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Research on Customer-Project Management and the Knowledge Necessary to Ensure a Project's Success

[1]Roopa Yashoda MN and [2]Dr. Rajrani Pandey

[1]Research Scholar, Sainath University, Jirabar, Jharkhand, India
[2]Professor, Sainath University, Jirabar, Jharkhand, India

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Corresponding Author: Roopa Yashoda MN

Abstract

In order to investigate how businesses might enhance their project success rates by incorporating knowledge management techniques and practices into a standard project lifecycle. A relatively new field and method in business, knowledge management is quickly gaining traction. Organizational sustainability and competitiveness may be enhanced by the use of this paper's proposed integrated approach, which merges knowledge management with project management. A small or medium-sized enterprise (SME) is a business with a relatively small number of employees serving its customers. They produce goods and services and manage their businesses in an innovative way, which allows them to compete with big companies. Subjects covered in the primary research include KM, CRM, CKM, PM, PKM, and PS. The current instance is evaluated using EFA to see if all six constructs (KM, CRM, CKM, PM, PKM, and PS) have the necessary components. To conduct the EFA, SPSS software version 20.0 was utilized.

Keywords: Customer, Project, Management, Success and Knowledge

Introduction

Every organization is composed of people in the form of employees, suppliers and customers; processes; tools and applications, and products. The products may be goods or services. Manufacturing organizations utilize suitable production processes and needful material and machinery to produce the targeted quantity of products to meet the demand of market and customers. Organizations experience ever growing competition due to globalization of markets, continuing technological innovations and dynamic consumer demands. To meet demand in such competitive world, the organizations are being pushed into situations to continuously review their existing products and processes and check whether to redesign them or look for new product development. In- depth market research and knowledge of products, processes and people would help the organizations to review their capabilities and present stand in the market so that they could develop proper plans to sustain in the competition.

In this process, new product development or customization of the products as indicated by the requirements of the customers is becoming a routine activity for several organizations. Such activities are treated as projects, because each of them will be a one-time development activity to suit the requirements of a particular customer. Maintenance of good relationships with the customers and getting their valuable feedback and information on a continuous basis will help the organizations to fine tune their business activities to meet or exceed the expectations of the customers. The success rate of projects decides the future of organizations. Knowledge in different dimensions helps the organizations for their growth. Organizations should properly manage the knowledge of employees on various issues like performance of products and processes, quality improvement, saving of time and cost. In the same way, the organizations should manage not only the relationships with the customers but also their knowledge for the growth of business and performance in all respects as well.

An SME is a company, organized by a limited number of personnel. They cultivate innovation in producing products/services and running business and such inclination enables them even compete with large organizations. Currently, in most of the countries, with the support of government, SMEs are highly contributing to large domestic production with low investment requirements. They are becoming technology-oriented industries, discouraging monopolistic practices of production and marketing by competing in both domestic and international markets. By contributing to the stable monitory growth of the country, Indian SME‟s are growing in number more than lakhs with investment of above one crore and recorded approximately 40 percent of industrial production and 6 percent to country's GDP.

Literature Review

The ultimate goal of any project is to satisfy its customers. Hence, project manager should be keen not only on developing the project but also on maintaining relationships with the customer(s) to understand and fulfil their problems, requirements and expectations. From the history of past projects either completed successfully or discontinued in the middle due to failures, lot of information can be accumulated and mined to understand the views and feelings expressed by the customers and this will become the knowledge about the customers and be useful as learning lessons to be applied in the running projects wherever necessary and appropriate. This approach will also lead to enhance the relationships with the customers of the current projects. According to Schindler (2002) [2], knowledge within projects is closely linked to PM methodology and communication practices. Conroy and Soltan (1998) [3] identified three knowledge bases in projects – organization, project-management and project-specific knowledge base. They also divided project-created knowledge into three general categories – technical, PM and project-related knowledge.

Knowledge is created and transferred on projects to capture and reuse the structured knowledge, capture and share the lessons learned from practice, embed knowledge in project's products and processes, identify sources and networks of expertise, structure and map knowledge needed to enhance performance and share knowledge from external sources (De Long *et al*. 1996) [1]. Knowledge transfers from and between projects in the form of expert, methodological, procedural and experience knowledge (Schindler, 2002) [2] and contributes to the overall knowledge base of organization (Frey *et al*. 2009) [4]. Schindler (2002) [2] interpreted that project knowledge management (PKM) comprises of not only the knowledge within projects but also the knowledge between different projects and knowledge about projects. Knowledge about projects represents the project landscape in the organization and the knowledge from and between projects leads to organizational knowledge base. Personalization and Codification are the two strategies that can be adapted by organizations to manage project knowledge (Fong, 2005) [5].

According to Polyaninova (2011) [6], successful PKM enables the project-oriented organizations and employees make better decision- making with the required information, which will save cost considerably in time and effort and add competitive advantage. Ordanini *et al*. (2008) [7] reported that the mix of knowledge and expertise developed within project teams positively influences the long-term success of an organization. Disterer (2002) [8] presented project phase wise description of linking KM to PM. During the definition and planning phases of project, the working steps, time and budgets are dedicated to identify the areas where new knowledge can be generated, capture and transfer knowledge and expertise. During execution and monitoring and controlling phases, the knowledge is usually created and captured as project work is under implementation and these phases document the knowledge in the form of lessons learned to be helpful for future projects.

SMEs can make quick decisions on changes to be made to processes or products and they do not face the issues of change resistance and management. Even with all such capabilities and flexibility, SMEs may experience failure in the market because of other reasons like improper standardization and maintenance of processes, lack of benchmarking to measure the efficiency of processes and products and lack of networking with business partners and competitors. According to Boughton and Arokiam (2000) [9], SMEs typically are not only adaptive and innovative in terms of products but also their manufacturing practices. To maintain competitive advantage, they are becoming increasingly proactive in improving their business operations (Boughton and Arokiam, 2000) [9]. According to Turner (2009) [10], in small enterprises, the median sized project is six months long and in medium-sized ones, it is nine months long.

In SMEs, projects account on an average for one third of their turnover (Turner, 2009) [10] and hence projects occupy important place in their revenue. Authors like Lindgren and Packendorff (2003) [11] and Casson and Wadeson (2007) [12] envisaged the project-based view of enterprise and its importance. Proper usage of PM methodology, tools and techniques can add more value to the success of projects and overall business of SMEs. After conducting preliminary investigations into PM practices in SMEs of high-tech and service industries in Ireland, Murphy and Ledwith (2007) [13] recommended that SMEs should create a formal structure to implement PM practices. The financial constraints may be hurdles in spending much on procuring PM tools in the case of small enterprises.

Research Methodology

The study, which is the main study, deals with a total of six constructs – KM, CRM, CKM, PM, PKM and PS.

Knowledge management (KM) consists of four major activities – capturing, storing, sharing and using knowledge within the organization.

Effectiveness of CRM depends on proper customer segmentation, effective attraction strategies, customer satisfaction and service management.

CKM has been described as a new organizational approach to capture, share and use the information, knowledge, experience and ideas related to customers.

PM software for work scheduling and control, PM software for resource scheduling, kick off meetings, risk management, and top-down estimating.

Effective PKM leads to proactive and timely decisions and impacts on all aspects of project performance in terms of quality, time and cost dimensions.

The PS success of a project is determined according to two dimensions – project performance and project learning.

Data Analysis

EFA is used to ensure the one-dimensionality of the measurement model by linking the constructs with the observed items. One-dimensionality is established when a set of scale items represents a common latent variable, that is, a factor or a construct. The present study applied EFA to the collected data by using principal components analysis as extraction method and Varimax as rotation method to check whether the relevant items measuring a particular factor are all loading on it sufficiently. EFA is applied to the present case to check whether each of the six constructs (KM, CRM, CKM, PM, PKM and PS) is loaded with the respective items should be checked. SPSS software version 20.0 was used for EFA.

Factor analysis is based on the correlation matrix of the variables included in the measurement model. These correlations require sufficient sample size. Large sample sizes are better than smaller ones because larger samples tend to minimize the probability of errors, maximize the accuracy of population estimates and stable loadings, and increase the generalizability of the results. It was suggested to follow the subject to item ratio as a measure for sample size, and some authors recommended a ratio of at least 1:5 with some stringent guidelines, and some authors like suggested the ratio of at least 1:10, which is the widely-cited rule of thumb, meaning that a bare minimum of 10 observations per variable is necessary. In the present study, there are six constructs and a total of 25 items. As per the above rule of thumb, there should be at least 250 observations. Since the study deals with data collected from 252 respondents in complete shape, the sample size is very much sufficient to perform EFA.

In addition, in EFA, the sampling adequacy can also be checked by using Kaiser-Meyer-Olkin measure of adequacy (KMO test) and Bartlett's test. KMO indicates sample adequacy and Bartlett's test of sphericity indicates the item correlation matrix not an identity matrix. KMO correlation ranges from 0 to 1 considered the value of 0.50 suitable for factor analysis. reported that a KMO value above the range of 0.60 – 0.70 can be considered as adequate for analyzing the output of EFA. In the present study, the value of KMO test is derived as 0.854, which is well above the accepted range of values. The $\chi 2$ value of Bartlett"s test of sphericity gives a chi-square output that must be significant with $p<0.05$ for factor analysis to be suitable (Tabachnick and Fidell, 2007) [14]. Bartlett"s test of sphericity is derived as 3828.754 with degrees of freedom (df) as 300 and a significance level of 0.000, which is less than 0.05. All these results are given in Table 1, which indicate the adequacy of the sample data and thereby the suitability of data for performing factor analysis. These results provide a strong support to move forward with the factor analysis.

Table 1: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.854
Bartlett's Test of Sphericity	Approx. Chi-Square	3828.754
	Df	300
	Significance	0.000

Communality is the proportion of variance of each variable that is explained by the factors. It is the sum of squared factor loadings for the variables. There are two types of communalities – initial and extraction. Initial communalities represent estimates of the variance in each variable accounted for by all the factors. Extraction communalities represent estimates of the variance in each variable accounted for by the factors in the factor solution. Communalities with small values indicate variables that do not fit well with the factor solution, and hence should possibly be dropped from the analysis. if an item is not related to other items or additional factor need to be explored, then the item communality will be less than 0.40, otherwise the more common magnitudes are 0.40 to 0.70. In this study, all the extracted communalities are large enough (close to or above 0.6) and there is no question of dropping any one item.

Table 2: Includes both the initial and extraction communalities.

	Initial	Extraction
KM1	1.000	0.760
KM2	1.000	0.840
KM3	1.000	0.811
KM4	1.000	0.650
CRM1	1.000	0.580
CRM2	1.000	0.752
CRM3	1.000	0.771
CRM4	1.000	0.692
PS1	1.000	0.676
PS2	1.000	0.636
PS3	1.000	0.727
PS4	1.000	0.636
PM1	1.000	0.696
PM2	1.000	0.708
PM3	1.000	0.749
PM4	1.000	0.662
PM5	1.000	0.592
PKM1	1.000	0.598
PKM2	1.000	0.736
PKM3	1.000	0.743
PKM4	1.000	0.666
CKM1	1.000	0.807
CKM2	1.000	0.839
CKM3	1.000	0.864
CKM4	1.000	0.817

Six factors are obtained and all of them together are accounting for 72 percent of total variance, with first factor of about 13.5 percent, second factor 13.3 percent, third one 12.6 percent, fourth 11.1 percent, fifth one 10.8 percent and the sixth factor accounted for 10.7 percent of variance. All these results are shown in Table 3.

Table 3: Total Variance Explained

Component	Initial Eigen values			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.658	30.630	30.630	7.658	30.630	30.630	3.368	13.470	13.470
2	2.906	11.625	42.255	2.906	11.625	42.255	3.330	13.321	26.791
3	2.597	10.388	52.643	2.597	10.388	52.643	3.142	12.568	39.359
4	1.923	7.693	60.336	1.923	7.693	60.336	2.785	11.141	50.501
5	1.581	6.326	66.662	1.581	6.326	66.662	2.699	10.796	61.297
6	1.342	5.370	72.032	1.342	5.370	72.032	2.684	10.735	72.032
7	.754	3.016	75.047						
8	.675	2.698	77.745						
9	.613	2.450	80.196						
10	.567	2.267	82.462						
11	.479	1.917	84.380						
12	.436	1.745	86.124						
13	.414	1.657	87.781						
14	.384	1.536	89.318						
15	.344	1.376	90.693						
16	.332	1.326	92.019						

Rotating of the resulting six factors by the Varimax method identified the degree of association (correlation) of each variable with each factor. the value of 0.50 or higher as a good rule of thumb for the minimum loading of an item without cross loadings. All the extracted six factors are loaded with the respective items with loadings above 0.5. All the four items of KM have loadings above 0.7 and similar is the case of loadings of all the items of the constructs of PKM and PS. Except the first item which has loading value of 0.589, all the three items of CRM have loadings above 0.7. All the four items of CKM have high loadings of above 0.8. The five items of PM have loadings above 0.65. Overall, all the six constructs have high item loadings above the reported minimum value of 0.50. All these results are given in Table 4. According to Costello and Osborne (2005) [15], a factor with fewer than three items is generally weak and unstable, and five or more strongly loading items (0.50 or better) are desirable and indicate a solid factor. In the present study, all the factors have four or more items with strong loadings above 0.5. The results of the present study well satisfied all these conditions in the case of all the six constructs.

Table 4: Rotated Component Matrix

	Component					
	1	2	3	4	5	6
KM1	.826					
KM2	.896					
KM3	.854					
KM4	.744					
CRM1		.589				
CRM2		.815				
CRM3		.828				
CRM4		.744				
CKM1			.832			
CKM2			.864			
CKM3			.862			
CKM4			.847			
PM1				.781		
PM2				.785		
PM3				.827		
PM4				.738		
PM5				.653		
PKM1					.754	
PKM2					.836	
PKM3					.852	
PKM4					.791	
PS1						.817
PS2						.780
PS3						.842
PS4						.780

Cronbach's alpha (a), which is a coefficient of reliability or consistency, in helpful in establishing construct reliability by measuring the internal scale reliabilities. It is a measure of internal consistency, that is, how closely a set of items are related as a group. Both Cronbach's alpha and EFA contribute to establish the one-dimensionality of the measurement model and reliability of the constructs. Hair *et al*. (2006) [16] reported the agreed upon limit of extremely high internal consistency as 0.8. In the present study, the reliabilities derived for the six constructs of KM, CRM, CKM, PM, PKM and PS are 0.893, 0.848, 0.932, 0.874, 0.843 and 0.829 respectively. All these derived values of Cronbach's alpha are much above the reported limit and hence the construct reliability is established for all the six factors. Therefore, in the present study, both EFA and the six constructs.

Structural Equation Modeling (SEM): Confirmatory factor analysis (CFA) to check model fit and estimate convergent and discriminant validity of the measurement model After confirming one-dimensionality of the six constructs with EFA and their reliability established by Cronbach's alpha (a), this study adopted CFA to check the measurement model fit and estimate convergent and discriminant validity of the model. In the measurement model, as shown in Fig. 1, KM acts as exogenous variable because it is not influenced by any other variable. Remaining five latent variables are influenced by other variables and are said to be endogenous. According to Hair *et al*. (2006) [16], convergent validity estimates the extent to which the measurement items of a particular construct converge or shares a higher proportion of common variance. Composite reliabilities (CR) and the average variance extracted (AVE) are useful parameters to establish convergent validity of the measurement model by testing the construct validity.

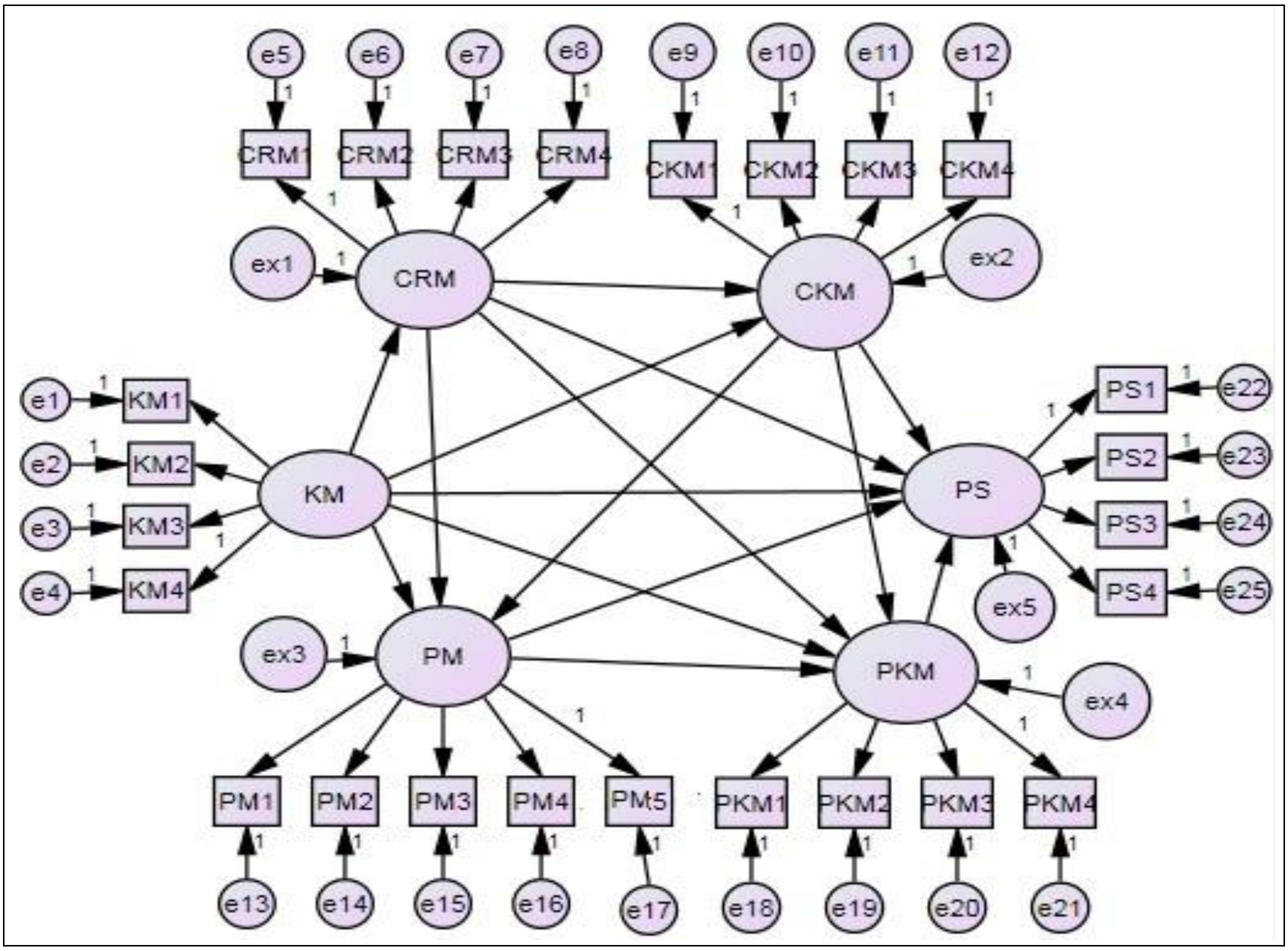

Fig 1: Measurement model

Since Cronbach's alpha may understate the reliability of constructs (Hair *et al*. 2006) [16], CRs are examined as measure of overall reliability of a set of heterogeneous, but similar measurement items. According to Chin *et al*. (2003) [17], a threshold value of 0.50 for CR indicates that the majority of the variance accounted for by the construct. Bagozzi and Yi (1988) [18] considered values greater than 0.6 as reliable CR values, whereas Chin *et al*. (2003) [17] and Hair *et al*. (2010) [19] considered values greater than 0.70 and Fornell and Larcker (1981) [20] reported values greater than 0.80 as more reliable CR values. For the present model, the CR values obtained for all the six constructs of KM, CRM, CKM, PM, PKM and PS are 0.926, 0.897, 0.951, 0.909, 0.893 and 0.886 respectively. All these values are in the range of 0.886 to 0.951, which is highly acceptable. The results are shown in Table 5.

Table 5: Uni-dimensionality, Construct reliability and Composite reliability of the measurement model

Factor	Items and Factor loadings	Cronbach's alpha	Composite reliability (CR)
Knowledge Management	KM1: 0.835	0.849	0.898
(KM)	KM2: 0.885		
	KM3: 0.873		
	KM4: 0.707		
Customer Relationship	CRM1: 0.690	0.845	0.895
Management (CRM)	CRM2: 0.783		
	CRM3: 0.809		
	CRM4: 0.781		
Customer Knowledge	CKM1: 0.852	0.863	0.907
Management (CKM)	CKM2: 0.886		
	CKM3: 0.913		
	CKM4: 0.869		
Project Management	PM 1: 0.776	0.831	0.886
(PM)	PM 2: 0.781		
	PM 3: 0.808		
	PM 4: 0.756		
	PM 5: 0.700		
Project Knowledge	PKM1: 0.652	0.863	0.907
Management (PKM)	PKM2: 0.785		
	PKM3: 0.825		
	PKM4: 0.769		
Project Success (PS)	PS 1: 0.735	0.831	0.886
	PS 2: 0.713		
	PS 3: 0.813		
	PS 4: 0.710		

Convergent validity results when each measurement item correlates strongly with its assumed theoretical construct. AVE is a strict measure of convergent validity (Hair *et al*. 2010) [19] and is a more conservative measure than CR. According to Fornell and Larcker (1981) [20] and Bagozzi and Yi (1988) [18], the AVE of value 0.50 and greater is acceptable. the AVE values for the constructs of KM, CRM, CKM, PM, PKM and PS are 0.692, 0.563, 0.725, 0.576, 0.655 and 0.653 respectively. All these values are in well acceptable range. Discriminant validity is the extent to which a latent variable discriminates from other latent variables. Here, each latent variable in the form of one KM activity has to be different from the other three KM activities. To achieve this, the AVE of one latent variable should exceed the shared variance with all other variables (Hair *et al*. 2010) [19]. As shown in Table 6, the AVE of one construct exceeds the shared variance with all other constructs and hence all the six constructs possess adequate discriminant validity. In addition, the AVE of each measure extracted more than or equal to 50 percent of variance, the cut-off value.

Table 6: Discriminant Validity of the measurement model

	KM	CRM	CKM	PM	PKM	PS
KM	0.692					
CRM	0.026	0.563				
CKM	0.012	0.045	0.725			
PM	0.038	0.029	0.033	0.576		
PKM	0.0038	0.0057	0.0097	0.0062	0.655	
PS	0.0037	0.0011	0.0009	0.0057	0.0044	0.653

A model is said to be good fit when it is reasonably consistent with the data, that is, the model is able to reproduce the data in the variance-covariance matrix form and does not require any re- specification. According to Tanaka (1993) [21], a number of alternative goodness of fit (GOF) measures are available with each one as unique and classified into three general groups – absolute fit indices, relative fit indices, parsimony fit measures and non-centrality-based indices. The absolute fit indices do not use an alternative model as a base for comparison. They include several indices like chi-square ($\chi 2$), goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), Helter's CN, root mean square residual (RMR) and standardized root-mean-square residual (SRMR).

The relative fit indices compare a chi- square for the model tested to one from a so-called null model or „baseline" or „independence" model. They include Incremental fit index (IFI), Tucker-Lewis's index (TLI) and Normed fit index (NFI). The parsimonious fit indices are relative fit indices that are adjustments to most of the fit indices mentioned above and include indices like PGFI (based on the GFI), PNFI (based on the NFI) and PCFI (based on CFI). The non-centrality parameter estimate is calculated by subtracting the degrees of freedom (df) of the model from the chi-square ($\chi 2$) and this value is adjusted for sample size and referred to as the rescaled non- centrality parameter. The non-centrality-based indices include indices like root-mean-square error of approximation (RMSEA) and comparative fit index (CFI). researchers should consider reporting more than one fit index as model fit criteria.

Table 7: Fit statistics of the measurement model

Model fit index	Recommended values	Derived values
χ2/df (χ2 = 489.9; df = 260; *p*<0.000)	<u><</u>2 or 3 (Browne & Cudeck, 1993; Kline, 1998; Ullman, 2001) [22, 23, 24]	1.88
GFI	> 0.90 (Hair *et al*. 2006) [16]	0.87
AGFI	≥ 0.80 (Hair *et al*. 2006) [16]	0.84
NFI	≥ 0.85 (Brown, 2014; Schermelleh-Engel *et al*. 2003; Mogre & Amalba, 2016) [25, 26, 27]	0.88
RFI	≥ 0.85 (Brown, 2014; Schermelleh-Engel *et al*. 2003; Mogre & Amalba, 2016) [25, 26, 27]	0.86
CFI	> 0.90 (Kline, 1998; Schermelleh-Engel *et al*. 2003; Brown, 2014) [23, 26, 25]	0.94
TLI	≥ 0.90 (Kline, 2011; Hu & Bentler, 1999; Bentler, 1990) [28, 29, 30]	0.93
RMSEA	< 0.06 (Browne & Cudeck, 1993; Hu & Bentler, 1999) [22, 29]; < 0.08 (Hair, *et al*. 2009) [31]	0.059
RMR	< 0.08 (Browne and Cudeck, 1993; Hu & Bentler, 1999) [22, 29]	0.053
SRMR	≤ 0.08 (Hu and Bentler, 1999; Brown, 2006; Byrne, 2010) [29, 32, 33]	0.033

From the above results, it can be interpreted that the goodness of model fit has been satisfactorily established along with convergent and discriminant validity. So, the CFA results demonstrated that the six-factor model of project success of SMEs, based on the KM, customer and project dimensions, is appropriate and possesses adequate reliability and criterion-related validity.

Conclusion

Enhancing project success in businesses through the combination of knowledge management and project management. We have gone over the meanings of terminology connected to knowledge management and project management. It lays the groundwork for future studies that aim to integrate knowledge management with project management and uncover the underlying cultural, process, and technological aspects that contribute to successful project completion. To help businesses remain competitive and viable in the long run, this article suggests a paradigm that merges knowledge management with project management. In order to determine if all six constructs (KM, CRM, CKM, PM, PKM, and PS) are properly loaded, EFA is applied to this situation. This EFA was conducted using SPSS software version 20.0. A good fit model is one that reproduces the data in the variance-covariance matrix form without requiring any re-specification and is substantially consistent with the data.

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