STRUCTURAL MODELING AND CRITICAL SUCCESS FACTORS FOR INDUSTRIAL PROJECTS MANAGEMENT

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ABSTRACT

The literature and viewed items show no statistical relationship between the approaches and critical factors and the relationship between critical factors and criteria for project evaluation. Managers and project managers do not have statistical data on the importance among the critical factors and the importance between critical factors and criteria of a basic structural model for project management. Here the basic formats of scientific articles were analyzed to develop a scientific article and follow strategies to determine the structural model evaluated with the goal analysis methodology for the management of industrial projects, and the identification of sequence patterns, articles, classification factors, calculations frequency factors, and statistical relationships between them within the proposed structural model.

Keywords: Critical Success Factors, Evaluation Criteria, Meta-Analysis, Structural Modeling, Project Management.

1. INTRODUCTION

It is pertinent to the project definition and noted that several definitions, one of which is a temporary endeavor undertaken to create a unique product or service ANSI / PMI 99-001-2004, NA (2004). Two concepts, or tools, very interrelated on processes of strategic planning, which most often can be found different interpretations and practical applications are the CSFs (Critical Success Factors) and KRA (Key Result Areas). The most effective use of CSF for consulting work experience is as a tool to identify the critical factors for positioning and competitiveness in a type of business (industry) determined. They can serve to analyze what they do and how the most successful competitors (competitive benchmarking) and, from this, determine strategies, policies and actions to overcome them. Therefore it is important to analyze literature through some definite method to check critical factors which are most important in the management of projects this paper uses meta-analysis methodology and also used basic descriptive statistics to show differences in the relationship between groups of factors.

II METHODS

In this section the meta-analysis (MA) method for finding information on the research is used. Although there is no single method for the preparation of MA, there is a research which excludes or adds some stage, however, there are definite steps that are listed below and make the algorithm followed in this study. Valles, A.(2008).The methodology consists of six stages which are: 1 Defining the Research Question (Components and scope),2 Selection Criteria and Factors. (Sources, bias search strategy and measurement),3Criteria for selecting publications(Year, country, language, origin),4 Collection of articlesof studies (Assessment of the quality of the publication),5Assessment of the quality of the publication (Likert scales, measuring instrument validation),6Statistical Analysis. Colin, E.N. (2007)

2.1 Definition of structural equation modeling (SEM)

This technique combines factor analysis with linear regression to test the goodness of fit of observed data to a hypothesized model and expressed by a diagram of trails. As a result, SEM provides the values within each relationship, and most importantly, a statistic that expresses the degree to which the data fit the proposed model, confirming its validity.

Among the strengths of SEM is the ability to construct latent variables: variables that are not directly measured, but are estimated in the model from a number of variables that co-vary with each other. This allows the modeler to explicitly capture the reliability of the model. Factor analysis, path analysis and linear regression represent special cases of structural equation model. Iacobucci, D. (2010).

It is a statistic for testing and estimating causal relations from statistical data and qualitative causal assumptions about art. Iacobucci, D. (2009). This definition has been articulated by the geneticist Sewall. Wright, S. (1921).

The structural equation models were born from the need to provide more flexibility in the regression models. They are less restrictive than the regression models allow for the fact include measurement errors in both criterion variables (dependent) as the predictor (independent) variables.

The methodology of Structural Equation Modeling is an area of statistical developing very young compared to regression models and factor analysis. SEM has a confirmatory nature more than an exploratory; is part of a theoretically relevant hypothesis in the context of interest. A major strength of this approach is its ability to develop constructs that estimate the latent variables based on some measurable variables.

2.2Applying the statistical analysis methodology SEM

With these 16 critical factors show a correlation table covariance between pairs of factors for each of the three criteria to evaluate: *finish on time the industrial project*, *fulfill the budget of the industrial project* and *fulfill the quality of the industrial project*, with a total of 256 correlations for each evaluation criteria, where the most significant correlations with P-value of $P < 0.01$ level are indicated, as shown in Tables 2.1, 2.2 and 2.3 giving a total of 11 critical factors considered for model building. All these values of correlation and covariance were calculated with SPSS 22 statistical software and they are shown below on table 2.4.

Table 2.1 Correlations for the latent variable 'finish the project on time'

CORRELATIONS FOR THE LATENT VARIABLE FINISH 'THE PROJECT ON TIME'								
		T. SUPPORT			T. OBJETIVES			T. TECHNOLOGY
T. PLAN	Pearson correlation	,342**	T. EFECTIVE	Pearson correlation	,262**	T. MANAGER	Pearson correlation	,387**
	Sig. (2-tailed)	0.000		Sig. (2-tailed)	0.000		Sig. (2-tailed)	0.000

		T. MANAGER			T. MANAGER
T. TECHNOLOGY	Pearson correlation	,386**	T. KNOWLEDGE	Pearson correlation	,429**
	Sig. (2-tailed)	0.000		Sig. (2-tailed)	0.000

Table 2.2 Correlations for the latent variable 'fulfall the quality of the industrial project'

CORRELATIONS FOR THE LATENT VARIABLES 'FULFALL THE QUALITY OF THE INDUSTRIAL PROJECT'								
		Q.PERSONAL			Q. MANAGEMENT			Q. COMUNICATION
Q. PLAN	Pearson correlation	,310**	Q. SUPPLY	Pearson correlation	,342**	Q. PARTICIPATION	Pearson correlation	,375**
	Sig. (2-tailed)	0.000		Sig. (2-tailed)	0.000		Sig. (2-tailed)	0.000

Table 2.3 Correlations for the latent variable 'fulall the budget of the industrial project'

CORRELATION FOR THE LATENT VARIABLE 'FULALL THE BUDGET OF THE INDUSTRIAL PROJECT'											
		B. PLAN			B. BUSINESS			B. EFECTIVE			B. BUDGET
B. BUSINESS	Pearson correlation	,340**	B. PERSONAL	Pearson correlation	,355**	B. COMUNICATION	Pearson correlation	,362**	B RISK	Pearson correlation	,341**
	Sig. (2-tailed)	0.000		Sig. (2-tailed)	0.000		Sig. (2-tailed)	0.000		Sig. (2-tailed)	0.000

Table 2.4 Critical success factors according to the bivariate correlation value

HIGHEST CORRELATION INDICATORS			
No	**CRITICAL SUCCESS FACTORS**	**CORRELATION**	**P-VALUE**
1	*Clear realistic objectives*	0.262	P<0.01
2	*Proven/familiar technology*	0.387	P<0.01
3	*Competent project manager*	0.386	P<0.01
4	*Support from senior management*	0.342	P<0.01
5	*Effective change mangement*	0.342	P<0.01
6	*Good communication/feedback*	0.375	P<0.01
7	*Skilled/suitably qualified/sufficient staff/team*	0.310	P<0.01
8	*Adequate budget*	0.341	P<0.01
9	*Strong business case/sound basis for project*	0.355	P<0.01
10	*Strong/detailed plan kept up to date*	0.340	P<0.01
11	*Effective monitoring/control*	0.362	P<0.01
reference: correlation matrix			
correlation is significative at level 0.01			

2.3 Development of a good theoretical model

In this section are proposed the most important critical factors resulting from the theoretical analysis of the factors found through meta-analysis, classification by frequency methodology and empirical results obtained from surveys conducted in companies in the region, which be evaluated by statistical tools such as exploratory factor analysis and confirmatory factor analysis to determine the structural equations where the success criteria are also related. In the figure 2.1 we can see the first structural model proposed.

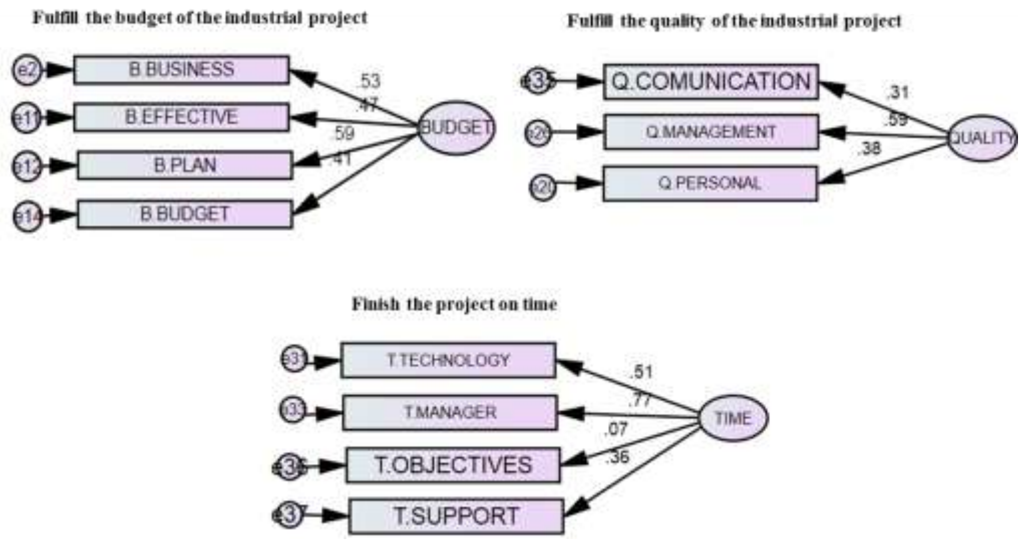

Figure 2.1 Proposed Structural Models

2.4Factor analysis

Factor analysis divides the variance of each indicator (derived from the correlation matrix and sample covariance) in two parts: (1) "common variance", the variance explained by the latent (s)variable (s), which it is estimated on the basis of shared variance with other indicators in the analysis; and (2) "unique variance" which is a combination of a specific reliable variance for the indicator and a random error variance.

There are two main types of model-based analysis of common factors: Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). Both tests are designed to reproduce the observable relationships between a set of indicators with a small set of latent variables. However, EFA and CFA differ primarily in the number and nature of a priori specifications and restrictions made in the measurement model of the latent variable. EFA is a data-driven (initially) so that no specifications made in relation to the number of common factors or the pattern of relationships between common factors approach. Rather, the researcher uses the EFA as an exploratory or descriptive technique to determine the appropriate number of common factors, and to check which measurement variables are reasonable indicators of various latent dimensions.

In CFA, the researcher specifies in advance the number of factors and pattern of load indicators factors, like other parameters, such as those bearing independence or covariance factors unique variances and indicators.

2.5 Exploratory Factor Analysis

The exploratory factor analysis (EFA) is a statistical approach to determine the correlation between variables in a dataset. This type of factor analysis provides a structure (a grouping of variables based on the strong correlations). In general, an EFA prepares the variables to be used to clean structural equation models. An EFA should always be conducted for new datasets. The advantage of an EFA on a CFA (confirmatory factor analysis) is that no theory is applied a priori to which elements belong to which constructs. This means that the EFA be able to detect problematic variables much more easily than the CFA. In this section we will develop of the EFA for this search.

2.5.1 Explained variance matrix by the method of principal components

In this section Matrix variance explained by the principal components method where the left section of the table shows the variance explained by the initial solution is shown. Only major factors in the initial solution are greater than 1. Overall eigenvalues, representing almost 65% of the variance for the original variables. This suggests that the three latent influences are associated with the use of the service, but there is room for a lot of unexplained variation.

The second section of the table shows the variance explained by the factors taken before rotation. The cumulative variability explained by these three factors in the extracted solution is about 55%, a difference of 10% of the initial solution. Thus, about 10% of the variation explained by the initial solution is lost due to single latent factors to the original variables and variability that simply cannot be explained by the model of factors.

The rightmost section of this table shows the variance explained by the factors extracted after rotation.

Table 2.5 Total explained variance matrix

Total explained variance

component	initial eigenvalues			Loads extraction sums squared			Loads rotation sums squared[a]
	Total	% variance	% accumulated	Total	% variance	% accumulated	Total
1	8.350	17.766	17.766	8.350	17.766	17.766	7.201
2	3.844	8.178	25.944	3.844	8.178	25.944	5.347
3	2.088	4.443	30.387	2.088	4.443	30.387	5.100
4	1.842	3.919	34.306				
5	1.744	3.710	38.016				
6	1.568	3.335	41.351				
7	1.479	3.147	44.497				
8	1.390	2.958	47.456				
9	1.266	2.695	50.150				
10	1.175	2.501	52.651				
11	1.122	2.386	55.037				
12	1.088	2.316	57.353				
13	1.037	2.206	59.559				
14	1.013	2.156	61.715				
15	.974	2.072	63.787				
16	.946	2.012	65.799				
17	.917	1.950	67.749				
18	.852	1.812	69.561				
19	.820	1.744	71.306				
20	.795	1.692	72.998				
21	.787	1.675	74.673				
22	.744	1.583	76.256				

Extraction method: Principal components analysis.

a. when the components are correlated, the sums of squared can not be added to obtain a total variance.

2.5.2 KMO and Barlett's test

This table shows two tests which indicate the suitability of the data for the detection of the structure. The measure of sampling adequacy Kaiser-Meyer-Olkin is a statistic that indicates the proportion of variance in the variables that may be caused by underlying factors. The high values (about 1.0) generally indicate that an analysis of factors may be helpful with your data. If the value is less than 0.50, the results of the factor analysis are unlikely to be useful.

Table 2.6 Initial KMO

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.789
Bartlett's Test of Sphericity	Approx. Chi-Square	2922.314
	df	1081
	Sig.	.000

Table 2.7 Final KMO

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.799
Bartlett's Test of Sphericity	Approx. Chi-Square	1827.043
	df	561
	Sig.	.000

2.5.3 Pattern Matrix

The elements of this matrix are called weights or loads. Indicate the weight between each observed variable and each factor. Should be interpreted as standardized slopes (beta) in a multiple regression analysis.

This section describes the configuration tables thrown through analysis shows, as well as the adjustments made through the exploratory factor analysis.

Table 2.8 Initial pattern matrix

Pattern Matrix[a]

	Component		
	1	2	3
Q.PLAN	.646		
Q.BUSINESS	.609		
Q.KNOWLEDGE	.585		
Q.COMUNICATION	.564		
Q.OBJECTIVES	.551		
Q.PERSONAL	.548		
T.SUPPORT	.515		
Q.EFECTIVE	.487		
Q.RISK	.483		
Q.MANAGER	.467		
Q.PARTICIPATION	.459		
T.OBJECTIVES	.455		
Q.MANAGEMENT	.435		
Q.BUDGET	.415		
Q.SUPPLY	.414		
T.KNOWLEDGE	.404		
T.EFECTIVE	.396		
Q.ADAPTATION	.390		
Q.SUPPORT	.383		
T.PLAN	.371		
Q.TECHNOLOGY	.346		
T.COMUNICATION	.336		
T.MANAGEMENT	.319		.301
B.KNOWLEDGE		.678	
B.TECNOLOGY		.603	
B.BUSINESS		.599	
B.PERSONAL		.584	
B.SUPPORT		.572	
B.MANAGER		.571	
B.PARTICIPATION		.570	
B.SUPPLY		.561	
B.COMUNICATION		.560	
B.OBJECTIVES		.532	
B.EFECTIVE		.496	
B.PLAN		.489	
B.MANEGEMENT		.488	
B.BUDGET		.478	-.303
B.RISK		.417	-.322
T.SUPPLY			.768
T.TECHNOLOGY			.727
T.ADAPTATION			.653
T.MANAGER			.442
T.RISK			.423
T.PERSONAL			.335
T.BUSINESS			.302
T.PARTICIPATION			
T.BUDGET			

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.[a]

a. Rotation converged in 6 iterations.

Table 2.9 Final pattern Matrix

Pattern Matrix[a]

	Component		
	1	2	3
B.KNOWLEDGE	.684		
B.BUSINESS	.604		
B.TECHNOLOGY	.601		
B.PERSONAL	.593		
B.COMUNICATION	.586		
B.PARTICIPATION	.572		
B.SUPPORT	.572		
B.MANAGER	.556		
B.OBJECTIVES	.551		
B.SUPPLY	.541		
B.EFECTIVE	.504		
B.PLAN	.497		
B.MANEGEMENT	.483		
B.BUDGET	.478		
Q.BUSINESS		.639	
Q.PLAN		.617	
Q.KNOWLEDGE		.601	
Q.OBJECTIVES		.584	
Q.COMUNICATION		.558	
Q.PERSONAL		.551	
Q.EFECTIVE		.527	
Q.RISK		.509	
Q.MANAGER		.507	
Q.PARTICIPATION		.481	
Q.SUPPLY		.464	
Q.MANAGEMENT		.455	
T.EFECTIVE		.437	
T.OBJECTIVES		.422	
T.KNOWLEDGE		.420	
T.SUPPLY			.739
T.TECHNOLOGY			.703
T.ADAPTATION			.655
T.MANAGER		.338	.444
T.RISK			.438

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.

a. Rotation converged in 4 iterations.

To interpret the factor solution must be interpreted Matrix configuration. Performance mode is similar to the matrix in the orthogonal rotated factors case. In the oblique case, the most important of all matrices obtained are setting Matrix and Matrix of correlation between the factors.Thus necessarily be included in the analysis results.

2.6 Confirmatory Factor Analysis

"Confirmatory Factor Analysis" (CFA) is a type of structural equation modeling that deals specifically with measurement models, that is, the relationship between observable measures or 'indicators' and latent variables or "factors". The objective measurement of the models of latent variables is set the number and the nature of the factors considered for the variance and covariance via a set of indicators. One factor is an unobservable variable that has greater influence than an observable measurement and is considered for correlations across these observable measurements.

The load factors dropped by the configuration matrix in the exploratory factor analysis, which are used to construct the first model using AMOS, are shown below in figure 2.2 for the initial proposed model and figure 2.3 for the final model with its covariance on error variables 31 and 33.

2.6.1 Goodness Fit Indices

P-value: Ap-value of 0.05 is used in common sociological research. It can also be addressed by increasing the size of the error of the sample obtained, reducing the possibility that the obtained data is coincidentally rare.

Comparative Fit Index (CFI):A rule of thumb for IFC and other comparative fit index is that values greater than 0.90 can reasonably indicate a good fit in the researcher's model (Hu and Beltler, 1999).

Root Mean Square Error of Approximation (RMSEA): The RMSEA is an index of "badness of fit" in which a value of 0 indicates better fit and higher values indicate poorer adjustment.

RMSEA≤0.06 indicates close fit proximity.
Values between **0.06** and **0.08** suggest a reasonable fit error.
RMSEA≥1 suggests a poor fit. (Hoyle 2012).

2.6.2 Modification Indices

Each parameter has a rate above a certain beginning modification. If the modification indices are not displayed, this means that none exceeds the specified threshold.

2.6.3 Initial Results.

In this section the initial proposed model with its regression loads and the goodness fit indices are shown in the figure 2.2.

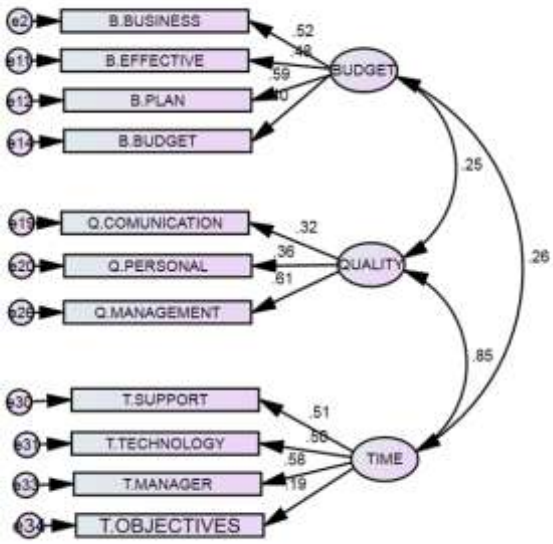

Figure 2.2 Initial model and its standardized estimations

Table 2.10 Initial P-value

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	25	61	41	0.023	1.488
Saturated model	66	0	0		
Independence model	11	231.196	55	0	4.204

Table 2.12 Initial CFI

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	0.736	0.646	0.895	0.848	0.886
Saturated model	1		1		1
Independence model	0	0	0	0	0

Table 2.14 Initial RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	0.05	0.019	0.074	0.486
Independence model	0.127	0.11	0.144	0

Table 2.16 Initial modification indices

			M.I.	Par Change
e34	<-->	BUDGET	4.217	0.053
e31	<-->	e33	6.342	0.115
e20	<-->	e31	5.398	-0.1
e19	<-->	e34	4.661	0.069
e14	<-->	e31	5.901	-0.103
e12	<-->	e34	5.212	0.078

2.6.4 Final Results

In this section the final model with its regression loads and the goodness fit indices are shown below. For this final model the error variables *e31* and *e33* were covariated as the modification indices showed the highest relation between them (table 2.16). This action generate a better modeling fit compared with the first model, we can confirm it with the goodness fit indices tables.

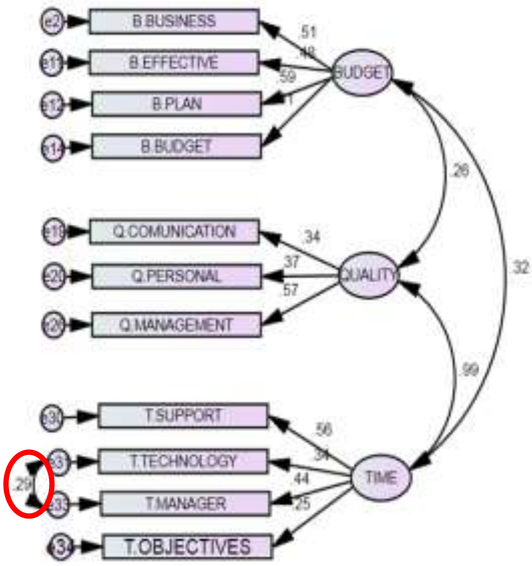

Figure 2.3 Final model and its standardized estimations

Table 2.11 Final P-value

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	26	49.327	40	0.148	1.233
Saturated model	66	0	0		
Independence model	11	231.196	55	0	4.204

Table 2.13 Final CFI

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	0.787	0.707	0.951	0.927	0.947
Saturated model	1		1		1
Independence model	0	0	0	0	0

Table 2.15 Final RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	0.034	0	0.063	0.794
Independence model	0.127	0.11	0.144	0

Table 2.17 Final modification indices

			M.I.	Par Change
e26	<-->	e31	7.208	0.111
e20	<-->	e31	4.358	-0.088
e14	<-->	e31	4.522	-0.088
e12	<-->	e34	4.806	0.074

In table 2.17 we can see the high relation among error variables *e26* and *e31*, however it is not able to covariate them because they are in different indicators set.

2.7 Hypothetical regression structural equation modeling

The traditional approach to integrating multiple regression analysis and factor analysis involves factoring a set of indicators of one or more predictors and outcomes, generating factor scores (which, as noted, are indeterminate) or creating unit-weighted composited of the highest-loading indicators, then using these variables as predictors or outcomes. SEM allows for these two components of the analytic strategy to be done simultaneously; that is, the relations between indicators and latent variables and the relations between variables are evaluated in a single model (Hoyle, 2012). Here we develop the equation model for this research.

$F_1 = \eta_1$ Latent variable 'Finish the Project on time'

$F_2 = \eta_2$ Latent variable 'Fulfill the quality of the Industrial Project.'

$F_3 = \eta_3$ Latent variable 'Fulfill the budget of the Industrial Project'

Regression equations:

$$Y_1=b_1+\lambda_1F_1+E_1$$
$$Y_2=b_2+\lambda_2F_1+E_2$$
$$Y_3=b_3+\lambda_3F_1+E_3$$
$$Y_4=b_4+\lambda_1F_1+E_4$$

$$Y_5=b_5+\lambda_5F_2+E_5$$
$$Y_6=b_6+\lambda_6F_2+E_6$$
$$Y_7=b_7+\lambda_7F_2+E_7$$

$$Y_8=b_8+\lambda_8F_3+E_8$$
$$Y_9=b_9+\lambda_9F_3+E_9$$
$$Y_{10}=b_{10}+\lambda_{10}F_3+E_{10}$$
$$Y_{11}=b_{11}+\lambda_{11}F_3+E_{11}$$

Structural model:

$$F3 = b12+b13+F1+b14+F2 +D3$$

Standardized regression weights:

			Estimate
B.BUSINESS	<---	BUDGET	0.511
B.EFECTIVE	<---	BUDGET	0.476
B.PLAN	<---	BUDGET	0.593
B.BUDGET	<---	BUDGET	0.409
Q.COMUNICATION	<---	QUALITY	0.343
Q.PERSONAL	<---	QUALITY	0.373
Q.MANAGEMENT	<---	QUALITY	0.567
T.SUPPORT	<---	TIME	0.562
T.TECHNOLOGY	<---	TIME	0.338
T.MANAGER	<---	TIME	0.44
T.OBJECTIVES	<---	TIME	0.253

III CONCLUTIONS

As can be seen, there are tests for goodness of fit with the confirmatory analysis of the greatest loads of indicators (endogenous variables), showing which of them should take more care, if we want to modify the subsequent results values of the latent variables, will be improved conditions and consequently endogenous variables decrease the size of the error in each case.

This contribution to the theory of project management is novel because by meta-analysis of a large number of indicators tentatively filtered the most important final indicators are obtained and statistically defined by SEM methodology and its relations with respect to the latent variables.

Recomendations

Indications of interest were observed in the survey of factors and most important criteria, the exogenous variable customer satisfaction. It is recommended to continue this research by adding exogenous latent variable customer satisfaction and their respective survey and change the model trajectories.

It is recommended to apply this methodology and replicate research in other sectors and industries to test the generality of the model.

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