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Empirical study impact of risk management on business performance: case of Algerian construction organization

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Abstract

Risk management takes place timidly in Algerian construction companies. the aim of this study is to develop a strategic Risk Management System RMS and identify the best ways to identify, analyze and manage all risk streams to help the construction business remain competitive. In order to achieve the set objective, a questionnaire survey is carried out in this study. We were received 113 questionnaires from various Algerian construction companies. the result has been analyzed using both technique exploratory EFA and confirmatory CFA in the factorials analysis. Moreover, in order to identify the relationships between the theoretical concept's correlation and stepwise, regression analyses were used. the results obtained allow us to verify the factors that positively influence the improvement of performance

Keywords: *Algerian Construction Companies , CFA, EFA, Performance, Risk Management.*

Introduction

The environment in which construction companies operate has undergone a major change over the past ten years. In that case ,the need of project management and strategy has become primary and the consideration of the different risks that sur-round our projects requires a change in behavior within companies(Baba Ahmed, A. N., & Megnounif, 2020). The accumulation of risks and the relentlessness of companies that want to control their environment form fertile ground which gives rise to reflections on risk management. These reflections are undoubtedly not recent, except the fact that this approach has changed since the 18th century.

Pervious researches doesn't interest on the relation of risk-management-business, they analysis on rapport the risk with performance(Mohammed HK, 2016) or risk management-business performance(Sohrabinejad & Rahimi, 2015).It is therefore important to understand what are the factors and elements related to the risks that we must manage? What is the set of practices of the risk management process that manages these? And what is the impact of these on the performance of the Algerian construction company. In order to answer this research problem, three main objectivates has been identified as follow: the development of a strategic model of

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the risk management system, the evaluation of the relationships between each factor of the system and finally the proposed theoretical model which will be tested and enhanced.

The objective of this paper is to empirically test the proposed theoretical model by Baba Ahmed and Megnounif (Baba Ahmed, A. N., & Megnounif, 2020) and to observe the current level of implementation of the risk management system (RMS) in Algerian construction companies. the proposed system is based on a structure of four (04) main functions (identification, analysis, evaluation and processing). To achieve a harmonious system, relationships are assumed to exist between these functions, which will produce more value and increase the intensity of the process(Baba Ahmed, A. N., & Megnounif, 2020) . These relationships are analyzed by the APTE method, in order to define the system in its basic functions and sub-functions that are related to the delivery of the product/service and meeting the requirements of the stakeholders.

the proposed mode has been empirically tested using a structured questionnaire survey. The data were collected over a period of 18 months from companies operating in Algeria. Relying on Exploratory and confirmatory analysis procedures with multiple regression analysis to develop measurement scales to measure the constructs of the proposed model, first, and then identify the relationship between these constructs, second. We had to use SPSS and AMOS software to carry out this work.

Theoretical Framework

In recent years, research has increasingly focused on risks and safety in the construction industry(Amit E, Dutta B, 2014; Breysse D, Chaplain M, 2009; Lehtiranta L, 2011; Sohrabinejad & Rahimi, 2015).This is due to accidents on site, the rapid deterioration of completed projects, delays in the delivery of projects, communication problems between the actors of a project. therefore, compliance with the risk management process has become essential.

The project success is influenced by the risk management (Rezakhani P, 2012). Previous research has demonstrated that risk management (RM) can affect business performance by improving construction processes (Jafari, M., Aghaei Chadegani, A., & Biglari, 2011; Mohammed H. K., Knapkova, 2016) and the researchers make different risk classification as Zulqarnain classify the risk on five factors: business, financial, technical, project and politic(Zulqarnain I, 2014) .Rezkhani propose five factors External, operational, managerial, technical and environmental(Rezakhani P, 2012). Megnounif and d Kara Zaitri establish six element (Natural, technical, environmental, human-related and managerial)(Megnounif, A., & Kara Zaitri, 2010). Gajewska and Ropel define the risk on nine dimension Financial, political, environment, technical, project, human, market, security and equipment(Gajewska E, 2011).Violante(Violante A, Dominguez C, 2018) and carr(Tah JHM, 2000)define the risk on

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two element (Internal and external). Mehdizadeh Rasool (Mehdizadeh R, 2012)rank the risk on tree class: Stakeholders, management and external (financial, political, legal, natural, context). Niet-Morote and Ruz-Vila(Nieto-Morote A, 2011) establish four part(Implementation, resources, engineering, management).

However, several studies have focused on the relationship: risks - business performance (Sohrabinejad, A., & Rahimi, 2015), or: risk management - business performance(Jafari, M., Aghaei Chadegani, A., & Biglari, 2011; Mohammed H. K., Knapkova, 2016) .It must be noted that all the previous researches have looked at the three relationships at the same time: types of risk – risk management – company performance. Which eventually became the purpose of this work.

The studies carried out locally such as (Hamzaoui F, 2015; Megnounif, A., & Kara Zaitri, 2010) and (BENACHENHOU, 2019)prompted us to analyze more closely the level of risk management within Algerian construction companies, how it is applied and what procedures are followed. Therefore, the RM system applied to the environment of the construction company will be considered as a process that transforms the input data (risk) into output data (company performance) Transformation occurs through four main functions: Identify, Analyze, Evaluate and Treat. The description of these functions and their sub-functions is given in the table 1. To improve the intensity of the process and make the system more relevant, relationships between these functions has been suggested. by measuring it from four perspectives grasp from a literature review: financial perspective, customer perspective, internal process perspective, and learning and growth perspective.

Table 1 Description of the RMS functions by APTE method

Functions	Description	Sub-functions
Identify	This function consists of developing a list of risks that may affect the project objectives.	List Document Represent Transmit Collect
Analysis	It is the systematic use of available information to identify hazards and estimate risk.	Use Estimate Supply Etablish
Evaluate	Its purpose is to compare the results of the risk analysis with the risk criteria.	Measure Compare List the causes Provide feedback
Treat	It consists of developing the different strategies and responses in the event of the occurrence of one of the identified risks.	Measure Select Evaluate

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responses
Document

The hypotheses of the RMS

Most previous works have focused on the relationship: risks

- business performance(Sohrabinejad, A., & Rahimi, 2015) or: risk management

- business performance(Jafari, M., Aghaei Chadegani, A., & Biglari, 2011; Mohammed H. K., Knapkova, 2016) None of these studies looked at the three relationships at the same time: types of risk – risk management – business performance (Chen.L.E, 2007).

This is precisely the objective of this work. (The proposed risk management and performance is shown in figure 1).

In order to test the suggested model 13 hypotheses has been suggested as follow:

Hypothesis 1 (H1)

Environmental, financial, technical, natural, political and managerial risks are positively linked to each other.

Hypothesis 2 (H2)

The risk group is positively related to the risk identification.

Hypothesis 3 (H3)

The risk group is positively related to the risk analysis.

Hypothesis 4 (H4)

The risk group is positively related to the risk rating.

Hypothesis 5 (H5)

The group of risks is positively related to the treatment of risks.

Hypothesis 6 (H6)

Risk identification is positively linked to the other functions of risk management.

Hypothesis 7 (H7)

Risk analysis is positively linked to other risk management functions.

Hypothesis 8 (H8)

The risk análisis is positively linked to other functions of risk management

Hypothesis 9 (H9)

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Risk analysis is positively linked to other risk management functions.

Hypothesis 10 (H10)

The learning perspective is positively related to the functions of the process.

Hypothesis 11 (H11): The process perspective is positively linked to the other functions of risk management.

Hypothesis 12 (H12): The customer perspective is positively linked to the other functions of risk management.

Hypothesis 13 (H13): The financial perspective is positively linked to the other functions of risk management.

Hypothesis 13 (H13) :the financial perspective is positively linked to other functions of risk management .

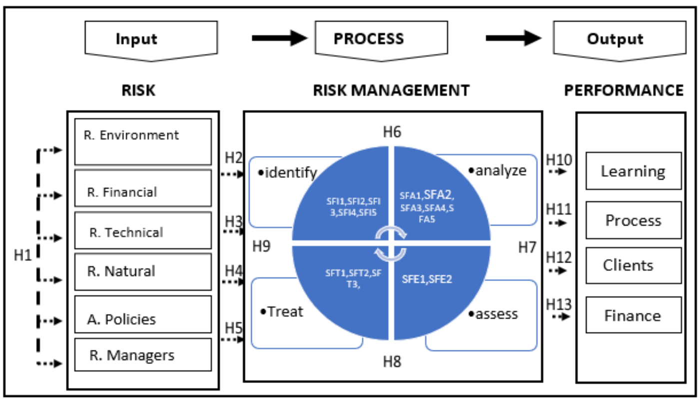

Figure1 The proposed risk management and performance model

Methodology

Questionnaire survey with the collaboration of Algerian construction companies has been conducted to test the hypotheses mentioned above. The questionnaire intended for the CEO or the general manager and the project managers was divided into four main sections : The 1st collects general information about the respondent and his company (status, size, region, position held, experience, etc.), the 2nd provide information about the existence of the risk in the company, the 3rd determine the level of importance and the current level of the functions of the RMS within the company and the 4th enable the collection of information on the performance of the company. We used a five-point Likert-type scale, ranging from 1 (totally disagree) to 5 (totally agree). This for measure the research variables.

The questionnaire includes a total of 125 statements (items). 211 questionnaires were distributed to Algerian construction companies, yet only 113 questionnaires were received this process lasted over a period of 18 months.

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To structure this work, the following a methodology shown schematically in Fig. 2. allows us to examine all the process of the RMS in the Algerian construction companies.

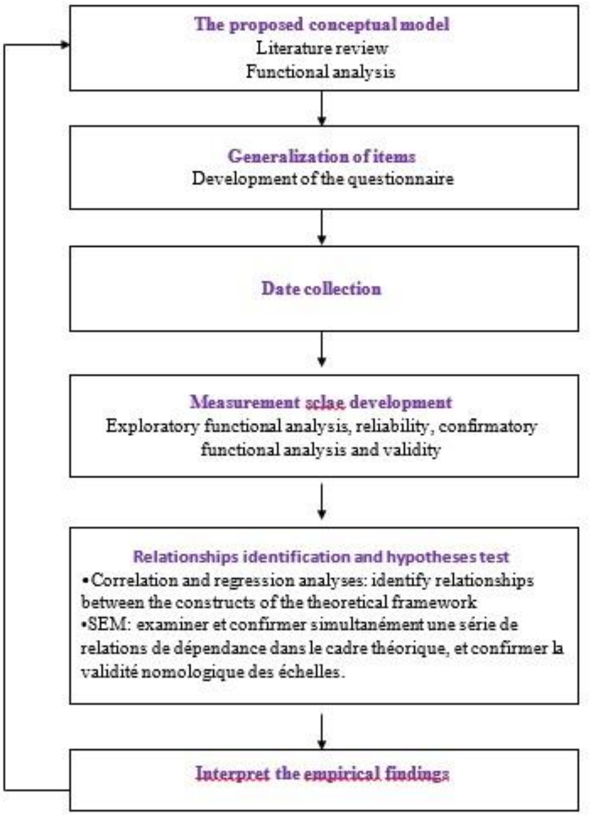

Figure 2 Strategy adopted in this research

Data analyses

The questionnaire has 14 constructs in the proposed theoretical framework. RN: Natural risks, RF: Financial risk RP: Political risks, RE: Environmental risks, RM: Managerial risks, RT: Technical risks, SFI: Identify, SFA: Analyze, SFE: Evaluate, SFT: Treat, PF: Financial perspective, PC: Customer perspective, PP: Process perspective, PA: Learning perspective.

The exploratory factor analysis (EFA) assesses the validity and internal consistency of scales used in a study. EFA helps identify the structure among the measurement variables for each construct and aids in data reduction.

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Fourteen constructs were analyzed in the study, and most of them showed significant sphericity except for one scenario, "managerial risks," which was excluded due to its low Kaiser-Meyer-Olkin (KMO) value. Overall, Cronbach's alpha, a measure of reliability, remained above 0.6 for the analyzed constructs.

Table2 Factorability of the EFA

Constructs	KMO	Bartlett's test sphericity	Anti-image
RF : Financials risks (2 factors)	0.682	158,74	0.011-0.874
RP : Politics risks (2 factors)	0.702	298.45	0.000-0.613
RM : Managerials risks (7 factors)	0.435	2344,74	0.000-0.298
RN : Naturals risks (2 factors)	0.805	584.12	0.001-0.757
RT : Technicals risks (1 factor)	0.761	490.54	0.007-0.553
RE : Environementals risks (2 factors)	0.807	842.31	0.000-0.439
SFI : Sub-function identify (2facteos)	0.788	898.359	0.001-0.473
SFA : Sub-function analyze (1factor)	0.864	777.596	0.001-0.345
SFE : Sub-function evaluate (2 factors)	0.861	1745.287	0.001-0.339
SFT : Sub-function treat (1 factor)	0.836	1731.357	0.001-0.183
PF : Financial perspective (1 factor)	0.796	332.18	0.19-0.907
PC : Customer perspective (1 factor)	0.766	471.50	0.016-0.337
PP : Internal process perspective (2 factors)	0.807	583.62	0.002-0.288
PA : Learning perspective (2 factors)	0.821	579,73	0.01-0.360

The results of the EFA are based on a synthesis of the literature review and previous empirical studies, these scales are considered "valid" (Pallant, 2020).Note that we have a sample of 113, we have considered a factor load of 0.50 and more at the level of 0.05, this for obtaining a power level of 80% (Pallant, 2020).

It should be noted that in our analysis, variables with a factor of less than 0.50 have been eliminated(Mohammed H. K., Knapkova, 2016) .In order to determine the number of factors to be considered, we used two criteria(Byrne, 2016)

- The Kaiser criterion where only factors with an own value of 1.0 and more were used;
- Catell landslide test where only factors above the elbow of eigenvalues were retained.

The data structure for the RF construct is as follows:

- The Construct has been perceived as having two dimensions (external and internal risks). Initial analysis of the main components confirmed that the RF construct had two components with eigenvalues greater than 1.0. The EFA identified two FAC1RF and FAC2RF factors; this explains 63.6% of the variance. The RF Cronbach alpha coefficient is 0.669 indicating good internal consistency.

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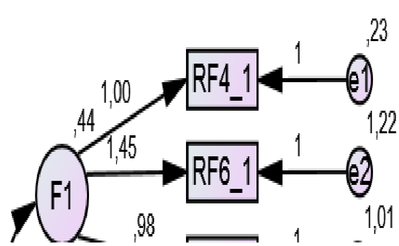
Consequently, the same steps and proceeded were employed in the same way for the following constructs: RP, RN, RT, RE, SFI, SFA, SFE, SFT, PF, PC, PP and PA .

Following this EFA on the 12 constructs we note that the KMO varies between 0.619 and 0.821 and the probability of the Bartlett sphericity test of 0.000 ($p<0.001$). From this we can conclude that the data are factorizable and that can accept the results of this factor analysis. With Cronbach Alpha we can say that the reliability of the measuring scale is satisfactory. The research revealed that in some constructs there is only one or two factors unlike the others. In which, only variables with a weight of more than 0.5 have been included in the definition of these factors. After conducting the EFA, confirmatory factory analyses were utilized in order to gather variables on the factors that will correspond to the theoretical model of the study.

Confirmatory Factoy Analysis

the results given in the tables of 3 through 16 represent the exploratory factory analysis, based on these results, models from the initial confirmatory factory analysis were used to test the multi-dimensionality and factorial validity of the constructs of the theoretical framework (Jöreskog, K. G., & Sörbom, 1993) AMOS software was used for the perfect completion of the CFA. For the estimation method for SEM analysis, the Maximum Likelihood Estimate (MLE) was used. The model was then evaluated by statistical means to determine the adequacy of its quality to fit the sample data. CFA were also used to reduce the number of variables to improve the parsimony of the scale structure. As shown in Tables 17 through 29, RF, RP, RN, RE, SFI, SFE, PP and PA were designed with two factors, while RT, SFA, SFT, PF, and PC were designed with only one factor derived from the EFA.

Table 17 EFA and CFA of the RF construct

Factor and measures variable	**EFA factor loading***	**CFA**			**Final model RF with standard estimation**
		SMC**	**Factor loading*****	**CR*******	
Financials risks					
Factor 1 :					
RF4_1	0.842	0.654	0.848	2.371	
RF6_1	0.817	0.433	0.800	4.79	
RF3_1	n				
RF5_1	0.657	0.294	0.724	6.227	
Factor 2 :					
RF1_1	0.772	0.134	0.807	2.062	
RF2_2	0.812	0.684	0.799	0.154	

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Note :
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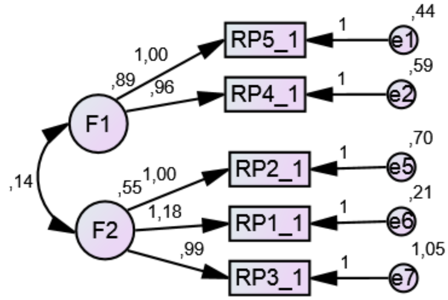
Table

Factor and measures variable	EFA factor loading*	CFA			Final model RP with standard estimation
		SMC**	Factor loading***	CR****	
Politicals risks					
Factor 1 :					
RP5_1	0.895	0.667	0.888	0.901	
RP4_1	0.819	0.578	0.904	1.307	
RP7_1	N				
RP6_1	N				
Factor 2 :					
RP2_1	0.846	0.438	0.835	5.241	
RP1_2	0.832	0.779	0.853	1.574	
RP3_2	0.729	0.338	0.759	6.06	



Note :
Vs :Variable (EP8) removed after evaluation

Table 1 EFA and CFA of the RP construct

Factor and measures variable	EFA factor loading*	CFA			Final model RN with standard estimation
		SMC**	Factor loading***	CR****	
Naturals Risks					
Factor 1 :					
RN5_1	0.892	0.774	0.893	4.648	
RN4_1	0.853	0.751	0.896	4.899	
RN3_1	0.801	0.732	0.895	5.246	
RN9_1	n				
RN6_1	n				
Factor 2 :					
RN8_1	0.830	0.181	0.949	6.724	
RN2_1	n				

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RN1_1	0.698	1.115	0.627	-0.349

Note :

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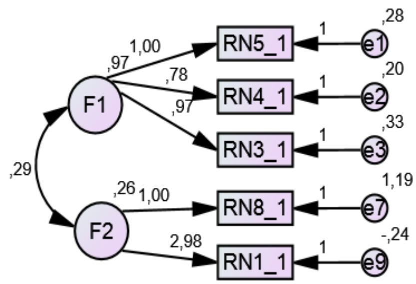
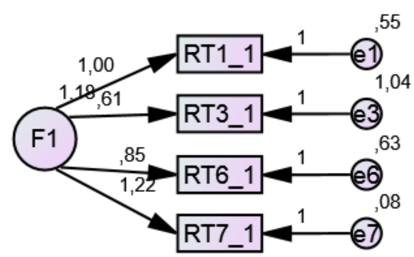


Table 2 EFA and CFA of the RN construct

Factors measure variable	**EFA factor loading***	**CFA**			**Final model RT with standard estimation**
		SMC**	**Factor loading*****	**CR******	
Technical Risks					
Factor 1 :					
RT1_1	0.832	0.684	0.891	5.653	
RT2_1	n				
RT3_1	0.680	0.300	0.706	7.223	
RT4_1	n				
RT5_1	n				
RT6_1	0.858	0.572	0.817	6.892	
RT7_1	0.854	0.959	0.933	0.853	



Note :
Vs :Variable (EP8) removed after evaluation

Table 3 EFA and CFA of the RT construct

Factors measure avriable	**EFA factor loading***	**CFA**			**Final model RE with standard estimation**
		SMC**	**Factor loading*****	**CR******	
Environnemental Risks					
Factor 1 :					
RE7_1	0.904	0.677	0.860	4.335	
RE9_1	0.839	0.635	0.878	4.892	

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RE8_1	0.675	0.583	0.826	5.424
RE10_1	N			
RE6_1	N			
RE2_1	N			
RE5_1	N			
RE4_1	N			
Factor 2 :				
RE3_1	0.870	0.094	0.922	6.500
RE1_1	0.734	1.755	0.695	-0.583

Note :
Vs :Variable (EP8) removed after evaluation

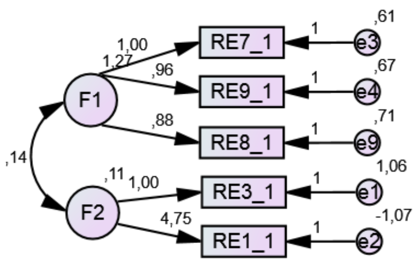

Table 4 EFA and CFA of the RE construct

Factors and measure variables	**EFA factor loading***	**CFA**			**Final model FI with standard estimation**
		SMC**	**Factor loading*****	**CR******	
Risks identification					
Factor 1 :					
SFI52NA_1	0.934	0.816	0.852	3.375	
SFI51NA_1	0.907	0.974	0.870	0.454	
SFI32NA_1	N				
SFI42NA_1	N				
Factor 2 :					
SFI21NA_1	N				
SFI41NA_1	0.744	0.883	0.850	1.591	
SFI11NA_1	0.737	0.570	0.729	5.946	
SFI13NA_1	N				
SFI12NA_1	0.599	0.280	0.677	6.972	

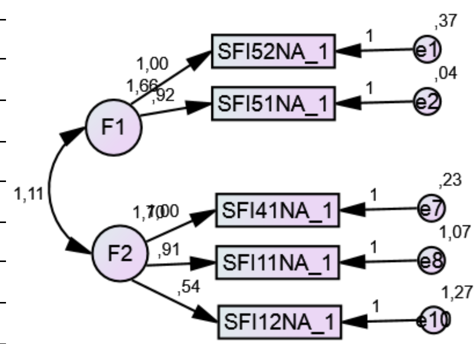

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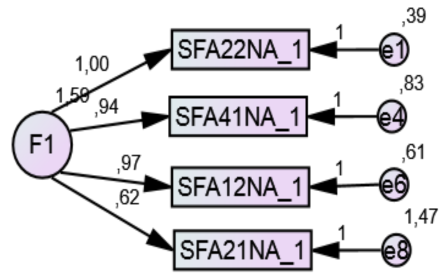
Table 5 EFA and CFA of the SFI construct

Factors and measure variables	EFA*	CFA			Final model FA with standard estimation
		SMC**	Factor loading***	CR****	
Risks Analysis					
Factor 1 :					
SFA22NA_1	0.913	0.803	0.906	3.541	
SFA31NA_1	N				
SFA23NA_1	N				
SFA41NA_1	0.840	0.628	0.856	5.791	
SFA11NA_1	,				
SFA12NA_1	0.830	0.711	0.875	4.961	
SFA42NA_1	N				
SFA21NA_1	0.628	0.294	0.673	7.109	



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Vs :Variable (EP8) removed after evaluation

Table 6 EFA and CFA of the SFA construt

Factors measure variable	EFA factor loading*	CFA			Final model FE with standard estimation
		SMC**	Factor loading***	CR****	
Risks Evaluation					
Factor 1 :					
SFE11NA_1	N				
SFE12NA_1	N				
SFE13NA_1	N				
SFE22NA_1	N				
SFE21NA_1	0.822	0.787	0.764	4.400	
SFE42NA_1	0.790	0.998	0.869	0.05	
Factor 2 :					
SFE32NA_1	0.950	0.317	0.921	7.237	
SFE31NA_1	0.942	0.854	0.918	3.539	
SFE43NA_1	0.887	0.910	0.920	2.238	
SFE41NA_1	n				

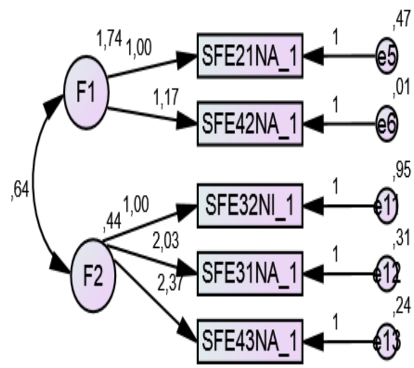

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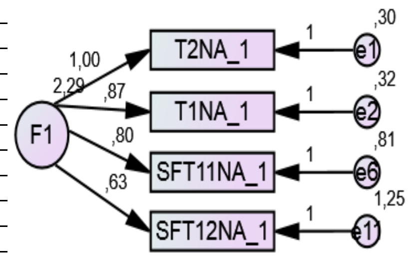
Tableau 7 EFA and CFA of the SFE construct

Factors measure variable	EFA factor loading*	CFA			Final model FT with standard estimation
		SMC**	Factor loading***	CR****	
Risks treatment					
Factor 1 :					
T2NA_1	0.925	0.884	0.928	3.289	
T1NA_1	0.914	0.845	0.924	4.211	
SFT4NA_1	n				
SFT21NA_1	n				
SFT22NA_1	n				
SFT11NA_1	0.858	0.643	0.873	6.571	
SFT32NA_1	n				
T3NA_1	n				
T4NA_1	n				
SFT13NA_1	n				
SFT12NA_1	0.735	0.419	0.773	7.084	
SFT31NA_1	n				



Note :
Vs :Variable (EP8) removed after evaluation

Table 8 EFA and CFA of the SFT construct

Factors measure variable	EFA factor loading*	CFA			Final model FT with standard estimation
		SMC**	Factor loading***	CR****	
Financial Perspective					
Factor 1 :					
PF2_1	0.942	0.926	0.950	1.513	
PF3_1	0.902	0.714	0.908	5.393	
PF4_1	n				
PF5_1	0.819	0.644	0.891	6.137	

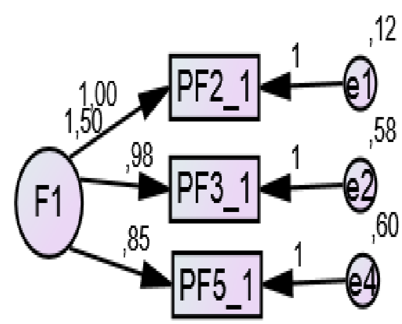


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Table 9 EFA and CFA of the PF construct

Factors measure avriable	EFA factor loading*	CFA		
		SMC**	Factor loading***	CR****
Customer Perspective				
Factor 1 :				
PC5_1	n			
PC3_1	0.895	0.886	0.938	2.259
PC4_1	0.894	0.835	0.931	3.267
PC2_1	0.862	0.517	0.849	6.864
PC1_1	n			

Note :
Vs :Variable (EP8) removed after evaluation

Final model PC with standard estimation

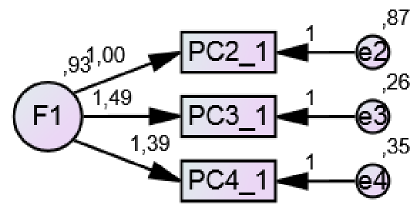


Table 10 EFA and CFA of the PC construct

Factors measure variable	EFA factor loading*	CFA		
		SMC**	Factor loading***	CR****
Perspective Processus				
Factor 1 :				
PP5_1	0.918	0.897	0.857	1.294
PP4_1	0.896	0.755	0.822	3.323
PP6_1	N			
Factor 2 :				
PP3_1	0.892	0.583	0.768	4.778
PP1_1	0.876	1.029	0.862	-0.243
PP2_1	n			

Note :
Vs :Variable (EP8) removed after evaluation

Final model PP with standard estimation

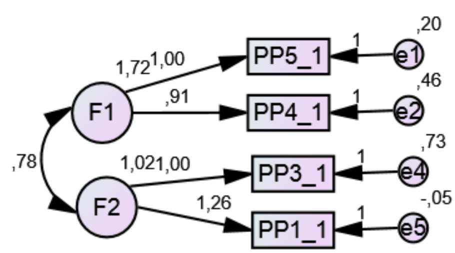
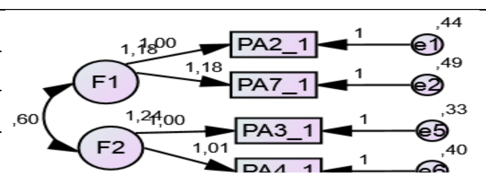


Table 11 EFA and CFA of the PP construct

Factors measure variable	EFA factor loading*	CFA		
		SMC**	Factor loading***	CR****
Learning perspective				
Factor 1 :				
PA2_1	0.917	0.729	0.914	2.273
PA7_1	0.863	0.769	0.910	1.870

Final model PA with standard estimation



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PA1_1	n			
PA6_1	n			
Factor 2 :				
PA3_1	0.899	0.787	0.917	1.788
PA4_1	0.887	0.759	0.919	2.078
PA5_1	n			

Note :
Vs :Variable (EP8) removed after evaluation

To begin the analysis, we will use the underlying EFA measurement variables related to their corresponding factors to begin the assessment process. Then, during the model evaluation process, we will identify possible measurement variables for the final CFA models that adequately match the data, based on statistical coefficients and adjustment indices(Hair Jr., J. F., Anderson, R. E., Tatham, R. L., & Black, 1998) .To obtain a good model, an assessment of the adequacy of the parameter estimates and the overall fit of the CFA models will be carried out for all constructed models. Adjustment of individual parameters has three aspects(Jöreskog, K. G., & Sörbom, 1993)

- The feasibility of parameter estimates
- Appropriateness of standard errors;
- Statistical significance of parameter estimates.

Several adjustment measures have been considered for the adjustment of the overall model of AF models:

- Absolute (Chi-square, probability level, CMA, GFI and AGFI;
- Incremental (Standard Chi-Square, IFN, IFI and TLI);
- Parsimonious (RMSEA, p close, AIC, BCC and ECVI).

In this study, if certain adequacy tests are not met, a re-specification of the model is considered and a new CFA is performed. After evaluation of all successive CFA models for all constructs, the final selected CFA models are shown in Tables 17trough 28. For the RF construct, the likelihood ratio test revealed a $\chi 2 = 30.7$ with a degree of freedom (L.D.) =8 and a probability= (0.000<0.2) (Byrne 2001). The model's absolute indices, such as RMR (0.101>0.05), GFI

(0.922> 0.90) and (AGFI 0.794<0.900), suggest an adjustment that requires model improvement to correct the AGFI value (Jöreskog, K. G., & Sörbom, 1993).Incremental fit measurement values (CFI (0.848), IFI (0.855) and TLI (0.715< 0.95), and NFI value (0.813>0.90) confirm fit to data.

The value of RMSEA for the model is 0.159. The 90% confidence interval for RMSEA, ranged from 0.102 to 0.221, these results indicate the correct accuracy but for the p value for the fit proximity test is 0.002 which remains much lower than 0.5. The AIC (56.66), BCC (58.39) and ECVI (0.521) values for the CFA model are lower than the independent model but slightly higher than the saturated model.

On the basis of these indices, we have to define our model in order to try to obtain a model that fits well with the data(Kot S, 2015) . These adjustment indices suggest that this initial hypothetical model is fairly consistent with the data. Our model therefore appears rather parsimonious. The largest change index values are in variable RF3. After an attempt, this variable was eliminated and the results improved, so this two-factor model represents a satisfactory fit to the data, and therefore confirms the scale's dimensionality. On the basis of these results, the measurement scale represented by the model was considered to have sufficient validity and reliability (0.529) to measure the RF construct in the subsequent multivariate analysis. For RP construct the likelihood ratio test revealed a $\chi 2$ =59.192 with a degree of freedom (D.L.) of 13 and a probability of (0.000<0.2)(Jöreskog, K. G., & Sörbom, 1993) . The model's absolute indices, such as RMR (0.125>0.05), GFI (0.872< 0.90) and (AGFI 0.724<0.900), propose an adjustment that requires modification and improvement of the model to correct the GFI and AGFI values(Jöreskog, K. G., & Sörbom, 1993) .

Incremental adjustment measurement values (CFI (0.839), IFI (0.843) and TLI (0.74< 0.95), and NFI value of 0.808<0.90) invalidate the adjustment to the data. The RMSEA value for the model is 0.178. The 90% confidence interval for RMSEA, ranged from 0.134 to 0.225, these results indicate the correct accuracy while the p value for the fit proximity test is 0.002 which remains much lower than 0.5. The AIC (56.66), BCC (91.5) and ECVI (0.796) values for the CFA model are lower than the independent model but slightly higher than the saturated model. Based on these indices, we need to define our model to try to obtain a model that fits the data well (James Jaccard; Michael A Becker, 2010).These adjustment indices suggest that this initial hypothetical model is fairly consistent with the data. Our model therefore appears rather parsimonious. The largest change index values are in variable RF3. After an attempt, this variable was eliminated and the results improved, so this two-factor model represents a satisfactory fit to the data, therefore confirming the scale's dimensionality. On the basis of these results, the measurement scale represented by the model was considered to have sufficient validity and reliability (0.529) to measure the RF construct in the subsequent multivariate

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analysis. For the RN construct the likelihood ratio test revealed a $\chi 2$ of 87.112 with a degree of freedom (D.L.) of 19 and a probability of (0.000<0.2)(Jöreskog, K. G., & Sörbom, 1993). The model's absolute indices, such as RMR (0.096>0.05), GFI (0.854< 0.90) and (AGFI 0.723<0.900), suggest an adjustment that requires a slight modification and improvement of the model in order to correct the GFI and AGFI values (Jöreskog, K. G., & Sörbom, 1993).Incremental fit measurement values (CFI (0.848), IFI (0.873) and TLI (0.715< 0.95), and NFI value of 0.813<0.90) invalidate the fit to the data.

The value of RMSEA for the model is 0.159. The 90% confidence interval for RMSEA, ranged from 0.142 to 0.218, these results indicate the correct accuracy except that the p value for the adjustment proximity test is 0.00 which remains much lower than 0.5. The AIC (121.11), BCC (124.08) and ECVI (1.081) values for the CFA model are lower than the independent model but slightly higher than the saturated model. Based on these indices, we need to define our model to try to obtain a model that fits the data well (James Jaccard; Michael A Becker, 2010).These adjustment indices suggest that this initial hypothetical model is fairly consistent with the data. Our model therefore appears rather parsimonious.

The highest change index values are found in the variables RN2, RN6 and RN9. After several tests, we managed to eliminate these variables and the results improved significantly. So, this two-factor model represents a satisfactory fit to the data, and therefore confirms the dimensionality of the scale. On the basis of these results, the measurement scale represented by the model was considered to have sufficient validity and reliability (0.874) to measure the RN construct in the subsequent multivariate analysis.

For the construct RT the likelihood ratio test revealed a $\chi 2$ of 121.62 with a degree of freedom (D.L.) of 14 and a probability of (0.000<0.2)(Jöreskog, K. G., & Sörbom, 1993) . The model's absolute indices, such as RMR (0.135>0.05), GFI (0.777< 0.90) and (AGFI 0.553<0.900), suggest an adjustment that requires a slight refinement of the model to correct the GFI and AGFI values(Jöreskog, K. G., & Sörbom, 1993) . Incremental fit measurement values (CFI (0.779), IFI (0.782) and TLI (0.669< 0.95), and NFI value of 0.761<0.90) invalidate the fit to the data. The RMSEA value for the model is 0.262. The 90% confidence interval for RMSEA, ranged from 0.220 to 0.306, these results indicate the correct accuracy except that the p value for the adjustment proximity test is 0.00 which remains much lower than 0.5. The AIC (149.62), BCC (151.77) and ECVI (1.336) values for the CFA model are lower than the independent model but slightly higher than the saturated model. Based on these indices, we need to define our model to try to obtain a model that fits the data well (James Jaccard; Michael A Becker, 2010). These adjustments indices suggest that this initial hypothetical model is fairly consistent with the data. Our model therefore appears rather parsimonious.

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The largest change index values are found in the RT2, RT4 and RT5 variables. After several tests, able to eliminate these variables and the results improved significantly. So, this one-factor model represents a satisfactory fit to the data, confirming the scale's dimensionality. On the basis of these results, the measurement scale represented by the model was considered to have sufficient validity and reliability (0.88) to measure the RT construct in the subsequent multivariate analysis.

For the construct RE the likelihood ratio test revealed a χ2 of 236.96 with a degree of freedom (L.D.) of 8 and a probability of (0.000<0.2)(Jöreskog, K. G., & Sörbom, 1993) . The model's absolute indices, such as RMR (0.136>0.05), GFI (0.740< 0.90) and (AGFI 0.580<0.900), suggest an adjustment that requires a slight modification of the model to correct the GFI and AGFI values(Jöreskog, K. G., & Sörbom, 1993) .Incremental adjustment measurement values (CFI (0.760), IFI (0.763) and TLI (0.683< 0.95), and NFI value of 0.734<0.90) invalidate the adjustment to the data.

The RMSEA value for the model is 0.231. The 90% confidence interval for RMSEA, ranged from 0.204 to 0.259, these results indicate the correct accuracy except that the p value for the adjustment proximity test is 0.00 which remains much lower than 0.5. The AIC (278.96), BCC (283.54) and ECVI (2.491) values for the CFA model are lower than the independent model but slightly higher than the saturated model. Based on these indices, we need to define our model to try to obtain a model that fits the data well (James Jaccard; Michael A Becker, 2010).

These adjustment indices suggest that this initial hypothetical model is fairly consistent with the data. The model therefore appears rather parsimonious. The largest change index values are found in the variables AR2, RE4, RE5, RE6 and RE10. After several tests, these variables were eliminated and the results improved significantly. So, this two-factor model represents a satisfactory fit to the data, and therefore confirms the dimensionality of the scale.

On the basis of these results, the measurement scale represented by the model was considered to have sufficient validity and reliability (0.906) to measure the RE construct in the subsequent multivariate analysis .For the construct SFI the likelihood ratio test revealed a χ2 of 165.12 with a degree of freedom (D.L.) of 26 and a probability of (0.000<0.2)(Jöreskog, K. G., & Sörbom, 1993) . The model's absolute indices, such as RMR (0.179>0.05), GFI (0.778< 0.90) and (AGFI 0.615<0.900), suggest an adjustment that requires a slight modification of the model to correct the GFI and AGFI values (Jöreskog, K. G., & Sörbom, 1993) . Incremental adjustment measurement values (CFI (0.824), IFI (0.826) and TLI (0.757< 0.95), and NFI value of 0.800<0.90) invalidate the adjustment to the data.

The RMSEA value for the model is 0.219. The 90% confidence interval for RMSEA, ranged from 0.187 to 0.251, these results indicate the correct accuracy except for the p value for the fit

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proximity test is 0.00 which remains much lower than 0.5. The AIC (203.12), BCC (206.85) and ECVI (1.814) values for the CFA model are lower than the independent model but slightly higher than the saturated model. Based on these indices, we need to define our model to try to obtain a model that fits the data well (James Jaccard; Michael A Becker, 2010). These adjustment indices suggest that this initial hypothetical model is fairly consistent with the data. Our model therefore appears rather parsimonious.

The largest change index values are in FSI32, SFI42, SFI21 and SFI13. After several tests, these variables were eliminated and the results improved significantly. So, this two-factor model represents a satisfactory fit to the data, and therefore confirms the dimensionality of the scale. On the basis of these results, the measurement scale represented by the model was considered to have sufficient validity and reliability (0.851) to measure the SFI construct in the subsequent multivariate analysis.

For SFA construct the likelihood ratio test revealed a $\chi2$ of 142.83 with a degree of freedom (D.L.) of 20 and a probability of $(0.000<0.2)$ (Jöreskog, K. G., & Sörbom, 1993) The model's absolute indices, such as RMR $(0.144>0.05)$, GFI $(0.772< 0.90)$ and (AGFI $0.590<0.900$), suggest an adjustment that requires a slight improvement of the model in order to correct the value of GFI and AGFI (Jöreskog, K. G., & Sörbom, 1993) Incremental fit measurement values (CFI (0.844), IFI (0.845) and TLI $(0.871< 0.95)$, and NFI value of $0.825<0.90$) invalidate the adjustment to the data.

The RMSEA value for the model is 0.234. The 90% confidence interval for RMSEA, ranged from 0.199 to 0.271, these results indicate the correct accuracy except that the p value for the adjustment proximity test is 0.00 which remains much lower than 0.5. The AIC (174.83), BCC (177.62) and ECVI (1.561) values for the CFA model are lower than the independent model but slightly higher than the saturated model. On the basis that these indices we need to define our model in order to try to obtain a model that fits well with the data(James Jaccard; Michael A Becker, 2010) . These adjustment indices suggest that this initial hypothetical model is fairly consistent with the data. our model therefore appears rather parsimonious.

The largest change index values are in FSA31, SFA23, SFA11 and SFA42. After several tests, these variables were eliminated leading to improving the results significantly as shown in Table 17 to 29 So, this one-factor model represents a satisfactory fit to the data, and therefore confirms the dimensionality of the scale. On the basis of these results, the measurement scale represented by the model was considered to have sufficient validity and reliability (0.848) to measure the SFA construct in the subsequent multivariate analysis.

For SFE construct the likelihood ratio test revealed a $\chi2$ of 307.94 with a degree of freedom (L.D.) of 34 and a probability of $(0.000<0.2)$ (Byrne 2001). The model's absolute indices, such

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as RMR (0.172>0.05), GFI (0.666< 0.90) and (AGFI 0.459<0.900), suggest an adjustment that requires a slight refinement of the model to correct the GFI and AGFI values (Jöreskog, K. G., & Sörbom, 1993). Incremental adjustment measurement values (CFI (0.821), IFI (0.822) and TLI (0.763< 0.95), and NFI value of 0.805<0.90) invalidate the adjustment to the data. The RMSEA value for the model is 0.268. The 90% confidence interval for RMSEA, ranged from 0.241 to 0.296, these results indicate the correct accuracy except for the p value for the fit proximity test is 0.00 which remains much lower than 0.5. The AIC (349.94), BCC (354.52) and ECVI (3.124) values for the CFA model are lower than the independent model but slightly higher than the saturated model. Based on these indices, we need to define our model to try to obtain a model that fits the data well (James Jaccard; Michael A Becker, 2010). These adjustment indices suggest that this initial hypothetical model is fairly consistent with the data. Our model therefore appears rather parsimonious. The largest change index values are in SFE11, SFE12, SFE13, SFE22, SFE41. After several tests, these variables were eliminated and the results improved significantly. So, this one-factor model represents a satisfactory fit to the data, and therefore confirms the dimensionality of the scale. On the basis of these results, the measurement scale represented by the model was considered to have sufficient validity and reliability (0.882) to measure the SFE construct in the subsequent multivariate analysis.

For SFT construct the likelihood ratio test revealed a $\chi 2$ of 648.6 with a degree of freedom (L.D.) of 54 and a probability of (0.000<0.2) (Jöreskog, K. G., & Sörbom, 1993). The model's absolute indices, such as RMR (0.185>0.05), GFI (0.593< 0.90) and (AGFI 0.412<0.900), suggest an adjustment that requires a slight improvement of the model in order to correct the value of GFI and AGFI (Jöreskog, K. G., & Sörbom, 1993). Incremental adjustment measurement values (CFI (0.665), IFI (0.668) and TLI (0.591< 0.95), and NFI value of 0.648<0.90) invalidate the adjustment to the data. The RMSEA value for the model is 0.314. The 90% confidence interval for RMSEA, ranged from 0.292 to 0.335, these results indicate the correct accuracy except for the p value for the fit proximity test is 0.00 which remains much lower than 0.5. The AIC (696.5), BCC (702.9) and ECVI (6.220) values for the CFA model are lower than the independent model but slightly higher than the saturated model. Based on these indices, we need to define our model to try to obtain a model that fits the data well (James Jaccard; Michael A Becker, 2010). These adjustment indices suggest that this initial hypothetical model is fairly consistent with the data. Our model therefore appears rather parsimonious. The largest change index values are found in the variables SFT4, SFT21, SFT22, SFT32, T3, T4, SFT13, SFT31. After several tests, these variables were eliminated and the results improved significantly. So, this one-factor model represents a satisfactory fit to the data, and therefore confirms the dimensionality of the scale. On the basis of these results, the measurement scale represented by the model was considered to have sufficient validity and reliability (0.898) to measure the SFT construct in the subsequent multivariate analysis.

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For PF construct, the likelihood ratio test revealed a $\chi 2$ of 6.836 with a degree of freedom (D.L.) of 2 and a probability of (0.0033<0.2) (Jöreskog, K. G., & Sörbom, 1993). The model's absolute indices, such as RMR (0.042<0.05), GFI (0.972< 0.90) and (AGFI 0.860<0.900), suggest an adjustment that requires a slight refinement of the model to correct the RMR and AGFI values (Jöreskog, K. G., & Sörbom, 1993). Incremental adjustment measurement values (CFI (0.986), IFI (0.986) and TLI (0.958> 0.95), and NFI value of 0.981>0.90) confirm the adjustment to the data. The RMSEA value for the model is 0.147. The 90% confidence interval for RMSEA, ranged from 0.036 to 0.274, these results indicate the correct accuracy except for the p value for the fit proximity test is 0.067 which remains much lower than 0.5. The AIC (22.836), BCC (23.583) and ECVI (0.204) values for the CFA model are lower than the independent model but slightly higher than the saturated model. Based on these indices, we need to define our model to try to obtain a model that fits the data well (James Jaccard; Michael A Becker, 2010). These adjustment indices suggest that this initial hypothetical model is fairly consistent with the data. The model therefore appears rather parsimonious. The largest change index values are in variable PF4. After several tests, these variables were eliminated leading to improving the results significantly. So, this one factor model represents a satisfactory fit to the data, and therefore confirms the dimensionality of the scale. On the basis of these results, the measurement scale represented by the model was considered to have sufficient validity and reliability (0.900) to measure the RF construct in the subsequent multivariate analysis.

For the PC construct, the largest change index values are found in the variable PC1 and PC5. Initial fit results revealed a poor fit requiring re-specification of the model. By eliminating the PC1 and PC5 variables, an acceptable model has been developed, and the results have clearly improved. Thus, this one-factor model represents a satisfactory fit to the data, therefore confirming the dimensionality of the scale. On the basis of these results, the measurement scale represented by the model was considered to have sufficient validity and reliability (0.892) to measure CP construction in the subsequent multivariate analysis.

For the PP construct, the largest change index values are in the variable PC1 and PC5. Initial fit results revealed a poor fit requiring re-specification of the model. Eliminating the PP2, PP6 variables resulted in a very acceptable model, and the results improved significantly. So, this one-factor model represents a satisfactory fit to the data, and therefore confirms the dimensionality of the scale. On the basis of these results, the measurement scale represented by the model was considered to have sufficient validity and reliability (0.892) to measure the PP construct in the subsequent multivariate analysis

For the PA construct we noted that the initial fit results revealed a poor fit requiring a re-specification of the model. By eliminating the PA1, PA5 and PA6 variables, a very acceptable model was developed and the results improved significantly. So, this one-factor model

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represents a satisfactory fit to the data, and therefore confirms the dimensionality of the scale. On the basis of these results, the measurement scale represented by the model was considered to have sufficient validity and reliability (0.803) to measure the AP construct in the subsequent multivariate analysis.

Regression and Correlation Analysis

The correlation and regression analyses were carried out on the basis of the results obtained during the EFA and CFA analyses.

- The Correlation analysis: is used to consider the relationship between the factors of the constructs of the theoretical framework;
- the Regression analysis: allows us to measure the degree of influence of each factor.

Pearson's product-moment correlation technique was used to determine the extent to which the variables were linearly related (Baba Ahmed, A. N., & Megnounif, 2021)

Tableau 30 Stepwise regression analysis with all process of RMS

Idependent variable	Dependent variable	R	R^2	Adj R^2
RFa	RFb	0,100	0,012	0,03
RFb	RFa	0,109	0,012	0,003
	RPa	0,118	0,014	0,005
RFa	SFIb	0,197	0,039	0,03
	SFAa	0,181	0,033	0,024
	SFEb	0,340	0,116	0,108
	SFTa	0,131	0,017	0,008
RFb	SFIb	0,265	0,07	0,062
	SFEb	0,315	0,0099	0,091
RPa	SFIa	0,385	0,148	0,141
	SFIb	0,230	0,053	0,044
	SFAa	0,526	0,277	0,270
	SFEb	0,497	0,247	0,240
	SFTa	0,582	0,339	0,333
SFIa	SFIb	0,432	0,186	0,180
	SFAa	0,333	0,110	0,103
	SFEa	0,420	0,176	0,169
	SFEb	0,528	0,278	0,272
	SFTa	0,343	0,117	0,110
SFIb	SFAa	0,624	0,389	0,384
	SFEa	0,589	0,346	0,342
	SFEb	0,478	0,228	0,222
	SFTa	0,651	0,423	0,419
SFAa	SFEa	0,913	0,833	0,832
	SFEb	0,582	0,338	0,333
	SFTa	0,887	0,786	0,784
SFEa	SFEb	0,662	0,438	0,434
	SFTa	0,887	0,786	0,784

SFTa	SFEb	0,591	0,349	0,343
PAa	SFIa	0,207	0,043	0,034
	SFAa	0,148	0,022	0,130
	SFTa	0,116	0,013	0,004
PPb	SFIa	0,245	0,06	0,052
	SFIb	0,187	0,035	0,026
	SFAa	0,136	0,018	0,01
	SFEb	0,332	0,110	0,102

The analysis showed that all eight constructs are positively associated with one another, as are their factors. We developed a regression analysis to measure the degree of influence of each construct. We performed the correlation analysis where the constructs were positively correlated with each other. In order to continue the analysis, specific dependent variables were assumed to be influenced by a set of independent variables. We entered into the regression model the independent variable that had a high correlation with a dependent variable. Moreover, developing a regression analysis allowed to measure the degree of influence of each constructed on the others. where, the correlation analysis has shown that constructed are positively correlated to each other. In order to continue step-by-step, the analysis, specific dependent variables were hypothesized as being influenced by a set of independent variables. the independent variable that had a strong correlation has been linked with a dependent variable in our regression model. The finding given in table 30 were significant and values ranged from 0.01 to 0.832. Globally, the results showed an interesting relationship between the different factors. The RF and RP are combined with 0,5 %; the variables RF and SFI with 3% and 6.2%; the variables RF and SFA with 2.4% ;the variables RF and SFE with 10.8 % and 9.1%; the variables RF and SFT 0.8%; the variables RP and SFI with 14.1% and 4.4% %; the variables RP and SFA with 27%;the variables RP and SFE with 24%;the variables RP and SFT with 33.3%; the variables SFI and SFA with 10.3% and 38.4%;the variables SFI and SFE with 16.9% and 27.2% and 34.2% and 22.2%;the variables SFI and SFT with 11% and 41.9%;the variables SFI and SFT with 11%;the variables SFA and SFE with 83.2% and 33.3%;the variables SFA and SFT with 78.8%;the variables SFE and SFT with 78.4% and 34.3% ;the variables PA and SFI with 3.4%;the variables PA and SFA with 13%;the variables PA and SFT with 0.4%;the variables PP and SFI with 5.2% and 2.6%;the variables PP and SFA with 1% and finally the variables PP and SFE with 10.2%. The results of regression are given in table 30, and the final proposed model with the relationships defined between the factors is shown in Figure 3.

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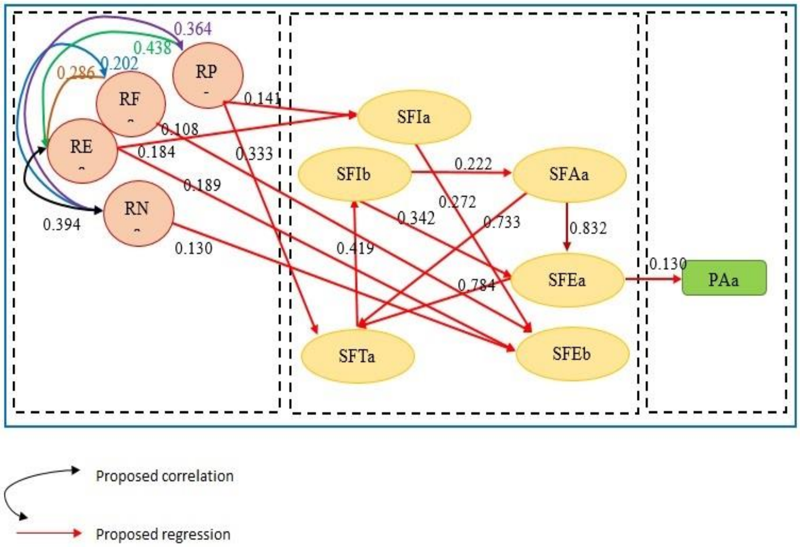

Figure 3 Relationship with factor of process

From the analyzes carried out, among the inputs to the process: political risks (environmental and legal) such as the unexpected change in the execution period or strikes are the most linked (0.270, 0.240 and 0.333) with the main functions of the RM, namely, the analyze function based on the list of identified risks and by estimating the probability and impact of the risks, the evaluate function by listing the causes of failure and success, and the treat function by following the two risk response strategies that are based on accepting or reducing risk.

The main functions are strongly linked to each other and form a complete cycle, such as risk analysis who is based on the list of identified risks and estimate the probability and impact of risks is strongly linked (0.832) with the risk assessment (measure and compare) through the choice of target values to be achieved.

It is also strongly linked (0.784) with the treatment of risks, which has the acceptance or reduction of risks as a response strategy. Risk assessment by listing the causes of failures and successes is strongly linked (0.784) with risk treatment.

The identification of risks (listing, documenting and transmitting) by developing RBS and using previous experiences, is moderately linked (0.384) to the analysis, (0.342) to the evaluation and (0.419) to the treatment of risks. RM functions are thus considered to be weakly linked to the output of our process. for example, the motivation of the employees to act in the best interest of the company is weakly linked (0.130) to risk analysis.

Finally, the analysis of the proposed model showed that Algerian companies carry out more analysis, assessment and treatment of risks than identification. We also notice that the Algerian company is gradually installing the RM process.

Conclusion

The results show that Algerian construction companies are gradually integrating the RM process. It is necessary to note that the method of distribution has an influence on the percentage of return of the questionnaires. We had 62% feedback distributed by hand against 38% feedback sent by email. Classifying risks into six groups (financial, political, natural, environmental, managerial and technical) has facilitated the treatment of risks through the functions and sub-functions of the RM process.

The model proposed in this article includes three main elements: the inputs (the different risk groups), the process (the four functions: identify, analyze, evaluate and treat) and the outputs (the 4 performance perspectives: financial perspective, client, learning perspective and process perspective).

In the empirical analysis, we noticed that the statistical analysis confirmed the relationships and connections previously proposed in the theoretical framework. We noticed that the financial, natural, environmental and political risk factors indirectly influence the performance factors of the company, this through the factors of the RMS activities. It is obvious that some factors have been more influential or sensitive to variations in other factors. Based on the results obtained, we can draw the following conclusions:

The functions of risk management are moderately known and installed in the Algerian construction company, it proceeds to the identification of risks by making site visits, by reviewing the GC and architectural plans, it consults the files of previous projects and it brings together the information obtained during the work sessions. It analyzes the risks based on the judgment of the experts for the estimation of the probability and the impact of the risks. It then assesses the risk by listing the causes of failures and the causes of successes that the risk can induce the strategy which is based on the reduction or acceptance of the latter.

Following the results obtained, it is recommended that the Algerian construction company deploy more human and material resources for the implementation of the RMS. It is also necessary to involve all the personnel of the company, starting with the senior managers in order to allow the company to achieve its set objectives and thus to be efficient.

The various research works developed for this study can contribute to the implementation of risk management activities in the company. It is necessary to mention the developments that could emerge as a result of our work: for example, as a study parameter, it is possible to take

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into consideration the location and/or the size of the company and then vary it to see its influence on the theoretical model. For future work researchers can broaden the scope of work by having a diverse sample in terms of size, type and location.

Conflict of interest

The authors declare that they have no conflict of interest.

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