Statistical equation modeling analysis for industrial projects, designing for critical factors and latent variables: quality, cost, time, and success

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Abstract The literature and viewed items on this subject show no statistical data examination regarding the relationship or approach between critical factors (CF) and their association or significance for project evaluation and corroborate for successful realization. Executives, project managers, and staff members have no statistical data on the matter and importance regarding CF, the influence for the possible outcomes, and scenarios; these factors and criteria yield neither a basic structural model on project management nor achievement rationale to conduct their time, process standards, efforts, and resources. For this work, we analyzed the basic formats of scientific articles under definite and established methods to develop a scientific study and strategies to determine an evaluated structural model, with the goal analysis methodology for the management on industrial projects, identifying sequence patterns, articles, classification factors, calculations frequency factors, and

statistical relationships between them, within the proposed path diagram structural model, simulated and examined regarding success.

Keywords Critical factors (CF) · Evaluation criteria · Meta-analysis · Structural modeling · Project management · Exploratory factor analysis · Confirmatory factor analysis · Latent variables

1 Introduction

It is pertinent noting some definitions for project characterization by the reviewed bibliography, first it is a temporary endeavor undertaken to create a unique product or service [1] (Project Management Institute, 2004). Two concepts are interrelated on the strategic planning processes, which most often get different interpretations and practical applications: critical success factors (CSFs) and key result areas (KRA).

The most effective use of CSF is for consulting work experience, to identify the critical factors for positioning and competitiveness in a determined business (industry). They can serve to analyze their influence and “Know how” of successful competitors (competitive benchmarking), from this, determine strategies, policies, and actions to overcome them.

Therefore, it is important to analyze literature through some definite methods, then check the critical factors which are most important in the management of projects, this paper uses meta-analysis (MA) methodology

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Fig. 1 Propose method

and basic descriptive statistics to show differences in the relationship between groups of factors, as shown in Fig. 1.

2 Methods

Meta-analysis takes a large quantity of quantitative extracted results on individual investigations, with the purpose of outcome integration and improve understanding, this systematic revision tries to reach conclusions from a variety of studies on the same subject, by analyzing procedures and standardized techniques. This statistical method is fundamental to delimitate the success criteria for industrial projects.

There is no single method for MA preparation, particular studies excludes or adds some stages; however, definite steps are listed next and make the algorithm followed in this study [2] (Valles, 2008).

The methodology consists of six stages which are next shown in Fig. 2.

Table 1 shows the result of applying meta-analysis to a sample data base of 85 articles and publications where there were found up to 27 critical factors for project management.

2.1 Definition of structural equation modeling (SEM)

This technique applies factor analysis with linear regression too test the observed goodness of fit from the collected data that conforms to a hypothesized model, this mathematical model is also expressed by a path diagram. SEM provides coefficients for each relationship, and most importantly, statistical indexes that express the degree to which the data fits the proposed model, confirming its validity.

Among the strengths of SEM is the ability to construct latent variables, which are not directly measured, but are estimated from a number of variables and their mutual covariance within the model, allowing it to capture the reliability of the model. Factor analysis, path analysis, and linear regression represent special cases

Fig. 2 Methodologies [3] (Colín, 2007)

for structural equation modeling [4] (Iacobucci, 2010). It is a statistic destined for testing and estimating causal relations from statistical data and qualitative causal assumptions [5] (Iacobucci, 2009). This definition has been articulated by the geneticist Sewall [6] (Wright, 1999).

SEM was born from the need to offer more flexibility for the regression models. It is less restrictive than the regression models, allowing the handler to include error measurements in both subordinate variables (dependent) as the predictor (independent) variables. The structural equation modeling methodology is a fresh area for developing statistics regression models, including factor analysis. SEM has a confirmatory nature more than an exploratory a major strength is the ability to develop constructs that estimate latent variables based around measurable variables.

Figure 3 and Table 2 show a path diagram graphic array and for the table the notation used for each element within the path diagram and SEM methodology; this is a representation for a set of equations.

2.2 Applying the statistical analysis methodology SEM

Tables 3, 4, and 5 show the CF covariance and correlation among factors, for each of the three criteria evaluated: 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

Table 1 Project critical factors

Number	Critical factors	Total number of quotes	Total percentage of quotes	Total percentage of articles mentioning the factor
1	Support from senior management	61	5 %	72 %
2	Clear realistic objectives	64	5 %	75 %
3	Strong/detailed plan kept up to date	61	5 %	72 %
4	Good communication/ feedback	40	3 %	47 %
5	User/client involvement	39	3 %	46 %
6	Skilled/suitably qualified/sufficient staff team	62	5 %	73 %
7	Effective change management	55	5 %	65 %
8	Competent project manager	56	5 %	66 %
9	Strong business case/ sound basis for project	58	5 %	68 %
10	Sufficient/well allocated resources	64	5 %	75 %
11	Good leadership	44	4 %	52 %
12	Proven/familiar technology	53	4 %	62 %
13	Realistic schedule	24	2 %	28 %
14	Risks addressed/assessed/managed	51	4 %	60 %
15	Project sponsor/champion	21	2 %	25 %
16	Effective monitoring/control	53	4 %	62 %
17	Adequate budget	33	3 %	39 %
18	Organizational adaptation/ culture/structure	57	5 %	67 %
19	Good performance by suppliers/contractors/consultants	33	3 %	39 %
20	Planned close down/review/acceptance of possible failure	46	4 %	54 %
21	Training provision	53	4 %	62 %
22	Political stability	15	1 %	18 %
23	Correct choice/past experience of project management of project management	52	4 %	61 %
24	Environmental influences	16	1 %	19 %
25	Past experience (learning from)	50	4 %	59 %
26	Project size (large)/level of complexity (high)/number of people involved (too many)/duration (over 3 years)	34	3 %	40 %
27	Different viewpoints(appreciating)	13	1 %	15 %

Table 2 Basic SEM Notation [8] (Cea. 2004)

Variable	Matrix zymology	Description
Y	Y	Observable dependent variable
X	X	Observable independent variable
λ	$\wedge$	Coefficient between variables (observed or latent)
ε	$\theta\varepsilon$	Associated error to Y
δ	θ_δ	Associated error to X
ξ	ξ	Independent latent variable
η	η	Dependent latent variable
ζ	Ψ	Associated error to η
β	B	Coefficient between latent dependent variables
γ	Γ	Coefficient between latent independent variables
φ	ϕ	Covariance matrix associated to ξ

for evaluation; the most significant correlations are indicated as long as their *P* value is greater than 0.01, a total of 11 critical factors to consider for model building as shown in Table 6.

2.3 Development of a good theoretical model

Resulting from the theoretical analysis of the factors through meta-analysis, classified by frequency and empirical results, obtained from surveys conducted in companies of the region, then evaluated by statistical tools such as exploratory factor analysis and confirmatory factor analysis to determine the structural equations where success criteria are also related. In Fig. 4, we can see the first structural model proposed and the most important critical factors regarding BUDGET (P.E.B.B) QUALITY (C.M.P.) and TIME (T.O.M.S.).

Fig. 3 Example of structural equation model [7] (Cea, 2004) **Table 3** Correlations for the latent variable ‘fulfill the budget of the industrial project

		T. SUPPORT
T. PLAN	Person correlation	.342**
	Sig. (two-tailed)	0.000
T. MANAGER	Person correlation	.387**
	Sig. (two-tailed)	0.000
T. EFFECTIVE	Person correlation	.262**
	Sig. (two-tailed)	0.000
T. TECHNOLOGY	Person correlation	.386**
	Sig. (two-tailed)	0.000
T. KNOWLEDGE	Person correlation	.386**
	Sig. (two-tailed)	0.000

Table 4 Correlations for the latent variable fulfill the quality of the industrial project'

		Q. PERSONAL
Q. PLAN	Person correlation	.310**
	Sig. (two-tailed)	0.000
Q. SUPPLY	Person correlation	.342**
	Sig. (2-taild)	0.000
Q. PARTICIPATION	Person correlation	.375**
	Sig. (two-tailed)	0.000

2.4 Factor analysis

Factor analysis divides the variance of each indicator 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 types of model-based analysis for 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 mostly in the number and nature of specifications and restrictions in the measurement model for the latent variable.

Table 5 Correlations for the latent variable fulfill the budget of the industrial project

		B. PLAN
B. BUSINESS	Person correlation	.340**
	Sig. (two-tailed)	0.000
B. PERSONAL	Person correlation	.355**
	Sig. (two-tailed)	0.000
B. COMMUNICATION	Person correlation	.362**
	Sig. (two-tailed)	0.000
B. RISK	Person correlation	.341**
	Sig. (two-tailed)	0.000

Table 6 Critical success factors according to the bivariate correlation value

Highest correlation indicators				
No	Critical success factors	Correlation	Critical success factors	P value
1	Competent project manager	0.386	Proven/familiar technology	$P < 0.01$
2	Good communication/feedback	0.375	User/client involvement	$P < 0.01$
3	Effective monitoring/control	0.362	Good communication/ feedback	$P < 0.01$
4	Strong business case/ sound basis for project	0.355	Support from senior management	$P < 0.01$
5	Proven/familiar technology	0.347	Training provision	$P < 0.01$
6	Support from senior management	0.342	Strong business case/ sound basis for project	$P < 0.01$
7	Effective change management	0.342	Training provision	$P < 0.01$
8	Adequate budget	0.341	Risks addressed/assessed/managed	$P < 0.01$
9	Strong business case/ sound basis for project	0.340	Support from senior management	$P < 0.01$
10	Skilled/suitably qualified/sufficient staff team	0.310	Strong business case/ sound basis for project	$P < 0.01$
11	Clear realistic objectives	0.262	Effective change management	$P < 0.01$

Reference: correlation matrix

*Correlation is significant at level 0.01

*Correlation is significant at level 0.05

EFA is data-driven, there are no specifications in relation to the number of common factors or the relationships array between common factors. Researchers use the EFA as a descriptive technique to determine the appropriate number of common factors, and to check, according to measurement, which variables are reasonable indicators for latent dimensions. In CFA, the researcher specifies in advance the number of factors and load pattern expected for indicators, as well as other parameters, such as independence or covariance factors and unique variances and indicators

2.5 Exploratory factor analysis

Exploratory factor analysis is a statistical approach to determine the correlation between variables in a dataset. This type of factor analysis provides a structure (grouping of variables based on the strong correlations). In general, an EFA prepares the variables to be used and clean the structural equation models. An EFA should always be conducted for new datasets.

The advantage of an EFA on a CFA is that no theory is applied to the elements fitting a construct. This means that the EFA is able to detect problematic variables more easily than CFA. In this section, we will develop EFA for this research.

2.5.1 Explained variance matrix by the method of principal components

The variance matrix (Table 7) is explained by the principal method components, the Initial Eigen values columns of the table display the variance explained by the initial solution, only 11 major factors have a total column value greater than 1; eigenvalues represent almost 55 % of the variance for the original independent variables. This suggests that the three latent influences are associated with the factors, but there is room for a lot of unexplained variations.

The loads' extraction sums squared section shows the variance explained by the factors taken before rotation. The cumulative variability explained by three factors is about 30 %, a difference of 10 % of the initial solution, this variation explains that the initial solution is missing a latent factor, indicating that the original variables and variability cannot explain the phenomena with precision. The rightmost section of this table shows the variance explained by the factors extracted after rotation.

2.5.2 KMO and Barlett's test

These tables show two tests which indicate the suitability of the data to detect the structure (Table 8, 9). The sample

Fig. 4 Path diagram proposed form for structural model

Table 7 Total explained variance matrix

Total explained variance							
Component	Initial Eigen values			Loads extraction sums squared			Loads rotation sums squared
	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	57.363				
13	1.037	2.206	59.559				
14	1.013	2.156	61.715				
15	0.974	2.072	63.787				
16	0.946	2.012	65.799				
17	0.917	1.950	67.749				
18	0.852	1.812	69.561				
19	0.820	1.744	71.306				
20	0.795	1.692	72.998				
21	0.787	1.675	74.673				
22	0.744	1.583	76.256				

Extraction method: principal components analysis

^a When the components are correlated, the sums of squared added to obtain a total variance

measurement for Kaiser-Meyer-Olkin adequacy indicates the proportion of variance in the variables that may be caused by underlying factors. Higher values of 1.0 indicate that a factors analysis is suitable for the data; for values lower than 0.50, the results of the factor analysis are unlikely to be useful.

2.5.3 Pattern matrix

The elements of this matrix are called weights or loads, they indicate the load between observed variable and factor. It

should be interpreted as standardized slopes (beta) resembling multiple regression analysis. Differences for the tables (Tables 10, 11) show the modifications made through the exploratory factor analysis.

The solution for the Configuration Matrix must be interpreted by the performance method, similar to the matrix in the orthogonal rotated factors case. The oblique item is the most important of all matrices obtained; this is by setting “Matrix and Matrix” correlation between factors; it is essential to include it in the results analysis.

Table 8 Initial KMO

KMO and Bartlett's test	
Kaiser-Meyer_olkin Measure of sampling Adequacy.	0.789
Bartlett's Test of Sphericity	
Approx. Chi-Square	2922.314
df	1081
Sig.	0.000

Table 9 Final KMO

KMO and Bartlett's test	
Kaiser-Meyer_olkin Measure of sampling Adequacy.	0.799
Bartlett's Test of Sphericity	
Approx. Chi-Square	1827.043
df	561
Sig.	0.000

Table 10 Initial pattern matrix

Pattern matrix			
	Component		
	1	2	3
Q. PALN	.646		
Q. BUSINESS	.609		
Q. KNOWLEDGE	.585		
Q. COMMUNICATION	.564		
Q. OBJECTIVES	.551		
Q. PERSONAL	.548		
T. SUPPORT	.515		
Q. EFFECTIVE	.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. EFFECTIVE	.396		
Q. ADAPTATION	.390		
Q. SUPPORT	.383		
T. PLAN	.371		
Q. TECHNOLOGY	.346		
T. COMMUNICATION	.336		
T. MANAGEMENT	.319		.301
B. KNOWLEDGE		.678	
B. TECHNOLOGY		.603	
B. BUSINESS		.599	
B. PERSONAL		.584	
B. SUPPORT		.572	
B. MANAGER		.571	
B. PARTICIPATION		.570	
B. SUPPLY		.561	
B. COMMUNICATION		.560	
B. OBJECTIVES		.532	
B. EFFECTIVE		.496	
B. PLAN		.489	
B. MANAGEMENT		.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 Rotation converged in 6 iterations

2.6 Confirmatory factor analysis

“Confirmatory Factor Analysis” (CFA) is a type of structural equation modeling that deals specifically with measured models, the relationship between observable measurements or “indicators” and latent variables or “factors.” The models objective for latent variables is to set the number and the nature of the factors considered for the variance and

Table 11 Final pattern matrix

Pattern matrix ^a			
	Component		
	1	2	3
B. KNOWLEDGE	.684		
B. BUSINESS	.604		
B. TECHNOLOGY	.601		
B. PERSONAL	.593		
B. COMMUNICATION	.586		
B. PARTICIPATION	.572		
B. SUPPORT	.572		
B. MANAGER	.556		
B. OBJECTIVES	.551		
B. SUPPLY	.541		
B. EFFECTIVE	.504		
B. PLAN	.497		
B. MANAGEMENT	.483		
B. BUDGET	.478		
Q. BUSINESS		.639	
Q. PLAN		.617	
Q. KNOWLEDGE		.601	
Q. OBJECTIVES		.584	
Q. COMMUNICATION		.558	
Q. PERSONAL		.551	
Q. EFFECTIVE		.527	
Q. RISK		.509	
Q. MANAGER		.507	
Q. PARTICIPATION		.481	
Q. SUPPLY		.464	
Q. MANAGEMENT		.455	
T. EFFECTIVE		.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

covariance by a kit of indicators or CF. One latent feature is an unobservable variable that has greater influence than an observable measurement and is considered for correlations across the model.

2.6.1 Goodness fit indices

P value is a common index used in sociological research, a *P* value of 0.05 is considered as a threshold to define an effective or ineffective study. The obtained error can also be addressed by increasing the size of the sample, reducing the possibility that the obtained data is coincidentally rare.

Comparative fit index (CFI): A rule of thumb for CFI and other comparative fit indexes is a value greater than 0.90, it can reasonably indicate a good fit in the researcher's model [9] (Bentler, 2006).

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, $RMSEA \leq 0.06$ indicates close fit proximity, values between 0.06 and 0.08 suggest a reasonable fit error. And $RMSEA \geq 1$ suggests a poor fit [10] (Hoyle, 2012).

2.6.2 Initial results: modification Index comparison

Each parameter has a rate above certain preliminary modification index; not displayed modification indexes indicate that they do not exceed the specified threshold. At this point, the initial results established an initial proposed model with its regression loads and the goodness fit indexes are shown in the Fig. 5. Figure 6 illustrates the comparisons between indexes for goodness of fit for the three structural models. Initial model shows a *P* value (Table 12) for an effective study, RMSEA (Table 13) that indicates a close fit proximity, and a CFI (Table 14) close to a reasonable error fit.

2.6.3 Partial results: covariation of CF

For this partial model, the error variables *e31* and *e33* were covariate (Fig. 7) as the modification indexes showed the

Fig. 5 Initial model and its standardized estimations

highest relation between them in Table 15. This generate a better modeling fit compared with the initial model, tables for goodness fit indices confirm the improvement since the CFI and RMSEA improved (Tables 16, 17, and 18).

In Table 19, we can see the high relation among error variables *e26* and *e31*, however is impossible to covariate them because they are in different indicators sets. Regression loads and goodness fit indexes for the partial model are shown next (Fig. 7). Figure 8 illustrates the comparisons between indexes for goodness of fit that the structural model displays regarding *P* value, RMSEA, and CFI to previous comparison.

2.6.4 Simulation of fourth variable final results

Figure 9 shows the construction for regression loads model with fore latent factors, adding an additional simulated latent variable (success). Tables 20 and 21 indicated the regression loads for each relation with in the model; also, the three goodness of fit indicators show an improved proportion compared to the previous models in Tables 22, 23, and

Fig. 6 Comparison of goodness fit indexes for proposed comparative initial structural model

Table 12 Initial *P* value

Model	NPAR	CMIN	DF	<i>P</i>	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 13 Initial CFI

Model	NFI Delta 1	RFI rho 1	IFI Delta 2	TLI rho 2	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 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

Fig. 7 Partial model and its standardized estimations**Table 15** 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

Table 16 Partial *P* value

Model	NPAR	CMIN	DF	<i>P</i>	CMIN/DF
Default model	26	49.327	41	0.148	1.233
Saturated model	66	0	0		
Independence model	11	231.196	55	0	4.204

Table 17 Partial CFI

Model	NFI Delta 1	RFI rho 1	IFI Delta 2	TLI rho 2	CFI
Default model	0.0787	0.707	0.951	0.927	0.947
Saturated model	1	1	1		
Independence model	0	0	0	0	0

Table 18 Partial 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 19 Partial 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

Fig. 8 Comparison of goodness fit indexes for proposed partial structural model

24. Figure 10 illustrates the comparisons between indexes for goodness of fit that the structural model displays regarding P value, RMSEA, and CFI to the proposed partial structural model.

If the analysis is repeated the discrepancy between $e7$ and $e10$ in Table 25 is reduced at least 5.013 for the covariance treatment as a free parameter, for the simulated latent variable run this P value decreases to 0.032. The correlation estimates and the standardized regression loads are re-calculated, as an example, when quality rises 1 for standard deviation, Q . COMMUNICATION is adjusted at 0.302 standard deviation on Table 21.

2.7 Hypothetical regression structural equation modeling

The traditional approach to integrating multiple regression analysis and factor analysis involves factoring a set of equations of one or more predictors and outcomes, generating fac-

tor scores; also the creation of composited unit-weighted of the highest-loading indicators, using these variables as predictors or outcomes. SEM allows for these two components of the analytic strategy to be done simultaneously, at this point the relations between indicators, latent variables and the relations between variables are incorporated in a single model to be evaluated (Hoyle, 2012), here we develop the equation model for this research.

Regression equations:

$$\begin{array}{lll}
 \text{BUDGET} & \text{QUALITY} & \text{TIME} \\
 X_1 = \beta_1 + \lambda_1 \xi_1 + \eta_1 & X_5 = \beta_5 + \lambda_5 \xi_5 + \eta_5 & X_8 = \beta_8 + \lambda_8 \xi_8 + \eta_8 \\
 X_2 = \beta_2 + \lambda_2 \xi_2 + \eta_2 & X_6 = \beta_6 + \lambda_6 \xi_6 + \eta_6 & X_9 = \beta_9 + \lambda_9 \xi_9 + \eta_9 \\
 X_3 = \beta_3 + \lambda_3 \xi_3 + \eta_3 & X_7 = \beta_7 + \lambda_7 \xi_7 + \eta_7 & X_{10} = \beta_{10} + \lambda_{10} \xi_{10} + \eta_{10} \\
 X_4 = \beta_4 + \lambda_4 \xi_4 + \eta_4 & & X_{11} = \beta_{11} + \lambda_{11} \xi_{11} + \eta_{11}
 \end{array}$$

Structural model:

$$\eta_1 = \beta_{12} + \xi_1 + \beta_{13} + \xi_2 + \beta_{23} + \xi_3 + \xi_1$$

Fig. 9 Final model regression loads between critical factors and the project success criteria

Table 20 The correlation estimates and the standardized regression loads

		Estimate
B. STRONG BUSINESS CASE BASIS FOR PROJECT	<--- BUDGET	0.511
B. EFFECTIVE MONITORING/CONTROL	<--- BUDGET	0.476
B. STRONG/DETAILED PLAN KEPT UP TO DATE	<--- BUDGET	0.593
B. ADEQUATE BUDGET	<--- BUDGET	0.409
Q. GOOD COMMUNICATION/FEEDBACK	<--- QUALITY	0.343
Q. SKILLED/SUITABLE QUALIFIED/SUFFICIENT STAFF/TEAM	<--- QUALITY	0.373
Q. EFFECTIVE CHANGE MANAGEMENT	<--- QUALITY	0.567
T. Proven/FAMILIAR TECHNOLOGY	<--- TIME	0.338
T. COMPETENT PROJECT MANAGER	<--- TIME	0.44
T. SUPPORT FROM SENIOR MANAGEMENT	<--- TIME	0.562
T. CLEAR REALISTIC OBJEcTIVES	<--- TIME	0.253

3 Conclusions

There are tests for goodness of fit with the confirmatory analysis for the greatest indicator loads or endogenous variables, bringing about which of the CF should be taken with more care while managing an industrial project; this is if we want to influence the subsequent results for the values for latent variables and improve conditions, consequently decrease the size

of the error in each case of the endogenous variables (Table 24).

This contribution to the theory of project management is novel because applying meta-analysis intended for a large number of indicators filtered the most important final CF so they can be carefully chosen and described statistically by SEM methodology to quantify and qualify the relations among independent variables

Table 21 The correlation estimates and the standard regression loads

		Estimate
Q. COMMUNICATION	<--- QUALITY	0.302
Q. PERSONAL	<--- QUALITY	0.337
Q. MANAGEMENT	<--- QUALITY	0.524
B. BUSINESS	<--- BUDGET	0.512
B. EFFECTIVE	<--- BUDGET	0.474
B. PLAN	<--- BUDGET	0.594
B. BUDGET	<--- BUDGET	0.406
T. OBJECTIVES	<--- TIME	1.238
T. SUPPORT	<--- TIME	0.496
T. TECHNOLOGY	<--- TIME	0.308
T. MANAGER	<--- TIME	0.377
Q. COMUNICATION	<--- CLF	0.104
Q. PERSONAL	<--- CLF	0.136
Q. MANAGEMENT	<--- CLF	0.321
B. BUSINESS	<--- CLF	0.049
B. BUSINESS	<--- CLF	0.015
B. PLAN	<--- CLF	0.002
B. BUDGET	<--- CLF	0.079
T. OBJECTIVES	<--- CLF	-1.757
T. SUPPORT	<--- CLF	0.242
T. TECHNOLOGY	<--- CLF	0.2
T. MANAGER	<--- CLF	0.262

Table 22 Final *P* value

Model	NPAR	CMIN	DF	<i>P</i>	CMIN/DF
Default model	37	31.878	29	0.032	1.099
Saturated model	66	0	0		
Independence model	11	231.196	55	0	4.204

Table 23 Final CFI

Model	NFI Delta 1	RFI rho 1	IFI Delta 2	TLI rho 2	CFI
Default model	0.862	0.738	0.986	0.969	0.984
Saturated model	1		1		1
Independence model	0	0	0	0	0

Table 24 Final RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	0.022	0	0.06	0.864
Independence model	0.127	0.11	0.144	0

Table 25 Final modification indices

			M.I.	Par Change
e7	<—>	e10	5.013	−0.092
e3	<—>	e10	5.781	0.098
e2	<—>	e10	4.506	−0.089

with respect to the latent variables with in a set of equations.

4 Recommendations

Indicators of interest were revealed in the survey of factors that are selected and defined as most important criteria this are the exogenous critical factors and the endogenous variable success. It is recommended to continue this research by adding and endogenous latent variable for customer satisfaction and the observable dependent variables for satisfaction, applying the matching methods to change the model, its trajectories, and the set of regression equations.

It is recommended to apply this methodology and replicate the research to test the generality of the model or in other sectors and industries; for manufacturing improvement projects, it can test their effect on product added value, employee performance, cost and quality for clients or other types of projects; for physiological research it is recommended to apply SEM as a test for the effect of lifestyle settings on health, educational institutions can use statistical equation modeling to find the didactic means that have an important association with student knowledge acquirement, regarding psychology this tool is able to find the mayor influences associated with personal happiness.

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Fig. 10 Comparison of goodness fit indexes for final structural model

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