topics researched and future topics for research.
- **Definition of CSFs in ERP implementation projects** –we defined a CSFs unified model for ERP implementations (see next section).
- **Analysis of CSFs relevance along ASAP implementation methodology phases** – using process quality management (PQM) method, we defined the relevance of these CSFs along the phases of a typical SAP implementation project.
- **Analysis of most critical processes in SAP implementation projects** – we extend the concept of most critical processes provided by PQM, and we defined a new criticality indicator for complex software projects such as an ERP implementation project. Based on this indicator we established the most critical processes in a typical SAP implementation project.

Nowadays, we are studying the interdependencies between CSFs. Next, we will attempt to define a set of metrics for each CSF. Next section describes our CSF unified model since this model is the basis for the study we present in this report.

2.1   Critical Success Factors Unified Model for ERP Implementations

Rockart (1979) was the first author that applied the CSF approach in the information systems area. He proposed the CSF method to help CEOs specify their own information needs about issues that were critical to their organizations, so that information systems could be developed

to meet those needs. According to his account, CSFs are "the limited number of areas in which results, if they are satisfactory, will ensure successful competitive performance for the organization". They have been applied to many aspects and tasks of information systems, and more recently to ERP systems implementations (ex. Bancroft et al. 1998, Brown and Vessey 1999, Clemons 1998; Dolmetsch et al. 1998, Gibson and Mann 1997, Holland et al. 1999, Kale 2000, Parr et al 1999, Stefanou 1999, Sumner 1999).

Based in a set of studies published by several authors, containing commented lists of CSFs in ERP implementations, Esteves and Pastor (2000) unified these lists and created a CSFs unified model (see figure 1). The advantage of this model is that it unifies a set of studies related with lists CSFs identified by other authors; the CSFs are categorized in different perspectives and, each CSF is identified and defined.

	Strategic	Tactical
Organizational	• Sustained management support • Effective organizational change management • Adequate project team composition • Good project scope management • Comprehensive business re-engineering • Adequate project sponsor role • Adequate project manager role • Trust between partners • User involvement and participation	• Dedicated staff and consultants • Appropriate usage of consultants • Empowered decision makers • Adequate training program • Strong communication inwards and outwards • Formalized project plan/schedule • Reduce trouble shooting
Technological	• Avoid customization • Adequate ERP implementation strategy • Adequate ERP version	• Adequate software configuration • Adequate legacy systems knowledge

Figure 1 – Our Unified critical success factors model.

A detailed explanation of this model can be found in Esteves and Pastor (2000). In previous work, we established the relevance of these CSFs along SAP implementation phases (Esteves and Pastor 2001b).

2.2 CSFs Along SAP Implementation Phases

In 1996, SAP introduced the Accelerated SAP (ASAP) implementation methodology with the goal of speeding up SAP implementation projects. ASAP was advocated to enable new customers to utilize the experience and expertise gleaned from thousands of implementations worldwide. The accelerated SAP (ASAP) implementation methodology is a structured implementation approach that can help managers achieve a faster implementation with quicker user acceptance, well-defined roadmaps, and efficient documentation at various stages. This is specifically targeted for small and medium enterprises adopting SAP.

The key phases of the ASAP methodology, also known as the ASAP roadmap, are: project preparation, business blueprint, realization, final preparation, go live & support. The structure of each phase is the following: each phase is composed of a group of work packages. These work packages are structured in activities, and each activity is composed of a group of tasks. For each task, a definition, a set of procedures, results and roles are provided in the ASAP roadmap documentation. According to a survey of Input company (Input 1999) organizations have been more satisfied with SAP tools and methodologies than with those of implementation partners. CSFs relevance along SAP implementation phases is described in figure 3 (source: Esteves and Pastor 2001b).

			Phase1	Phase2	Phase3	Phase4	Phase5
Organizational Perspective	Strategic	Sustained Management Support	8	5	5	6	8
		Effective Organizational Change	6	9	6	5	6
		Good Proj. Scope Management	5	4	4	5	5
		Adequate Proj. Team Composition	5	4	4	4	4
		Meaningful Business Process Reengineering	4	7	4	4	5
		User Involvement and Participation	5	8	10	7	5
		Proj. Champion Role	10	10	9	10	10
		Trust Between Partners	5	4	4	5	5
	Tactical	Dedicated Staff and Consultants	5	5	4	5	6
		Strong Communication Inwards and Outwards	7	7	5	6	8
		Formalized Proj. Plan/Schedule	9	7	7	7	5
		Adequate Training Program	5	5	5	7	4
		Preventive Trouble Shooting	4	4	7	9	7
		Usage of Appropriate Consultants	5	4	4	4	4
		Empowered Decision Makers	3	5	5	5	4
Technological Perspective	Strategic	Adequate ERP Implementation Strategy	5	4	4	4	4
		Avoid Customization	4	4	4	4	4
	Tactical	Adequate ERP Version	4	4	4	4	4
		Adequate Software Configuration	5	6	10	6	6
		Adequate Legacy Systems Knowledge	3	4	4	4	4

Figure 2- CSFs relevance along the ASAP implementation phases.

Next step consists in the establishment of the relationships between CSFs. The whole scheme of relationships is represented in figure 3.
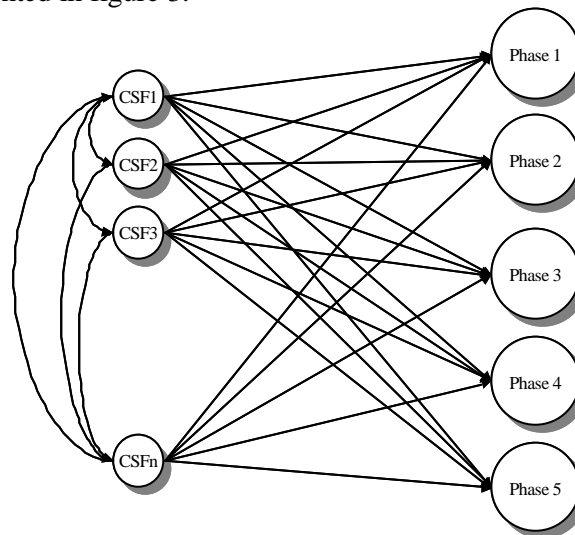
Figure 3 – Relationships between CSFs and, CSFs and ASAP phases.

3. Research Methodology Proposal

The aim of this study is to investigate the relationships among CSFs and between CSFs and ERP success. The CSFs were defined in a previous stage (see section 2). Data for this study will be collected using questionnaire survey. A Part of the survey is presented in appendix A. It has three parts: project description, project general characteristics and then, questions related with the different CSFs. Our research methodology will have four important steps:

- **Development of the questionnaire** – this step is done.
- **Data collection** – we are currently seeking respondents and defining our sample.
- **Data analysis** – this step is to analyze the items reliability. Individual item reliability is assessed by examining the loadings and cross-loadings of each of the construct's

indicators. There are two possible techniques, Cronbach's alpha test and composite reliability (see section 4.5.1).

- **PLS usage** - we attempt to use Partial Least Squares (PLS) to establish the relationship between the different CSFs. PLS is a well established technique for estimating path coefficients in structural models and has been widely used in various research studies (e.g. Fornell and Bookstein 1982, Cool et al. 1989, Fornell et al. 1990, Johanson and Yip 1994, Birkinshaw et al. 1995). PLS method has gained interest and use among researchers in recent years because of its ability to model latent constructs under conditions of non-normality and small to medium sample sizes (Chin 1998, Compeau and Higgins 1995). Section 4 explains in detail this method and how we will apply it.

4. Structural Equation Modeling

4.1 SEM Overview

Structural Equation Modeling (SEM) techniques such as LISREL and PLS are second generation data analysis techniques that can be used to test the extent to which IS research meets recognized standards for high quality statistical analysis (Bagozzi and Fornell 1982). SEM represents a technique which (Chin 2000):

- Combines an econometric perspective focusing on prediction.
- A psychometric perspective modeling latent (unobserved) variables inferred from observed – measured variables.
- Resulting in greater flexibility in modeling theory with data compared to first generation techniques.

SEM is a largely confirmatory, rather than exploratory, technique. That is, a researcher is more likely to use SEM to determine whether a certain model is valid, rather than using SEM to "find" a suitable model. According to Gefen et al. (2000, p. 4), "the intricate causal networks enable by SEM characterize real-world processes better than simple correlation-based models". Therefore, SEM is more suited for the mathematical modeling of complex processes to serve both theory (Bollen 1989) and practice (Dubin 1976) than first generation regression models. Unlike first generation regression tools, "SEM not only assesses the *structural model* - the assumed causation among a set of dependent and independent constructs – but, in the same analysis, also evaluates the *measurement model* – loadings of observed items (measurements) on their expected latent variables (constructs)" (Gefen et al. 2000, p. 5). Gefen et al. (2000, p. 6) mention that SEM techniques "also provide fuller information about the extent to which the research model is supported by the data than in regression techniques".

4.2 SEM Methods and Their Usage

Gefen et al. (2000) analyzed the extent to which SEM is being used in IS research (see table 1). They analyzed three major IS journals (MIS Quarterly, Information & Management and Information Systems Research) during the four year period between January 1994 and December 1997. Gefen et al. (2000, p. 7) pointed out that: "table 1 clearly shows that SEM has been used with some frequency for validating instruments and testing linkages between constructs in two or three widely known IS journals".

SEM approaches	I&M (n=106)	ISR (n=27)	MISQ (n=38)	All three journals
PLS	2%	19%	11%	7%
LISREL	3%	15%	11%	7%
Other*	3%	11%	3%	4%
Total	8%	45%	25%	18%

*Other includes SEM techniques such as AMOS and EQS.

Table 1 – Use of structural Equation Modeling tools (source Gefen et al. 2000).

Issues	LISREL	PLS	Linear Regression
Objective of overall analysis	Show that the null hypothesis of the entire proposed model is plausible, while rejecting path-specific null hypotheses of no effect	Reject a set of path-specific null hypotheses of no effect.	Reject a set of path-specific null hypotheses of no effect.
Objective of variance analysis	Overall model fit, such as x2 or high AGF1.	Variance explanation (high R-square)	Variance explanation (high R-square)
Required theory base	Requires sound theory base. Supports confirmatory research.	Does not necessarily require sound theory base. Supports both exploratory and confirmatory research.	Does not necessarily require sound theory base. Supports both exploratory and confirmatory research.
Assumed distribution	Multivariate normal, if estimation is through ML. Deviations from multivariate normal are supported with other estimation techniques.	Relatively robust to deviations from a multivariate distribution.	Relatively robust to deviations from multivariate distribution, with established methods of handling non-multivariate distributions.
Required minimal sample size	At least 100-150 cases.	At least 10 times the number of items in the most complex construct.	Supports smaller sample sizes, although a sample of at least 30 is required.

Table 2 – Comparative analysis between techniques (Gefen et al. 2000).

Compared to the better known factor-based covariance fitting approach for latent structural modeling (exemplified by software such as LISREL, EQS, COSAN, and EZPATH), the component-based PLS avoids two serious problems: inadmissible solutions and factor indeterminacy (Fornell and Bookstein 1982). The philosophical distinction between these approaches is whether to use structural equation modeling for theory testing and development or for predictive applications (Anderson and Gerbing 1988). In situations where prior theory is strong and further testing and development is the goal, covariance based full-information estimation methods (i.e., Maximum Likelihood or Generalized Least Squares) are more appropriate. Yet, due to the indeterminacy of factor score estimations, there exists a loss of predictive accuracy. This, of course, is not of concern in theory testing where structural relationships (i.e., parameter estimation) among concepts are of prime concern.

For application and prediction, a PLS approach is often more suitable. Under this approach, it is assumed that all the measured variance is useful variance to be explained. Since the approach estimates the latent variables as exact linear combinations of the observed measures, it avoids the indeterminacy problem and provides an exact definition of component scores. Using the iterative estimation technique (Wold 1981), the PLS approach provides a general model which encompasses, among other techniques, canonical correlation, redundancy analysis, multiple regression, multivariate analysis of variance, and principal components. Because the iterative algorithm generally consists of a series of ordinary least squares analyses, identification is not a

problem for recursive models nor does it presume any distributional form for measured variables.

Chin and Newsted (1999) provided a summary of the comparison between the different SEM techniques using as criteria: objectives, approach, assumptions, parameter estimates, latent variable scores, epistemic relationship between a latent variable and its measures, implications, model complexity and sample size (see table 3).

Criterion	PLS	LISREL
Objective	Prediction oriented	Parameter estimated
Approach	Variance based	Covariance based
Assumptions	Predictor specification (non parametric)	Typically multivariate normal distribution and independent observations (parametric)
Parameter estimates	Consistent as indicators and sample size increase (i.e., consistency at large)	Consistent
Latent variable scores	Explicitly estimated	Indeterminate
Epistemic relationship between a latent variable and its measures	Can be modelled in either formative or reflective mode	Typically only with reflective indicators
Implications	Optimal for prediction accuracy	Optimal for parameter accuracy
Model complexity	Large complexity (e.g., 100 constructs and 1000 indicators)	Small to moderate complexity (e.g., less than 100 indicators)
Sample size	Power analysis based on the portion of the model with the largest number of predictors. Minimal recommendations range from 30 to 100 cases.	Ideally based on power analysis of specific model – minimal recommendations range from 200 to 800.

Table 3 – comparison between SEM techniques (source: Chin and Newsted 1999).

4.3 SEM Components

SEM involves three primary components (Chin 2000):
- Indicators (often called manifest variables or observed measures/variables). Indicators are usually represented as squares. For questionnaire-based research, each indicator represents a particular question.
- Latent variables (or construct, concept, factor). Latent variables are normally drawn as circles. Latent variables are used to represent phenomena that cannot be measured directly.
- Path relationships (correlational, one-way paths, or two way paths). These relationships are defined using arrows.

The graphical representation of SEM is represented in figure 4. A structural equation model may include two types of latent constructs--exogenous and endogenous. The are represented in the following way:
- Exogenous constructs - ξ.
- Endogenous constructs - η.

These two types of constructs are distinguished on the basis of whether or not they are dependent variables in any equation in the system of equations represented by the model. Exogenous constructs are independent variables in all equations, in which they appear, while endogenous constructs are dependent variables in at least one equation--although they may be independent variables in other equations in the system. In graphical terms, each endogenous

construct is the target of at least one one-headed arrow, while two-headed arrows only target exogenous constructs.
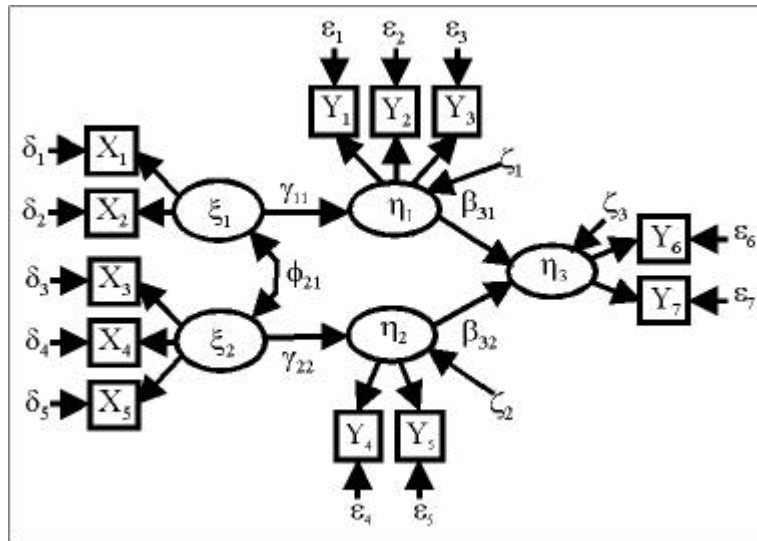

Figure 4 – Graphical representation of a SEM model (source: Rigdon 1996).

Parameters representing regression relations between latent constructs are typically labelled with:
- γ - the regression of an endogenous construct on an exogenous construct.
- β - the regression of one endogenous construct on another endogenous construct.

Typically in SEM, exogenous constructs are allowed to covary freely. Parameters labelled with the Greek character "phi" (ϕ) represent these covariances. This covariance comes from common predictors of the exogenous constructs, which lie outside the model under consideration.

Manifest variables associated with exogenous constructs are labelled X, while those associated with endogenous constructs are labelled Y. Otherwise, there is no fundamental distinction between these measures, and a measure that is labelled X in one model may be labelled Y in another. Few SEM researchers expect to perfectly predict their dependent constructs, so model typically include a structural error term, labelled with the character ζ.

4.4 SEM Notation

SEM models are represented in a variety of notations, but the most commonly use is the one of Jöreskog (1973, 1977) known as LISREL. The SEM model has two primary components, a latent variable and a measurement model. The latent variable is

$$\eta = \alpha + B\eta + \Gamma\xi + \zeta. \quad (1)$$

Where:
- η is an m x 1 vector of latent endogenous variables,
- ξ is an n x 1 vector of latent exogenous variables,
- α is an m x 1 vector of intercept terms,
- B is an m x m matrix of coefficients that give the influence of the ηs on each other,
- Γ is an m x n matrix of coefficients for the effect of the ξ on η, and
- ζ is the m x 1 vector of disturbances that contains the unexplained parts of the ηs.

The traditional LISREL notation has two equations for the measurement model:

$$y^* = v_y + \Lambda_y \eta + \delta, \qquad (2)$$

$$x^* = v_x + \Lambda_x \xi + \delta, \qquad (3)$$

Where:
- y^* is the p x 1 vector of indicators of the latent variables in η,
- v_y is the p x 1 vector of intercept terms,
- Λ_y is the p x m factor loading matrix of coefficients giving the linear effect of η on y^*, and
- δ is the p x 1 vector of measurement errors or disturbances.

Analogous definitions and assumptions hold for (3).

In relation to indicators, they can be categorized in formative and reflective indicators. Formative indicators (also known as cause measures) "are measures that form or cause the creation or change in a latent variable" (Chin 1998). Examples of formative indicators would be the amount of beer, wine, consumed as indicators of mental inebriation.

4.5 SEM Measurement Model

A measurement model is "a device for connecting observed, or indicator, variables to one or more latent variables such that 'true' values on the latter can be separated from error" (Bacon 1999). Joreskorg and Sorbom (1993) mentioned that a measurement model consists of a set of observed indicators, which serve for respective measurement instruments of the latent variables. The measurement model consists of:
- X and Y variables that are measures of the exogenous and endogenous constructs, respectively. Each X should load onto one ξ, and each Y should load onto one η.
- λ_x representing the path between an observed variable X and its ξ, i.e., the item loading on its latent variable.
- θ_δ representing the error variance associated with this X item, i.e., the variance not reflecting its latent variable ξ.
- λ_y representing the path between an observed variable Y and its η, i.e., the item loading on its latent variable.
- θ_ε representing the error variance associated with this Y item, i.e., the variance not reflecting its latent variable η.

SEM users typically recognize that their measures are imperfect, and they attempt to model this imperfection. Thus, structural equation models include terms representing measurement error. In the context of the factor analytic measurement model, these measurement error terms are uniqueness or unique factors associated with each measure. Measurement error terms associated with X measures are labelled with the character δ while terms associated with Y measures are labelled with ε. Conceptually, almost every measure has an associated error term. In other words, almost every measure is acknowledged to include some error. According to Cheng (2001, p. 652), "prior to the test of the hypothesized relationships among constructs, the measurement model must hold. If any indicators do not measure its underlying construct and/or are not reliable, the model must be modified before it can be 'structurally' tested". Next, we discuss the issue of reliability.

4.5.1. Reliability

According to (Vogt 1993, p. 195), "reliability of a measure is the extent to which it provides consistent results from one application to the next, or the degree to which it is free of random error". Individual item reliability is assessed by examining the loadings and cross-loadings of each of the constructs's indicators. Operationally, reliability is defined as the internal

consistency of a scale, which assesses the degree to which the items are homogeneous. Cronbach's alpha is a widely used measure of internal consistency (Cronbach 1951, Nunnaly 1978).

The main techniques for analysis are the internal consistency measures (such as Cronbach's alpha) and composite reliability measures. Cronbach's alpha "tends to be a lower bound estimate reliability, whereas IC is a closer approximation under the assumption that the parameter estimation are accurate" (Chin 1998, p. 320). Churchill (1979) suggests that Cronbach's alpha be the first measure ones uses to assess quality of the instrument. Cronbach's alpha can be considered an adequate index of the inter-item consistency reliability of independent and dependent variables if those constructs have reliability values of 0.7 or greater (Nunnally 1978, Sekaran 1992).

The appropriate measures to use with survey instruments that generally tackle a number of constructs are commonly referred to as measures of composite reliability (Werts et al. 1974). The composite reliability measure proposed by Werts et al. (1974), which is an alternate conceptualization of reliability, represents the proportion of measure variance attributable to the underlying trait. The Werts et al. (1974) composite reliability represents the ratio of trait variance to the sum of trait and error variance. Scales with composite reliability greater than 50 percent are considered to be reliable although Nunnaly (1978) suggests the value of 0.6.

4.5.1.1. Cronbach's Alpha Test

Cronbach's alpha measures how well a set of items (or variables) measures a single unidimensional latent construct. When data have a multidimensional structure, Cronbach's alpha will usually be low. Technically speaking, Cronbach's alpha is not a statistical test - it is a coefficient of reliability (or consistency). Cronbach's alpha can be written as a function of the number of test items and the average inter-correlation among the items:

$$a = \frac{N \times \bar{r}}{1 + (N-1) \times \bar{r}}$$

Here N is equal to the number of items and r-bar is the average inter-item correlation among the items. One can see from this formula that if you increase the number of items, you increase Cronbach's alpha. Additionally, if the average inter-item correlation is low, alpha will be low. As the average inter-item correlation increases, Cronbach's alpha increases as well. This makes sense intuitively - if the inter-item correlations are high, then there is evidence that the items are measuring the same underlying construct. This is really what is meant when someone says they have "high" or "good" reliability. They are referring to how well their items measure a single unidimensional latent construct. Thus, if you have multidimensional data, Cronbach's alpha will generally be low for all items. In this case, run a factor analysis to see which items load highest on which dimensions, and then take the alpha of each subset of items separately.

4.5.1.2. Composite Reliability

Cronbach's alpha is the typical procedure to assess reliability. However, Cronbach alpha is based on a restrictive assumption that all indicators are equally important. An alternative conceptualization of reliability is that it represents the proportion of measure variance attributable to the underlying dimension (Werts et al. 1974). According to Chin et al. (1996, p.33), "while Cronbach's alpha with its assumption of parallel measures represents a lower bound estimate of internal consistency, a better estimate can be gained using the composite reliability formula" also known as "latent variable reliability". The technique was suggested by

Werts et al. (1974), see also Dillon and Goldstein (1984) and Fornell and Larker (1981). The composite reliability ρ_c of a measure X, with indicators $X_1, X_2,\ldots, X_n$ is given by:

$$r_c = \frac{\left(\sum\limits_{i=1}^{n} \lambda_i\right)^2 \text{var } X}{\left(\sum\limits_{i=1}^{n} \lambda_i\right)^2 \text{var } X + \sum\limits_{i=1}^{n} \text{var}(e_i)}$$

where:
- λ_i, is the factor loading of X_i.
- var X is the variance of X (i.e., available in a SEM equation measurement model).
- e_i is the error variance for X_i.

4.6 SEM Structural Model

In SEM, the structural model includes the relationships among the latent constructs. It is the set of exogenous and endogenous variables in the model, together with the direct effects (straight arrows) connecting them, and the disturbance terms for these variables (reflecting the effects of unmeasured variables not in the model). This stage of analysis involves the evaluation of the relationships between the latent variables. "If a structural model has non-significant paths, it reveals the need to propose new relationships on condition that these new paths are theoretically justified. The process is to produce a series of nested structural models for testing. These structural models must be developed one by one where later models must be stemmed from previous models and must have theoretical grounds" (Cheng 2001, p. 654). According to Cheng (2001) the best fitting structural model refers "to a model that is the best in achieving the goodness-of-fit indices among all tested structural models.

4.7 SEM Steps

Next we explain the different steps of SEM methodology (Bollen and Long 1993, p. 1):
- **Step 1: Specification** - Statement of the theoretical model in terms of equations or a diagram.
- **Step 2: Identification** - The model can in theory be estimated with observed data (to learn the general rules of identification).
- **Step 3: Estimation** - The model's parameters are statistically estimated from data. Multiple regression is one such estimation method, but most often more complicated methods are used. (For a list of estimation programs and their links look at Joel West's page.)
- **Step 4: Model it** - The estimated model parameters are used to predict the correlations or co-variances between measured variables and the predicted correlations or co-variances are compared to the observed correlations or co-variances (to see measures of model fit).

Cheng (2001) proposed an incremental approach to apply SEM techniques (see figure 5). This approach distinguishes clearly the analysis of SEM measurement and structural models.
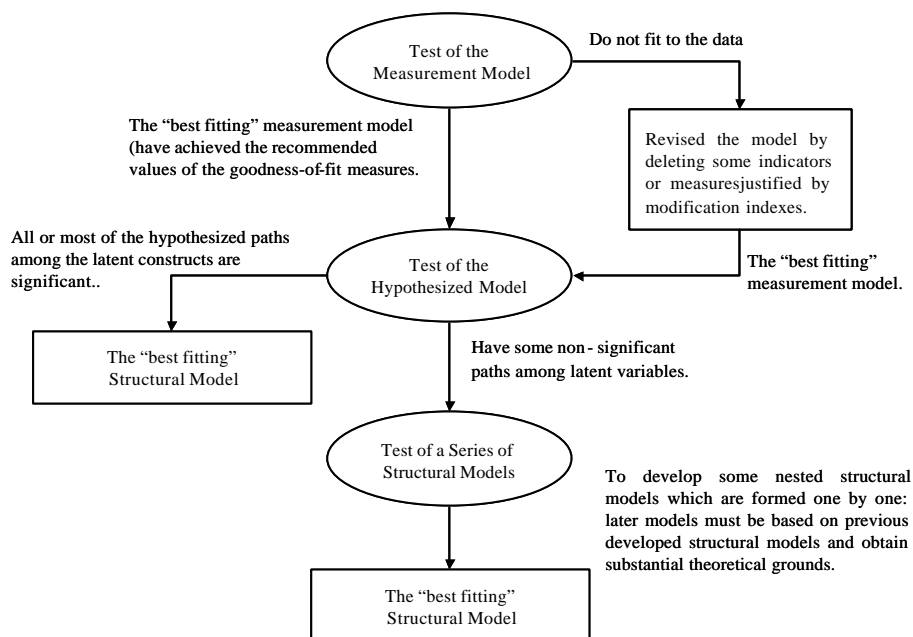
Figure 5 – SEM incremental approach proposed by Cheng (2001).

5. PLS Method

In this section we explain in detail the PLS method. We start by a PLS method overview, then, we discussed the issue of sample size and finally, we describe the statistics that must be worked out with PLS method.

5.1 PLS Overview

Partial Least Squares (PLS) was invented by Herman Wold (mentor to Karl Jöreskog, founder of SEM). Nowadays, PLS is a well-established technique for estimating path coefficients in structural models and has been widely used in various research studies (e.g. Fornell and Bookstein 1982, Cool et al. 1989, Fornell et al. 1990, Johanson and Yip 1994, Birkinshaw et al. 1995). Section 5.2 presents an analysis by Gefen et al. (2000) about the usage of SEM techniques including PLS. The conceptual core of PLS is an iterative combination of principal components analysis relating measures to constructs, and path analysis allowing the construction of a system of constructs (Thompson et al. 1995). The hypothesising of relationships between measures and constructs, and constructs and other constructs is guided by theory. The estimation of the parameters representing the measurement and path relationships is accomplished using Ordinary Least Squares (OLS) techniques.

PLS can be a powerful method of analysis because of the minimal demands on measurement scales, sample size, and residual distributions. Although PLS can be used for theory confirmation, it can also be used to suggest where relationships might or might not exist and to suggest propositions for later testing.

Finally, PLS is considered better suited for explaining complex relationships (Fornell, Lorange, and Roos, 1990; Fornell and Bookstein, 1982). As stated by Wold (1985, p. 589), "PLS comes to the fore in larger models, when the importance shifts from individual variables and parameters to packages of variables and aggregate parameters". Wold states later (p. 590), "In large, complex models with latent variables PLS is virtually without competition". PLS modeling consists of three sets of relations (Fornell and Cha 1992):
  • Inner relations – the inner relations specify the relationships between different latent constructs,

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- Outer relations – the outer relations describe the relationships between the latent variables and the set of manifest variables and,
- Weight relations – the weights relations define the estimated latent constructs as weighted aggregates of the observed variables.

In PLS, two kinds of measurement models can be specified: reflective and formative. The reflective model assumes that the manifest variables are a reflection of the latent constructs. In contrast, the formative model assumes that the observed variables form the latent construct. Chin (2000) refers the conditions when we might consider using PLS:
- Do you work with theoretical models that involve latent constructs?
- Do you have multicollinearity problems with variables that tap into the same issues?
- Do you want to account for measurement error?
- Do you have non-normal data?
- Do you have a small sample set?
- Do you wish to determine whether the measures you developed are valid and reliable within the context of the theory you working in?
- Do you have formative as well as reflective measures?

As in multiple linear regression, the purpose of PLS is to build a linear model, $Y=XB+E$, where:
- Y is an n cases by m variables response matrix,
- X is an n cases by p variables predictor (design) matrix,
- B is a p by m regression coefficient matrix,
- E is a noise term for the model, which has the same dimensions as Y.

5.2 Computational Approach

The standard algorithm for computing partial least squares regression components (i.e., factors) is non-linear iterative partial least squares (NIPALS). There are many variants of the NIPALS algorithm, which normalize or do not normalize certain vectors. The following algorithm, which assumes that the X and Y variables have been transformed to have means of zero, is considered to be one of most efficient NIPALS algorithms (Statsoft 2001).

For each $h=1,\ldots,c$ where $A_0=X'Y$, $M_0=X'X$, $C_0=I$, and c given,
1. compute q_h, the dominant eigenvector of $A_h'A_h$
2. $w_h=G_hA_hq_h$, $w_h=w_h/\|w_h\|$, and store w_h into W as a column
3. $p_h=M_hw_h$, $c_h=w_h'M_hw_h$, $p_h=p_h/c_h$, and store p_h into P as a column
4. $q_h=A_h'w_h/c_h$, and store q_h into Q as a column
5. $A_{h+1}=A_h - c_hp_hq_h'$ and $B_{h+1}=M_h - c_hp_hp_h'$
6. $C_{h+1}=C_h - w_hp_h'$

The factor scores matrix T is then computed as $T=XW$ and the partial least squares regression coefficients B of Y on X are computed as $B=WQ$. An alternative estimation method for partial least squares regression components is the SIMPLS algorithm (de Jong, 1993), which can be described as follows.

For each $h=1,\ldots,c$, where $A_0=X'Y$, $M_0=X'X$, $C_0=I$, and c given,
1. compute qh, the dominant eigenvector of $A_h'A_h$
2. $w_h=A_hq_h$, $c_h=w_h'M_hw_h$, $w_h=w_h/sqrt(c_h)$, and store w_h into W as a column
3. $p_h=M_hw_h$, and store p_h into P as a column
4. $q_h=A_h'w_h$, and store q_h into Q as a column
5. $v_h=C_hp_h$, and $v_h=v_h/\|v_h\|$
6. $C_{h+1}=C_h - v_hv_h'$ and $M_{h+1}=M_h - p_hp_h'$
7. $A_{h+1}=C_hA_h$

Similarly to NIPALS, the T of SIMPLS is computed as T=XW and B for the regression of Y on X is computed as B=WQ'.

5.3 Sample Size

Sample size can be smaller, with a strong rule of thumb suggesting that it be equal to the larger of the following: (1) ten times the scale with the largest number of formative (i.e., causal) indicators (note that scales for constructs designated with reflective indicators can be ignored), or (2) ten times the largest number of structural paths directed at a particular construct in the structural model. A weak rule of thumb, similar to the heuristic for multiple regression (Tabachnik and Fidell,1989, p. 129), would be to use a multiplier of five instead of ten for the preceding formulae. An extreme example is given by Wold (1989) who analyzed 27 variables using two latent constructs with a data set consisting of ten cases. In general, the most complex regression will involve:

    (1) The indicators on the most complex formative construct, or
    (2) The largest number of antecedent constructs leading to an endogenous construct

Sample size requirements become at least ten times the number of predictors from (1) or (2) whichever is greater (Barclay et al. 1995). Second order factors can be approximated using various procedures. One of the easiest to implement is the approach of repeated indicators known as the hierarchical component model suggested by Wold (cf. Lohmöller, 1989, pp. 130-133). In essence, a second order factor is directly measured by observed variables for the entire first order factors. While this approach repeats the number of manifest variables used, the model can be estimated by the standard PLS algorithm. This procedure works best with equal numbers of indicators for each construct.

Nevertheless, being a limited information method, PLS parameter estimates are less than optimal regarding bias and consistency. The estimates will be asymptotically correct under the joint conditions of consistency (large sample size) and consistency at large (the number of indicators per latent variable becomes large). Furthermore, standard errors need to be estimated via resampling procedures such as jackknifing or bootstrapping (cf. Efron and Gong, 1983). Rather than being viewed as competitive models, the covariance fitting procedures (i.e., ML and GLS) and the variance-based PLS approach has been argued as complementary in nature.

5.4 PLS Statistics

According to Gefen et al. (2000), a set of PLS statistics must be worked out in order to verify our model. At the measurement model level, PLS estimates item loadings and residual covariance. At the structural level, PLS estimates path coefficients and correlation among the latent variables, together with the individual R^2 and Average Variance Extracted (AVE) of each of the latent constructs.

AVE is calculated as: $\sum \lambda_i^2 \text{var}(F) / (\sum \lambda_i^2 \text{var}(F) + \sum \theta_{ii})$ where λ_I, F, and θ_{ii} are the factor loading, factor variance, and unique/error variance respectively. If F is set at 1, then θ_{ii} is the 1-square of λ_i. T-values of both paths and loadings are then calculated using either a jackknife or a bootstrap method. Good model fit is established with significant path coefficients, acceptably high R^2 and internal consistency (construct reliability) being above 0.70 for each construct (Thompson et al. 1995). Convergent and discriminant validity are assessed by checking that that AVE of each construct is larger than is correlation with the other constructs, and each item has a higher loading (calculated as the correlation between the factor scores and the standardized measures) on its assigned construct than the other constructs.

6. An Example

Based on a literature review and a web survey we made (for more details see: Esteves and Pastor 2001a), we defined an interdependence model between project sponsor, project manager roles and ERP project success. We started by providing a definition for both the project sponsor and the project manager figure:

– The ERP project sponsor is the person devoted to promote the ERP project, who has the ownership and responsibility of obtain the project resources. He must control and monitor the project, helping remove obstacles in order to facilitate the success of the ERP project. Usually this figure is a senior executive of the company.

– The ERP project manager is the person devoted to plan, lead and control the project on the run in its several tasks. He is also responsible for ensuring the scope is properly and realistically defined, and communicating it to the whole company. One of his/her most important tasks is to promote good working relationships across the project.

The interdependence model is represented in figure 3 with the standard notations of the SEM approach. Based on these interdependencies, we define three hypotheses for further research:

   H1 - there is a positive relationship between project sponsor role and project manager role
   H2 - there is a positive relationship between project sponsor role and the success of the ERP implementation project.
   H3 - there is a positive relationship between project manager role and the success of the ERP implementation project.
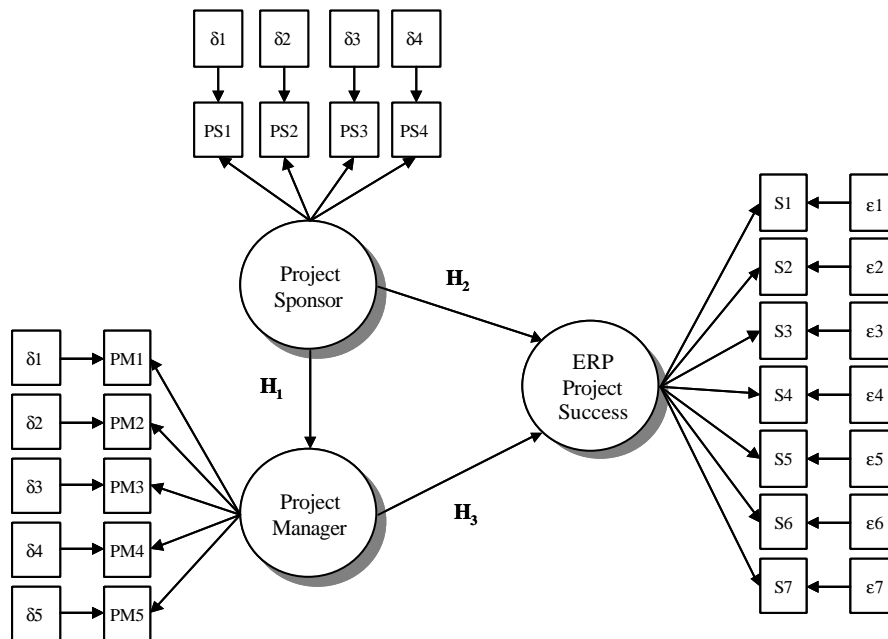

Figure 6 – SEM model for project sponsor, project manager and their interdependencies in ERP implementation projects.

As explained in the SEM components section, the variables in squares represent the indicators, in our case they are the items of the survey developed. The variables in squares labelled ε_i and δ_i represent the error associated with each item. The survey to collect data (see appendix A) uses a likert scale to measure the opinion of respondents in each indicator. As illustrated in figure 6, the model consists of two independent variables (project sponsor and project manager) and one dependent variable (ERP project success).

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An alternative to the graphical representation (figure 6) is to represent the model specification using the SEM notation described in section 4.4. In this example it is:

$$[ERP \text{ Pr} ojectSucce \text{ } ss] = [\boldsymbol{a}\mathbf{l}] + [\tilde{a}_{1PS} \quad \tilde{a}_{2PM}]\begin{bmatrix} \text{Pr } ojectSpons \text{ } or \\ \text{Pr } ojectManag \text{ } er \end{bmatrix} + [\boldsymbol{z}_1]$$

$$\begin{bmatrix} PS1 \\ PS2 \\ PS3 \\ PS4 \end{bmatrix} = \begin{bmatrix} \boldsymbol{n}1 \\ \boldsymbol{n}2 \\ \boldsymbol{n}3 \\ \boldsymbol{n}4 \end{bmatrix} + \begin{bmatrix} \boldsymbol{l}_{1PS} & 0 \\ \boldsymbol{l}_{2PS} & 0 \\ \boldsymbol{l}_{3PS} & 0 \\ \boldsymbol{l}_{4PS} & 0 \end{bmatrix}\begin{bmatrix} \text{Pr } ojectSpons \text{ } or \\ \text{Pr } ojectManag \text{ } er \end{bmatrix} + \begin{bmatrix} \boldsymbol{d}_1 \\ \boldsymbol{d}_2 \\ \boldsymbol{d}_3 \\ \boldsymbol{d}_4 \end{bmatrix}$$

$$\begin{bmatrix} PM1 \\ PM2 \\ PM3 \\ PM4 \\ PM5 \end{bmatrix} = \begin{bmatrix} \boldsymbol{n}1 \\ \boldsymbol{n}2 \\ \boldsymbol{n}3 \\ \boldsymbol{n}4 \\ \boldsymbol{n}5 \end{bmatrix} + \begin{bmatrix} 0 & \boldsymbol{l}_{1PM} \\ 0 & \boldsymbol{l}_{2PM} \\ 0 & \boldsymbol{l}_{3PM} \\ 0 & \boldsymbol{l}_{4PM} \\ 0 & \boldsymbol{l}_{5PM} \end{bmatrix}\begin{bmatrix} \text{Pr } ojectSpons \text{ } or \\ \text{Pr } ojectManag \text{ } er \end{bmatrix} + \begin{bmatrix} \boldsymbol{d}_1 \\ \boldsymbol{d}_2 \\ \boldsymbol{d}_3 \\ \boldsymbol{d}_4 \\ \boldsymbol{d}_5 \end{bmatrix}$$

$$\begin{bmatrix} S1 \\ S2 \\ S3 \\ S4 \\ S5 \\ S6 \\ S7 \end{bmatrix} = \begin{bmatrix} \boldsymbol{n}1 \\ \boldsymbol{n}2 \\ \boldsymbol{n}3 \\ \boldsymbol{n}4 \\ \boldsymbol{n}5 \\ \boldsymbol{n}6 \\ \boldsymbol{n}7 \end{bmatrix} + \begin{bmatrix} \boldsymbol{l}_{1ERPS} \\ \boldsymbol{l}_{2ERPS} \\ \boldsymbol{l}_{3ERPS} \\ \boldsymbol{l}_{4ERPS} \\ \boldsymbol{l}_{5ERPS} \\ \boldsymbol{l}_{6ERPS} \\ \boldsymbol{l}_{7ERPS} \end{bmatrix}[ERP \text{ Pr} ojectSucce \text{ } ss] + \begin{bmatrix} \boldsymbol{e}_1 \\ \boldsymbol{e}_2 \\ \boldsymbol{e}_3 \\ \boldsymbol{e}_4 \\ \boldsymbol{e}_5 \\ \boldsymbol{e}_6 \\ \boldsymbol{e}_7 \end{bmatrix}$$

7.   Considerations

This technical research report proposes the usage of a statistical approach named Partial Least squares (PLS) to define the relationships between CSFs for ERP implementation projects. Some researchers have evidenced the relationships between these CSFs, however no one has defined in a formal way these relationships. PLS is one of the techniques of structural equation modeling approach. Therefore, this report presents an overview of this approach. We provide an example of PLS method modeling application, in this case we use two CSFs. However, our project will be extended to all the CSFs of our unified model.

To compute the data, we are going to use PLS-graph developed by Wynne Chin. This software has been under development for the past 9 years. Academic beta testers include Queens University, Western Ontario, UBC, MIT, University of Michigan, Wharton University, etc. (Chin 2000).

8. References

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Appendix A

Project Description

Company.	
Type of company	
Project duration:	
Start date:	
ERP system implemented:	
Number of users:	
Your function in the ERP project:	
Your e-mail:	

Project General Characteristics

		Strongly disagree	Disagree	Undecided	Agree	Strongly agree
S1	This project was finished in the expected time					
S2	This project was finished on budget					
S3	The project obtained the expected functionality					
S3	The system is being used by its intended users					
S4	The project benefited the potential users					
S5	If you could go back and start again, you would implement the ERP system in the same way					
S6	The ERP system chosen was the adequate					
S7	The implementation of the ERP system had a positive impact on the organisation culture and values					

Project Specific Questions

		Strongly disagree	Disagree	Undecided	Agree	Strongly agree
	Project sponsor role					
PS1	The project sponsor reviewed the scope periodically					
PS2	The project sponsor inquire frequently					
PS3	The project sponsor got the resources for the project					
PS4	Project sponsor shown commitment and support with the project					
	Project manager role					
PM1	The project manager reviewed the scope periodically					
PM2	The project manager motivated the team along the project					
PM3	The project manager had frequent meetings with project team					
PM4	The project manager skills included technical, business and organisational skills					
PM5	The project manager reported the project status to his superiors in a regular basis					