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Structural equation modeling of critical success factors in the programs of development regional

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A B S T R A C T

The Structural Equation Modeling SEM using SmartPLS.V3 software was used in this study to model the priority of CSFs of program management under four categories (program planning, strategy of the organization, stakeholders, and construction program performance) associated with Regional Development Programs RDPs in Iraqi provinces. Based on the literature review, the identified CSFs of program management have been explored through a systematic review approach. This model investigated the relationship and effect of CSFs on program management of regional development. The measurement model underwent three iterations to fulfil the threshold criterion, which included Cronbach's a being more than 0.7, CR being greater than 0.7, and AVE being more significant than 0.5. As a result, the model met the convergent validity. For every path modelling and hypothesis, the structural model is evaluated. The model produced a GoF of (0.524), regarded as sufficiently high to be considered for obtaining adequate global PLS model validity. The model's global GoF performance was also assessed, and the findings met the criteria. It is clear from the final model that there may be a connection between the main program management groups, as shown by the path model confirmed.

1. Introduction

This study developed a Structural Equation Model SEM to explain and uncover the relationships among CSFs for RDPs executing in the Iraqi construction sector, identified from previous literature (As discussed in chapter two). The model aids in a better comprehension of the CSF phenomenon and its effects on program management execution.

Furthermore, this chapter presents the background to statistical modelling and SEM and its types, along with the type selected in this study, Partial Least Squares (PLS-SEM) and discusses its six-step modelling process in three sections: data preparation; PLS modelling for the outer relationships (i.e., measurement models); and PLS modelling for the inner relations (i.e., the structural models of the main PLS model).

In this study, focuses upon Regional Development Programs RDPs in Iraq, which is considered one of the types of the program management methodology because it includes a set of related projects that are implemented by the Iraqi governorates to improve the developmental reality of the governorates, in addition are one of the most important aspects of administrative decentralization by giving the provinces and provinces a percentage of financial allocations according to the criterion of relative importance of the population in each province, as administrative decentralization means the distribution of administrative functions between the central government and local governments , but acting under supervision and control of the central government.

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2. Concept of Structural Equation Modeling SEM

The second-generation multivariate analytic method recognized as SEM combines the viewpoints of econometrics and psychometrics. It has been widely used in a variety of fields, such as psychology, management and organizational behavior, marketing and construction management. SEM combines multiple regression modelling and factor analysis and is a powerful tool enabling researchers to model relationships between multiple unobservable latent variables known as constructs, measured by multiple observed variables (i.e., measurement items) in a single attempt. It can define a model, explaining the entire set of relationships. It also estimates multiple and interrelated dependence relationships and model errors in measurements for the observed variables and tests a priori substantive/theoretical and measurement assumptions against empirical data (Zaid Alkilani, 2018).

There are predicted and predictor constructs in structural equation models. Predicted constructs are unobserved dependent variables, and predictor constructs are unobserved independent variables used to predict other constructs. For example, in this study, CSFs are a predictor construct of a program's performance execution, deemed the predicted construct. SEM focuses on predicting and modelling constructs inferred from measurement items (Dominic, & Theuvsen, 2015). Further justification for adopting SEM is provided below:

1. This research's theoretical framework was built upon collected, observed variables (i.e., measurement items) and grouped into unobservable latent variables (i.e., constructs). SEM allows various theoretical models to be tested to understand how sets of variables describe constructs and how these constructs are related to each other. SEM is recommended in this case because it enables the construction of unobservable variables and combines factor analysis and multiple regression features, allowing the study of a model's measurement and structural properties (Schumacker & Lomax, 2016).

2. Studying the constructs' validity and reliability was necessary, given the exploratory character of this research. SEM was used because it allows simultaneous assessment of the reliability and the validity of the items in each measurement model (i.e., construct) and, at the same time, can estimate the relationships among the independent and dependent constructs, which is not possible to the same extent with multiple regressions and factor analysis (Aibinu & Al-Lawati, 2010).

Generally, an outer model and an inner model both compensate for SEM. The inner model is also referred to as a structural model, whereas the outer model is referred to as a measurement model, manifests, or items. The outer model demonstrates the connections between the constructs and the factors. In contrast, the inner model depicts the relationship between independent variables (Exogenous) and dependent variables (Endogenous) (Sarstedt et al., 2021), as shown in Fig. 1.

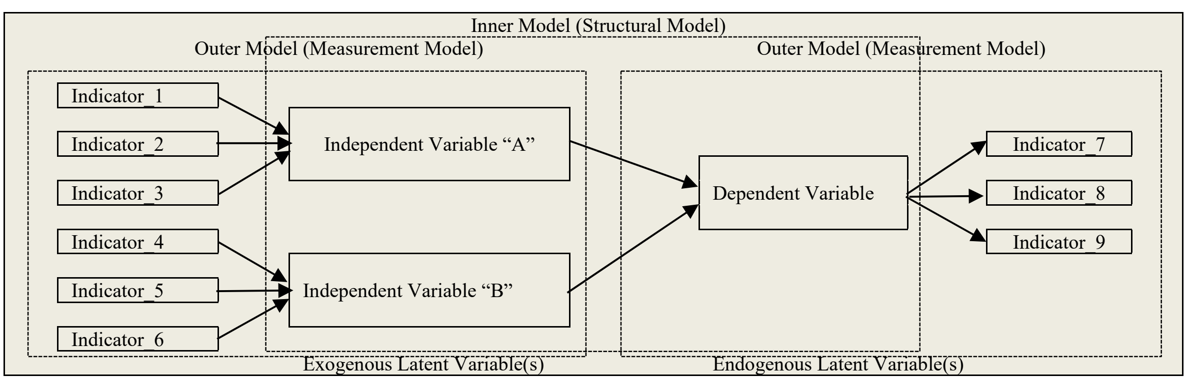

Fig. 1. Framework of SEM (Sarstedt et al., 2021)

3. Type of Structural Equation Modeling SEM

There are two types of SEM-based approaches, covariance- and component-based. The covariance-based approach (CB-SEM) is primarily used to confirm the theory and has been well accepted in social science research. Some covariance-based software packages include AMOS, EQS, Mplus, SEPATH and RAMONA. The component-based approach, also known as partial least squares (PLS-SEM), is primarily used to develop theories in exploratory research. PLS-SEM may be used to avoid restrictive assumptions underlying a maximum likelihood estimation. Some PLS-based SEM model software packages include LVPLS, PLSGUI, VisualPLS, PLS-graph and SmartPLS (Zaid Alkilani, 2018). In this study, SmartPLS 3.0 software was utilized. The justifications for using PLS-SEM for this study are provided below:

1. This study's main objective is to innovate an optimum strategic policy for infrastructure program management in Iraqi RDPs. Its sub-objectives include exploring the main CSFs model that determines the main constructs of this model and investigating the relationships between the model's constructs. One of the major concerns is the predictive power of the research model, mainly because this study is exploratory. PLS-SEM can be considered an appropriate analysis tool

because its capabilities allow for simultaneous testing of relationships among measurement items of respective constructs and between multiple predictors and predicted constructs (Nitzl & Chin, 2017).

2. Regarding the data collected for this study, the CSFs are perception-based and measured on a 5-point Likert scale (1 = not apply; 5 = apply highly) (See Appendix). They are of unknown distribution; thus, normality cannot be demonstrated. PLS-SEM is considered preferable to CB-SEM because PLS does not presume any distributional form of measured variables. Indeed, PLS is distribution-free and hence suitable for data from non-normal or unknown distributions (Nitzl & Chin, 2017). It uses a resampling method to validate the model. When parametric assumptions (such as normality) are doubtful, resampling provides a reliable alternative to statistical inference based on these assumptions by validating models using random subsets of data, as in bootstrapping. PLS is suitable where the assumption of normality is in doubt (Aibinu & Al-Lawati, 2010).
3. Only 105 responses were used in this study. The use of CB-SEM was inappropriate as it requires a sample of between 200 and 800; the more significant, the better. PLS does not need a large sample size: 30 to 100 cases are sufficient (Nitzl & Chin, 2017).

4. Model development and assessment process

The development and evaluation processes used to create and evaluate the structural model are presented in this section. Fig. 2 shows the complete procedure for creating and assessing SEM. It includes six main processes, including developing hypotheses and assigning a route model and data inputs, executing algorithms, evaluating measurement data and structural models, and testing hypotheses.

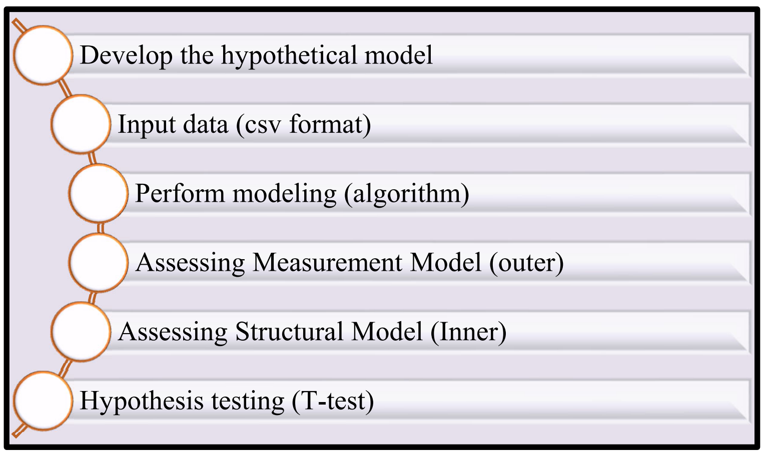

Fig. 2. Steps PLS-SEM Modelling Process

4.1 Hypothetical model

Creating a hypothetical model by assuming the route model to anticipate the relationship between constructs is the first stage in developing SEM. The previous studies serve as a baseline for the first use of this research in the Iraqi construction sector, especially in the RDPs. Abusafiya and Suliman (2017) designed PLS-SEM using the cost overrun as a dependent variable to investigate the relationships between the causes and effects of cost overrun in a building project in Bahrain.

Fig. 3 presents the proposed path model and its hypotheses. A total of six hypotheses are proposed for the model as follows:

Hypothesis 1: CSFs of program planning have a significant positive effect on CSFs of a strategy of the organization.

Hypothesis 2: CSFs of program planning have a significant positive effect on the CSFs of stakeholders.

Hypothesis 3: CSFs of program planning have a significant positive effect on CSFs of construction program performance.

Hypothesis 4: CSFs of the organization's strategy have a significant positive effect on the CSFs of stakeholders.

Hypothesis 5: CSFs of a strategy of the organization have a significant positive effect on CSFs of construction program performance.

Hypothesis 6: CSFs of stakeholders have a significant positive effect on CSFs of construction program performance.

The structural model must pass the assessment procedure outlined in the following subsections in order to accept or reject these hypotheses. The hypothetical model will be converted into Smart-PLS to represent the relationships between the variables.

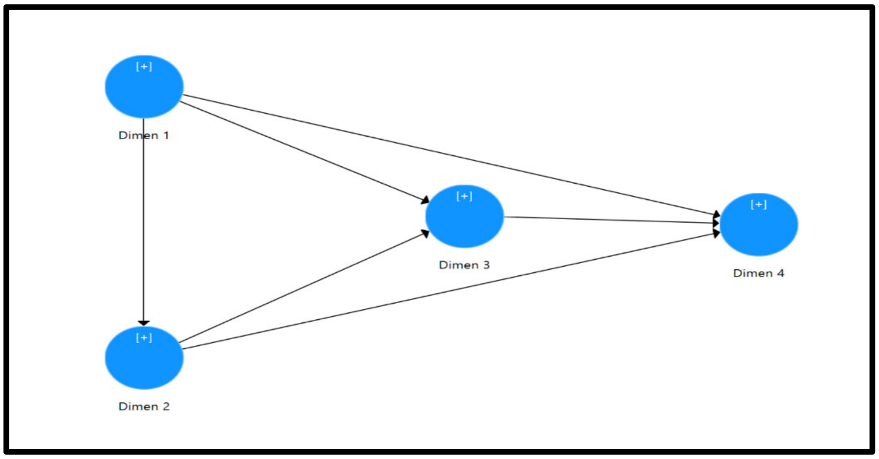

Fig. 3. Hypothetical Model of CSFs Relationships. [Researcher]

4.2 Sampling for the survey

As aforementioned in the previous chapter, the targeted respondents for this study are engineers from all the management levels and different directorates in the Iraqi Ministry of Planning and provinces whose specialists are in the RDPs.

4.3 Data input

The study finalized 105 respondents as core data for generating the model. A five-point Likert-type scale was used to know the application of critical success factors in executing projects of RDPs. The final numbers of CSFs are 29, which yields (105 × 29 = 2,730) data used to develop the SEM. These values were entered into an Excel spreadsheet and then saved as a CSV file to be compatible with Smart-PLS. After that, the data is transferred into Smart-PLS for further analysis.

4.4 Path model creation in Smart-PLS

Following the creation of the hypothetical model, the items/manifests are assigned to the relevant independent variable by importing the related data. Fig. 4 shows the screenshot of the model after setting the manifest. Fig. 4 illustrates the model after assigning the manifests to their corresponding latent variables. The colour of the latent variables turned blue after setting the manifests, showing that all the latent variables are active for further analysis. The total number of manifests is 29 items.

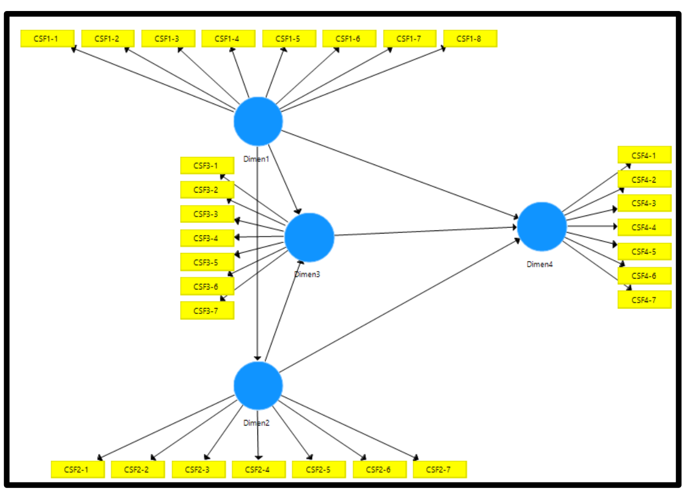

Fig. 4. Assigned manifests of the model (Smart-PLS output) [Researcher]

4.5 Model Execution Process

The PLS method must first be performed to determine each manifest's loadings. The next stage is the modelling procedure, when all the manifestations have been connected to their corresponding latent variables. The assessment criteria, which include both the outer model (measurement model) and the inner model (structural model), are the primary parameters produced from the algorithm (Memon & Rahman, 2014). The following section explains the criteria of model assessments.

4.6 Criterions of model assessment

The previous Researcher created several rules and standards for both the model's inner and outer models that may be used to evaluate the model's validity and reliability. Table 1 summarizes the standard model evaluation guidelines. The evaluation standards for the model's measurement and structural models are shown in Table 1. Several requirements must be met for the model to be considered an appropriate representation for studying the structural relationships between CSFs in program management.

5 Assessment of Measurement Model

To ensure that the research techniques and data are reliable and valid, it is essential while constructing PLS-SEM to examine the measurement's validity and reliability before producing the study findings. Assessing the model's internal consistency is critical since it allows for further study of the connection between the items. The two requirements for the standard methods are to achieve the first condition, a model performance utilizing individual item reliability and convergent validity, and the second condition, the discriminant validity assessment, which is done after the first condition has been met. This requires a few iterations of the study where factors with low loading are left out (Henseler et al., 2015, 2016).

Table 1
Model Assessment Criterions

Assessment of measurement model (Outer model)		
Criterion	Details	Reference
Internal consistency (composite reliability) /Indicator reliability	The reliability must be >0.7	Sarstedt et al., 2021 Forne et al., 1994
	The outer loading must be >0.7 for the indicator	
	If the deletion procedure must improve the AVE and composite reliability, outer loading, which has a value between 0.4 and 0.7, should be removed.	
Convergent validity	Indicators with outer loading below 0.7 should be eliminated	
	Individual item reliability (>0.70)	
	The average variance extracted (>0.50)	
Discriminate validity	Cross loading: When a factor is part of one construct, its outer loading is greater than if it were part of another.	
	According to the Fornell-Larcker criteria, the square root of AVE for the construct to which the factor belongs must be greater when compared to other constructions.	
Assessment of structural model (Inner model)		
The coefficient of determination (R2)	Chin (1998) recommended the R2 value of 0.67, 0.33 and 0.19 and measured them as substantial, moderate and weak, respectively	Sarstedt et al., 2021 Henseler et al., 2015
Effect size (f2)	Less than 0.02: no effect 0.02–0.15: small effect 0.15–0.35: medium effect More than 0.35: large effects	Cohen, 2013
Predictive relevance (Q2)	Fornell and Cha indicated that if the cv-red value is more than zero, the model is predictively relevant; if it is less than zero, the model is not predictively suitable.	Forne et al., 1994
The goodness of fit of the model (GoF)	0.10 as small GoF 0.25 as medium GoF 0.36 as large GoF	Chin, 1998; Cohen, 2013

5.1 Convergent Validity (Testing Model's Performance)

Testing the measurement model to ensure its convergent validity and individual item reliability must be done simultaneously with running the PLS algorithm because these two criteria are related (Henseler et al., 2015, 2016). The extent to which one measure relates well with another measure of the same constructs is called convergent validity (Sarstedt, 2021). The achievement of three parameters is required to verify the convergent validity. Internal consistency (Cronbach's alpha), which must be more than 0.7, composite reliability (CR), which must be greater than 0.7 (Nagapan, 2014), and average variance extracted (AVE), which must be greater than 0.5 (Mohamad et al., 2015). In the case of an exploratory study, 0.60 to 0.70 is acceptable. Sarstedt et al. (2021) described the individual item reliability criterion, which states that each item or manifest must achieve more than 0.5, and any factor that holds a value less than 0.5 has to be deleted, and the iteration process and model performance must restart until achieving the minimum from the previous. Iterations were carried out in this research till the validity and reliability criteria were satisfied. The specific parameters collected from the first iteration are shown in Table 2. The parameters of the measurement model assessment obtained from running the PLS algorithm for the first iteration. In addition, it shows the detailed and arranged factor loading for all the CSFs and the parameters of convergent validity assessment resulted running the first iteration.

Table 2

Factor Loading and Convergent Validity Assessment Results of First Iteration (Smart-PLS Output) [Researcher]

ID	Dimensions	Critical Success Factor	Factor loading	AVE	Composite reliability	Cronbach's alpha
CSF1-1	Program Planning	Proper allocation of Program budget to projects	0.584	0.533	0.900	0.872
CSF1-2		Program Budget Estimate	0.593			
CSF1-3		High-Level Program Business Case	0.712			
CSF1-4		Establishing program priorities	0.750			
CSF1-5		Program Plan and Roadmap	0.800			
CSF1-6		Effective program time management	0.793			
CSF1-7		Effective program cost management	0.793			
CSF1-8		Strong and integrated Program management office	0.777			
CSF2-1	The strategy of the organization	Strategic alignment of Program goals with organization strategy	0.638	0.538	0.890	0.855
CSF2-2		presenting a detailed breakdown of the expected functions of a PMO inside	0.651			
CSF2-3		Development of new technologies/materials	0.706			
CSF2-4		related projects	0.769			
CSF2-5		final program benefits	0.794			
CSF2-6		Provide leadership across all levels.	0.779			
CSF2-7		Match Requirements to Resources	0.781			
CSF3-1	Stakeholders	Effective communication	0.697	0.470	0.859	0.810
CSF3-2		Understanding the stakeholders' attitude	0.732			
CSF3-3		Knowledge of the exact information needs of top management	0.758			
CSF3-4		Control disputes and conflicts	0.515			
CSF3-5		Satisfaction of equipment and material suppliers	0.661			
CSF3-6		Public satisfaction	0.647			
CSF3-7		Stakeholders willing to involve	0.756			
CSF4-1	Construction program performance	Quality projects	0.781	0.545	0.893	0.859
CSF4-2		Procurement and Supply Chain Management	0.740			
CSF4-3		Right risk management	0.798			
CSF4-4		Safe projects	0.606			
CSF4-5		the appropriate way to measure projects benefits	0.703			
CSF4-6		Environmental Assessment	0.737			
CSF4-7		Efficient and optimized use of available resources	0.784			

To choose which factor to delete, Sarstedt et al. (2021) said that any manifest less than 0.7 is deleted to improve the CR and AVE. As a result, an iterative check is done to meet the required standards. In regards to assessing the convergent validity of the measurement model for the first iteration, Table 2 shows that one construct (Stakeholders CSF3) has less than the criteria described in each parameter. This requires further repetition by deleting poorly measured manifests to achieve the standard values to develop a fit model. In the second iteration, any factor that attains less than 0.6 outer loadings is deleted and then checking the outcomes.

Table 3

Factor Loading and Convergent Validity Assessment Results of Second Iteration (Smart-PLS Output) [Researcher]

ID	Dimensions	Critical Success Factor	Factor loading	AVE	Composite reliability	Cronbach's alpha
CSF1-3	Program Planning	High-Level Program Business Case	0.704	0.623	0.908	0.878
CSF1-4		Establishing program priorities	0.768			
CSF1-5		Program Plan and Roadmap	0.812			
CSF1-6		Effective program time management	0.831			
CSF1-7		Effective program cost management	0.832			
CSF1-8		Strong and integrated Program management office	0.782			
CSF2-3	The strategy of the organization	Development of new technologies/materials	0.733	0.644	0.900	0.861
CSF2-4		related projects	0.817			
CSF2-5		final program benefits	0.796			
CSF2-6		Provide leadership across all levels.	0.837			
CSF2-7		Match Requirements to Resources	0.825			
CSF3-2	Stakeholders	Understanding the stakeholders' attitude	0.797	0.625	0.834	0.701
CSF3-3		Knowledge of the exact information needs of top management	0.797			
CSF3-7		Stakeholders willing to involve	0.779			
CSF4-1	Construction program performance	Quality projects	0.797	0.586	0.894	0.858
CSF4-2		Procurement and Supply Chain Management	0.759			
CSF4-3		Right risk management	0.800			
CSF4-5		the appropriate way to measure projects benefits	0.686			
CSF4-6		Environmental Assessment	0.754			
CSF4-7		Efficient and optimized use of available resources	0.790			

Table 3 shows the factor loading for CSFs and the parameters of convergent validity assessment resulting from the second iteration. After deleting one item, the factor loading improved to achieve the threshold value.

Table 4
Factor Loading and Convergent Validity Assessment Results of the Three Iteration (Smart-PLS Output) [Researcher]

ID	Dimensions	Critical Success Factor	Factor loading	AVE	Composite reliability	Cronbach's alpha
Program Planning				**0.623**	**0.908**	**0.878**
CSF1-3		High-Level Program Business Case	**0.702**			
CSF1-4		Establishing program priorities	**0.768**			
CSF1-5		Program Plan and Roadmap	**0.812**			
CSF1-6		Effective program time management	**0.831**			
CSF1-7		Effective program cost management	**0.833**			
CSF1-8		Strong and integrated Program management	**0.782**			
The strategy of the organization				**0.644**	**0.9**	**0.861**
CSF2-3		Development of new technologies/materials	**0.731**			
CSF2-4		related projects	**0.817**			
CSF2-5		final program benefits	**0.797**			
CSF2-6		Provide leadership across all levels.	**0.837**			
CSF2-7		Match Requirements to Resources	**0.826**			
Stakeholders				**0.625**	**0.834**	**0.701**
CSF3-2		Understanding the stakeholders' attitude	**0.797**			
CSF3-3		Knowledge of the exact information needs of	**0.794**			
CSF3-7		Stakeholders willing to involve	**0.781**			
Construction program performance				**0.586**	**0.894**	**0.851**
CSF4-1		Quality projects	**0.805**			
CSF4-2		Procurement and Supply Chain Management	**0.777**			
CSF4-3		Right risk management	**0.795**			
CSF4-6		Environmental Assessment	**0.761**			
CSF4-7		Efficient and optimized use of available re-	**0.816**			

After deleting CSF4-5, iteration three was conducted, and the result from it shown in Table 4, the results show that the factor loading for CSFs and the CR for all the constructs is more than 0.7 and the AVE is more than 0.5 and these results achieved the criteria of convergent validity.

5.2 Discriminant validity

Checking the discriminant validity is the next stage in evaluating the measurement model after ensuring that the model performed as expected and met all criteria. Discriminant validity is the degree to which the manifests differentiate among the constructs or measure different concepts by evaluating the correlation among measures of potentially overlapping constructs (Wong, 2013). Cross-loadings (Henseler et al., 2015,2016) and the Fornell and Larcker (1981) criteria are used to evaluate the discriminant validity.

5.2.1 Cross loading

Cross-loading analyzes the degree to which each manifest has a greater loading correlation with the independent variables in order to evaluate the discriminant validity. When applied to other constructs, the outer loading of each related construct has a more significant impact than its total loading (Sarstedt et al., 2021).

Table 5
Cross-loading analysis

CSF	Program Planning	The strategy of the organization	Stakeholders	Construction program performance
CSF1-3	**0.702284**	0.406615	0.530021	0.359434
CSF1-4	**0.767833**	0.503837	0.507132	0.460831
CSF1-5	**0.812197**	0.459999	0.521486	0.39941
CSF1-6	**0.83123**	0.580075	0.566348	0.357037
CSF1-7	**0.832831**	0.478963	0.579423	0.378663
CSF1-8	**0.782262**	0.615649	0.559558	0.459353
CSF2-3	0.614793	**0.731135**	0.535405	0.430684
CSF2-4	0.471461	**0.817137**	0.506859	0.504429
CSF2-5	0.466072	**0.797415**	0.506978	0.621661
CSF2-6	0.530546	**0.837345**	0.49174	0.436932
CSF2-7	0.515166	**0.825831**	0.524765	0.56991
CSF3-2	0.481865	0.454491	**0.797043**	0.449984
CSF3-3	0.572011	0.488226	**0.794469**	0.466895
CSF3-7	0.575329	0.569855	**0.780756**	0.474387
CSF4-1	0.376304	0.470799	0.437531	**0.804554**
CSF4-2	0.379391	0.420387	0.446646	**0.777262**
CSF4-3	0.442149	0.523724	0.420236	**0.794788**
CSF4-6	0.355986	0.486125	0.4282	**0.761192**
CSF4-7	0.455955	0.608176	0.567105	**0.816101**

Table 5 shows the cross-loading analysis. It is demonstrated that the values generated in bold from cross-loading for each manifest have a higher value if placed in another construct/group, indicating the discriminant validity concerning cross-loading is achieved.

5.2.2 Fornell and Larcker criterion

By examining the square root of AVE with latent variable correlations, the Fornell and Larcker criteria are also used to evaluate the discriminant validity of the model, where the square root construct should be greater than its maximum correlation with any other constructs. The Fornell and Larcker criteria required that the latent variable explain its indicator's variance better than other latent variables. Fornell and Larcker are considered an effective approach for assessing the discriminant validity of PLS-SEM. It works by comparing the square root of the AVE with the independent variable correlations (Sarstedt et al., 2021). The latent variable correlation generated from running the PLS algorithm is shown in Table 6.

Table 6
Latent variable correlation

	Program Planning	The strategy of the organization	Stakeholders	Construction program performance
Program Planning	**0.789401**			
The strategy of the organization	0.649055	**0.802656**		
Stakeholders	0.690086	0.641125	**0.790788**	
Construction program performance	0.511827	0.642131	0.587476	**0.79102**

Table 6 demonstrates the correlations of the latent variables. It is shown that the root square of AVE at the diagonal matrix for each variable is higher than the non-diagonal values, which are indicated in boldface and satisfy the criterion of Fornell and Larcker; therefore, discriminant validity is fulfilled. The following step is to discuss the outcomes of the measurement model assessment.

6. Discussion of Measurement Model Results

The measurement model has been verified and assessed by satisfying all the prerequisite criteria prescribed in a table (1) by running three subsequent iterations of algorithms. The first step achieved is convergent validity, the degree to which factors are related to measuring their corresponding constructs. From the data in Table 4 and Table 5, the factor loadings are more than 0.7 and vary among items.

The constructs under causative factors are program planning, the organization's strategy, stakeholders, and construction program performance. For the first program planning, the most loaded factor is effective program cost management with 0.833 loadings, which exhibited the significance of this factor compared to other adjacent factors, which duly proved the lack of awareness toward managing cost in construction RDPs. Regarding the second causative construct, which is the organization's strategy, providing leadership across all levels of the strategy of the organization factor with (0.837) loadings is the most important factor. It interprets higher contributions with the strategy of the organization in the RDPs. The third causative construct is stakeholders, in which an understanding of the stakeholders' attitude factor (0.797) has the most loading factor under the construct. This explains that to achieve the benefits of RDPs, an understanding of the stakeholders' attitudes must be realized. Regarding the fourth construct construction program performance, the most weighted factor is efficient and optimized use of available resources (0.816), and that described the significant relationship of the resource's availability in the performance construction of RDPs

Referring to Table 4, all the measures of convergent validity achieved the threshold criteria in which Cronbach's a is more than 0.7, CR is more than 0.7, and AVE is more than 0.5. Hence the model satisfied the convergent validity.

The discriminant is checked in the second stage to ensure the construct has the strongest connection to its manifestations compared to other constructs. When the discriminant validity is evaluated using cross-loading and Fornell and Larcker criteria, it is determined to be an acceptable and valid discriminant.

In conclusion, the measurement model is assessed for its validity and reliability, and it can be concluded that the iteration process applied and modifications have positively improved the model's performance. All the weak manifests were deleted, and after iteration three, the required threshold values were accomplished for all the criteria. Therefore, the measurement model is assessed, and a further structural model is carried out.

7. Assessment of Structural Model

Once the validity and reliability of the outer model have been proven, the following step is to assess the inner model by evaluating the model's predictive capabilities and relationships among constructs. The structural model is the networked relationship connecting the hypothetical model. This assessment aims to examine the relationship between dependent and IV (Ab Hamid et al., 2017), and the significant steps to assess the structural model are presented in different figures.

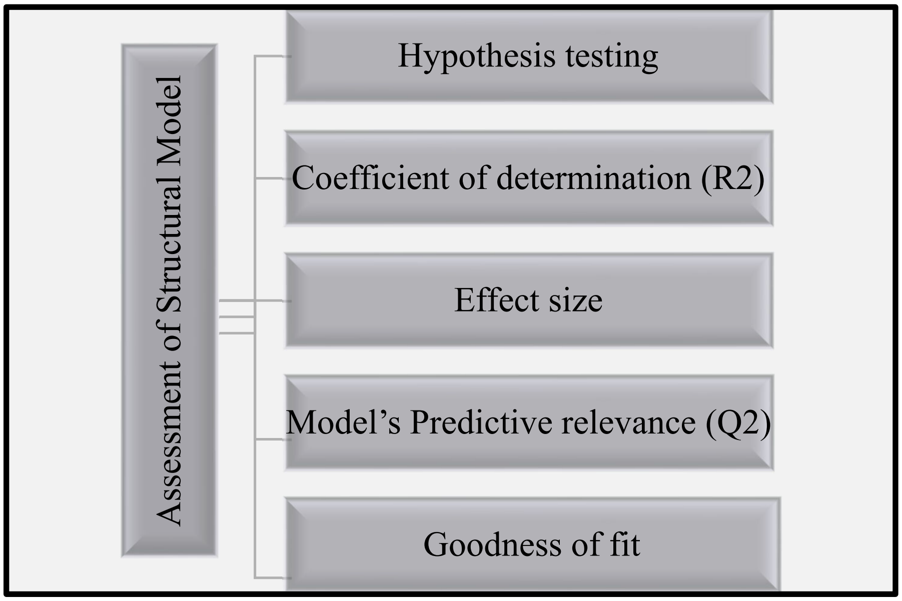

Fig. 5. Assessment steps of structural model (Zaid Alkilani, 2018)

Fig. 5 shows the steps required to assess the structural model, which sequentially starts by testing the predefined hypothesis and then checking the ability of independent variables to measure the dependent variables using the coefficient of determination. After that, to evaluate the model's performance, consider the effect size and the predictive relevance by assessing the model's confidence and checking its goodness of fit (GoF).

7.1 Hypothesis Testing

The hypothesis testing aims to check statistical significance values and examine the proposed relationship between constructs in which the independent variables significantly affect the dependent variables that are affected by effect factors. Both t-values and p-values are used as cutoff values to assess if the relationship is significant or not, where T-value must be more than (1.96) or P-value must be less than (0.05) (Falk & Miller, 1992).

The results of hypothesis testing using SmartPLS3's bootstrapping are shown in Table 7. To ensure the results were as stable as possible, the bootstrapping procedure was carried out using subsamples of 5000 (Yuan, 2012). Table 7 shows that five of the six hypotheses significantly interact with the pre-assigned path model. These consist of the groups or constructs with a p-value of less than 0.05 and a T-value of more than 1.96. According to the data gathered from respondents, the independent factors (constructs/groups) that have no significant impact on the dependent variables cannot be used to determine the degree of dependency. Therefore, more research is required to enhance the model.

Table 7
Model Hypothesis Testing

Hypothesis	Relationships	t-Values	P-Values	Decision
H1	Between CSFs of program planning and strategy of the organization	10.127	**0.000**	Supported
H2	Between CSFs of program planning and stakeholders	5.677	**0.000**	Supported
H3	Between CSFs of program planning and construction program performance	0.226	**0.821**	Not supported
H4	Between CSFs of the strategy of the organization and stakeholders	3.492	**0.001**	Supported
H5	Between CSFs of the strategy of the organization and construction program performance	3.667	**0.000**	Supported
H6	Between CSFs of stakeholders and construction program performance	2.825	**0.005**	Supported

7.2 Coefficient of determination (R^2)

A statistical measurement used to assess how closely the regression predictions match the data is known as the coefficient of determination. It represents the degree of variance in the dependent variables in PLS-SEM and may be used to describe one or more predictor factors (Tenenhaus et al., 2005). In other words, it assesses how well independent variables can assess dependent ones. [Falk and Miller] recommended an R^2 value of 0.10 as the lowest acceptable value for the model as a cutoff value. However, Chin (1998) suggested that R-values over 0.67 be considered significant, while those between 0.67 and 0.33 are considered moderate, and those below 0.19 are weak.

In this study, the value is obtained as 0.421, 0.541 and 0.465 for the strategy of the organization, stakeholders and construction program performance, respectively, as shown in Table 8. According to Chin's recommendation, the model can be considered significant since it exceeded (0.421), which is explained due to the less complexity of the model in which a more predictive latent variable increases the coefficient of determination (Tenenhaus et al., 2005).

Table 8
Coefficient of Determination (R^2)

Latent construct	R Square	Remarks
the strategy of the organization	0.421	Moderate
stakeholders	0.541	Moderate
construction program performance	0.465	Moderate

7.3 Effect size

Effect size (f2), determined as the increase in R-squared of the latent variable in which the path is associated, is a measure of the relative influence of exogenous latent variables on an endogenous latent construct by the average variation in R2 (Vinzi et al., 2010). According to the procedure-related by [Cohen, J.], the effect size of the latent variables endogenous can be assessed if the value of f^2 becomes less than 0.02 and is then considered to have no effect, from 0.02 to 0.15 is a small effect, from 0.15 to 0.35 is medium effect size, and more than 0.35 is a significant effect. Table 9 shows the f^2 values after running the algorithm for the model. The results show different size effects of the exogenous variables on the endogenous variables for CSFs groups.

Table 9
Effect size (f^2) for the model

	CSF1	CSF2	CSF3	CSF4
CSF1		0.727928	0.282379	0.00073
CSF2			0.140466	0.18407
CSF3				0.069649

7.4 Model's Predictive relevance (Q^2)

The model's ability to predict values from the data is illustrated by predictive relevance (Q2). For model confidence, Q2 is a type of statistical validation (Wetzels et al., 2009). It is obtained using the blindfolding approach, defined as the sample reuse technique that eliminates each distance (D) of the data points from the endogenous construct indicators and estimates the parameters using the remaining data point (Henseler et al., 2015, 2016). The blindfolding approach is only applied to latent constructs with a reflective measurement. The suggested omission distance ranges from 5 to 12 (Sarstedt et al., 2021). Cross-validated redundancy (cv red) and cross-validated communality (cv comm), two metrics generated in smart-PLS, are used to evaluate the model for evaluation purposes. Fornell & Larcker (1981) recommended that if the cv-red value is more than 0, the model exhibits predictive significance; nevertheless, if the value is less than 0, the model is shown to lack predictive relevance.

Table 10 shows the predictive relevance values for dependent variables. It is shown that all the values are more than (0). Therefore, this indicates the model has satisfactory predictive relevance and is fit to predict endogenous variables.

Table 10
Predictive relevancy (Q2) for endogenous variables

Latent construct	Q^2
the strategy of the organization	0.258
stakeholders	0.321
construction program performance	0.270

7.5 Goodness of fit

For all endogenous constructs, the geometric mean of the average communality and average coefficient of determination is measured using the GoF index (Yuan, 2012). It is also used to analyze the reflective indicators and is taken into account when determining the model's overall fit and validity. The main goal of calculating GoF is to see whether the research model for component measurement and the structural model of its overall performance should be taken into consideration [Vinzi et al., 2010). Numerous people have criticized the cutoff value of GoF, and Zaid Alkilani (2018) recommended that it should be set to 0.5 for commonality. However, 0.10 was recommended as a small GoF, 0.25 as a medium GoF, and 0.36 as a big GoF. (Cohen, 2013). The following formula is used manually to calculate GoF (Hooper et al., 2018):

$$GoF = \sqrt{(R^2 \times AVA)} \quad (1)$$

Referring to Table 4 and Table 8, the overall average value of AVE is 0.63, and the average value of R2 is 0.467, then GoF is calculated as follows:

$$GoF = \sqrt{(0.467 \times 0.63)} = 0.524$$

The standard criteria proposed by Wetzels et al. (2009) indicated that GoF is considered when determining the assessment of GoF value. There is no fit if the GoF value is less than 0.1, a small fit if it is between 0.25 and 0.36, a medium fit if it is between 0.25 and 0.36, and a good fit if it is more than 0.36. In accordance with the GoF formula's result (0.524) and the standards recommended by Wetzels et al. (2009). It could be said that the GoF for the model is significant adequate to be considered to achieve sufficient global PLS model validity.

After completing all structural model evaluations, the developed hypothetical model is provided, followed by examining the relationships between the CSFs for program management in the RDPs. Consequently, Fig. 7 presents the final PLS-SEM model showing the relationship between CSFs.

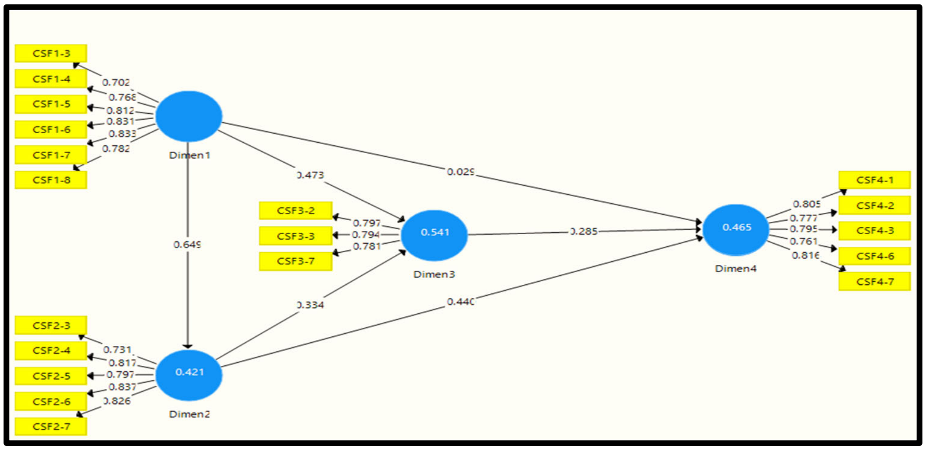

Fig. 7. Final PLS-SEM Model of CSFs [Researcher]

Fig. 7 shows the final PLS-SEM for the relationship between CSFs of program management in the RDPs. From this Figure, the path coefficient indicates relationship strength, which shows the extent of the relationship between CSF groups. It is stated that program planning has a strong relationship with the strategy of the organization, while the weak relation was between the program planning with construction program performance and the path coefficient values explain this.

8. Discussion of Structural Model Results

The created model aimed to examine the relationships between CSFs groups in the RDPs in provinces; thus, a comprehensive investigation of the collaborative relationships is required to take preventative measures for the CSFs at the early stages of the program. After completing the model analysis using SEM-PLS, the following subsection discusses the CSFs clusters.

- ***First conclusion***

Program Planning is an essential prerequisite for implementing any program; based on the result, there is a higher substantial relationship with the CSFs of a strategy of the organization in RDPs in provinces. At the same time, there is a lower substantial relationship with the CSFs of construction program performance; this indicates that while programs are developed in conformity with the policies of the provinces when execution starts, it differs from what was initially planned. As a result, the province's actual completion rate for the RDP was low. Therefore, it must be taken into consideration to take corrective steps regarding the progress following what is expected while executing the programs.

- ***Second conclusion***

Regarding CSFs of a strategy of the organization group, there is a significant association between it and the CSFs stakeholders' group, also with the CSF's construction program performance group for the RDPs in provinces, where the total effect of it was (0.140466) and (0.18407), respectively. The effect size can be evaluated if the value of *f*2 is more than 0.02 and then is considered an effect.

- ***Third Conclusion***

Construction program performance construct have a significant association moderate and goodness of fit with other CSF groups in RDPs in provinces by R^2 is (0.465) and *GoF* is (0.524) for the model is large enough to be considered to obtain sufficient global PLS model validity. It is conceivable to use the model in order to increase the performance of the implementation of RDPs in the provinces of Iraq by raising CSFs, which would result in a third iteration of the process. A substantial correlation between CSFs and RDP deployment is shown by data analysis. Indeed, this empirical evidence of the connection between CSFs and the execution of projects in RDPs improves the body of knowledge in the Iraqi construction sector and, to a broader extent, the program management of regional development in provinces and information exchange in the program's settings.

9. Summary

The SEM using SmartPLS.V3 software was used in this chapter to model the priority of CSFs of program management under four groups (program planning, strategy of the organization, stakeholders, and construction program performance) associated with RDPs in Iraqi provinces. Based on the literature review, the identified CSFs of program management have been explored through a systematic review approach (see Chapter two). This model investigated the relationship and effect of CSFs on program management of regional development.

The measurement model underwent three iterations to fulfil the threshold criterion, which included Cronbach's a being more than 0.7, CR being greater than 0.7, and AVE being more significant than 0.5. As a result, the model met the convergent validity.

For every path modelling and hypothesis, the structural model is evaluated. The model produced a GoF of (0.524), regarded as sufficiently high to be considered for obtaining adequate global PLS model validity. The model's global GoF performance was also assessed, and the findings met the criteria outlined in Cohen (2013) and Wetzels et al. (2009). It is clear from the final model shown in Fig. 7 that there may be a connection between the main program management groups, as shown by the path model confirmed.

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