Assessment of the effect of external risk factors on the success of an oil and gas construction project

Mukhtar A. Kassem, Muhamad Azry Khoiry and Noraini Hamzah
Department of Civil Engineering, Faculty of Engineering and Built Environment, Universiti Kebangsaan, Bangi, Malaysia

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Abstract

Purpose – Construction projects in the oil and gas sector are greatly affected by external risk factors, especially those related to the economy, politics, security and stability factors. Hence, this research aimed to investigate the fundamental relationship between the external risk factors and their effects on the construction project success using Structural Equation Modeling method and PLS-SEM approach.

Design/methodology/approach – Data collected through a structured survey distributed to projects teams in the oil and gas sectors in Yemeni companies involved in mega construction projects. A hierarchical model for assessing causative external risk factors and their effects on project success was developed and analyzed using Smart PLS 3 software of SEM.

Findings – The findings showed that economic, political, force majeure and security-related risk factors had a strong effect on project success. Besides, the Coefficient of Determination (*R*-squared value) equals 0.743, represented the proportion of variation in the dependent variable(s), which can be explained by one or more predictor variable. Moreover, the predictive relevance value *Q*2 is 0.375 above zero, which indicates that the conceptual model can predict the endogenous latent constructs. The calculated Goodness of Fit (GoF) Index of the model was 0.699, which shows that the developed model had substantial explanatory power to represent the relationship between the cause of external risk factors to and the effect on construction project success.

Research limitations/implications – This research was limited to the oil and gas construction projects in Yemen as case study.

Practical implications – Practically, this study highlights the external risk factors that cause a negative effect on the success of oil and gas construction projects in Yemen. The research model of these factors is the first step in the risk management process to develop strategic responses for risks and explain the relationship between cause and effect on project success.

Social implications – The model of external risks factors that cause the failure of construction projects helps develop response strategies for these risks, thereby increasing the chances of project success reflected in the oil and gas sector, which is a main tributary of the national economy in developing countries.

Originality/value – There is a need to improve the planning of economic and security performance as well as to mitigate political risk factors effects on project success and other risk factors discussed in this study, which effect on construction project success according to their priorities.

Keywords Construction projects, External risk factors, Oil and gas projects, PLS-SEM, Structural equation modeling

Paper type Research paper

Introduction

In developing countries with weak economies, unstable policies and increased security unrest, such as Yemen, the effect of external risk factors on construction projects in the oil

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and gas sector is significant and leads to an impact on the final cost and schedule of the project and may ultimately lead to a halt and failure to achieve the objectives of the project. Most international oil and gas companies are opting to market outside their home countries to support the growth of their profit. International construction projects involve both the uncertainties that arise in local construction projects and those from the complex risks particular to the international transactions (Song *et al.*, 2012). The purpose of this study is to explain the relationship between external risk factors and study their impact on project success by examining the effect of external risks on achieving project objectives, cost overruns and time overruns for the construction project in the oil and gas sector in Yemen. This is to assist the project team and decision-makers in identifying appropriate strategies to respond to these risks and mitigate their impacts on the project in a timely manner.

The pressures of globalization have generated more opportunities for construction firms to enter the international construction markets, especially in the oil and gas sector Wan Ahmad *et al.* (2016). Hence, international oil and gas projects have a high possibility of loss because they exposed to more varied and complex risks than domestic projects. The construction prosperity, supported by prompt economic and population increase, has attracted oversea contractors to export their services to the developing countries such as Yemen, especially in the oil and gas sector. In this research, the multinational or overseas oil and gas construction projects are involved parties; hence, the risks identified based on the external factors which produced due to the project environment rather than the internal risk aspects as set forth in the previous studies such as Rodhi *et al.* (2018), Thuyet *et al.* (2007), El-Sayegh *et al.* (2018), Khodeir and Mohamed (2015).

Construction has a significant risk incorporated into its economic framework, as do many other sectors in a free business environment. The process of construction is complex from start to finish and is identified by many uncertainties. Nonetheless, several contractors have developed a number of thumb rules that they follow in risk management. Such guidelines are generally based on the experience and judgment of the contractor. Uncertainty is seldom calculated by contractors and the uncertainties involved in a project were routinely evaluated. In fact, although these risks are measured, the impacts (potential impact) associated with these risks are less regularly analyzed. Based on Al-Bahar and Crandall (1990), one reason might be the lack of a rational straightforward way to combine all the facets of risk systematically into a prioritized and manageable scheme.

According to Hair *et al.* (2019), the PLS-SEM approach is very interesting to many researchers as it helps them to approximate complex models with many constructs, indicator variables and structural paths without relying on the data distributional assumptions. More specifically, PLS-SEM is a causal-predictive approach to SEM that emphasizes the prediction of statistical models whose architectures are built to provide causal explanations.

Literature review

The importance of oil and gas and its projects in the national economy is also inversely related to the impact of Yemen's economy on construction projects in the oil and gas sector, for example, economic crises and low oil prices could lead to the disruption of some projects and the cancellation of some plans. According to Adeleke *et al.* (2016), political, economy and technology factors helped the construction companies to reduce the chance of risk occurs during the construction activities. In developing countries, such as Yemen, politics plays a significant role in their economic and social aspects, and political instability usually results in a negative impact on the economy, especially for multinational corporations. Political unrest causes the departure of oil workers to their countries, and the majority of projects discontinued. Khodeir and Mohamed (2015) established that political unrest is always associated with economic unrest and the decrease in investments; such a decrease severely affects the currency prices that, in turn, have significant effects on imported materials or the fees of foreign consultants.

Many of the studies have stated that the community surrounding the projects has a high impact, especially on the sustainable sectors, such as the oil and gas sector. In Yemen, oil companies have responsibilities and obligations toward the community, and this considered a type of compensation for the potential environmental impacts resulting from the operations of oil and gas exploration (Kassem *et al.*, 2019b). The stability of the society adjacent to the oil sector substantially assists in the smooth execution of projects without objections or impediments. The oil and gas construction projects have witnessed many historical catastrophes that eventually laid the groundwork for professional practices to the industry based on the work by Davies *et al.* (2010). The severe safety failures resulted in substantial financial losses and environmental impacts and increased awareness in the oil and gas construction world towards safety implementation in the construction activities such as structure installation, foundation piling and materials fabrication.

Environment and safety-related considered as critical risk factors in oil and gas projects and the noncompliance of security, safety and environmental standards may lead to the suspension of projects at different periods (Kassem *et al.*, 2019a). These interruptions adversely affect the achievement of project objectives based on cost and schedule. Thuyet *et al.* (2007) determined that environmental and social impact assessments are required for infrastructure projects to not only satisfy regulatory requirements but also maintain productivity and competitiveness throughout the life of the project. Security risks in unstable countries, such as Yemen, represent a significant impediment to development and the completion of construction projects, especially in the oil and gas sector. Alsharif and Karatas (2016) investigated the delaying factors of nuclear power plant projects and confirmed that these projects categorized as modifications, maintenance, engineering and facilities. Alaghbari *et al.* (2007) identified that force majeure risk considered as the third general category of delays of the projects. These delays commonly called "acts of God" because no party can be held liable for their occurrence. However, the majority of contracts allow the contractor to obtain an extension of time for excusable delays, but no additional money is involved. Studies on oil and gas contain force majeure as an essential risk factor affecting the projects.

According to Abusafiya and Suliman (2017), the cost performance is one of the essential criteria to measure construction project success; thus it's proven that it is not uncommon to see a construction project failing to achieve its objectives within the specified cost in the contract. The schedule, budget and quality usually measure the success of the project. Widely, different risks can affect these three basic dimensions versus the success of the project. Moreover, these risks may be associated with different types, which depend on many factors, because of the unique character, complexity and dynamic nature of the construction activities (Kashwani and Nielsen, 2017). These risks can cause losses that lead to increased costs, time delays, lack of quality projects and may lead to stop or failure the projects. One of the challenges facing construction projects is how to assess the risks of cost overruns and project execution within the schedule.

The project's performance is usually measured by its duration, budget and quality. These three fundamental dimensions can largely be affected by different risks as compared to project success. Furthermore, these risks may be related to various types which rely on many factors because the project activities are unique, complex and dynamic. These risks can contribute to losses, which lead to higher costs, delays in time, a lack of quality projects and could lead to project cessation or failure to achieve project objectives. The main relationship between the success of the construction project and the risk factors can be determined by verifying the impact of the factors on the main components of the project as explained in the above-mentioned studies, which are the cost and schedule as well as the quality and this is what we will examine in the subsequent chapters of this study. Samarah and Bekr (2016) performed a correlation analysis to evaluate the empirical relationship between causes and effects by analyzing the empirical relationships between causes and effects. However, Sambasivan and Soon (2007) found that client and contractor-related factors could result in time overrun, while, contract-related factors could result in cost overrun and client, contract, relationship-related and external factors could lead to conflicts. In addition, client and contract-relationship-related factors could result in disputes to be settled through an arbitration process, whilst client – labor – contract, relationship-related and external factors could result in disputes to be settled through a litigation process. Moreover, factors and effects may have either direct or indirect relationships, both of which have been studied by many authors.

The suggest model consists of different and unpredictable external risk factors that are not directly related to the engineering risks of the project and those that are not directly related to the project and are considered non-engineering and not readily foreseeable. External factors that could pose risks during the first phase of the construction project should be predicted, while non-predictive factors could involve uncertainties; it should also be appreciated in order to complete the project, as these risks will lead to a direct and timely impact on project, time and quality of project revision, we can notice this classification still not covering all construction project risks and there are some critical external risks still missing in this research. The reviewed literature included articles, conference proceeding and published books linked to the related research area. This detailed literature review is to identify all the external risk factors that may occur in oil and gas construction projects. These factors range from essential factors in construction projects management to those factors resulting from economic, political, environment, local people, the security and force majeure. Categorization of the factors is based on the source of risk for analysis purposes found in the previous research by Kassem *et al.* (2019). Moreover, this classification system grouped the identified risk factors in 6 categories and 20 external risk factors, listed in Figure 1.

Chin (1998) reported that like many multivariate statistical techniques, structural equation modeling (SEM) is a relatively recent innovation. However, SEM has played a prominent role in academic ethics for many areas, including marketing and management, and has begun to influence finance, accounting and project management. When researchers deal with relationships between combinations such as satisfaction or ambiguity of role, position or relationship between causes and effect, SEM is likely to be the preferred method. The purpose of this study is to provide data analysis by SEM using PLS as an approach to understanding the relationship between the causes and effects of external risks in the construction projects of the oil and gas sector.

Methodology

The literature review aided in having a better understanding of investigating external risk factors, affecting project success. The quantitative design was employed to test the hypotheses proposed in this study. A survey was designed for respondents to investigate the risk factors affecting project success in oil and gas construction projects in Yemen. The survey questionnaire consisted of four sections. The first section was before the main body, and it aimed to introduce the objectives of the study. The second section captured the basic profile of respondents, including their positions, experiences, and company. The third section was designed to identify the risk factors influencing project success which included client

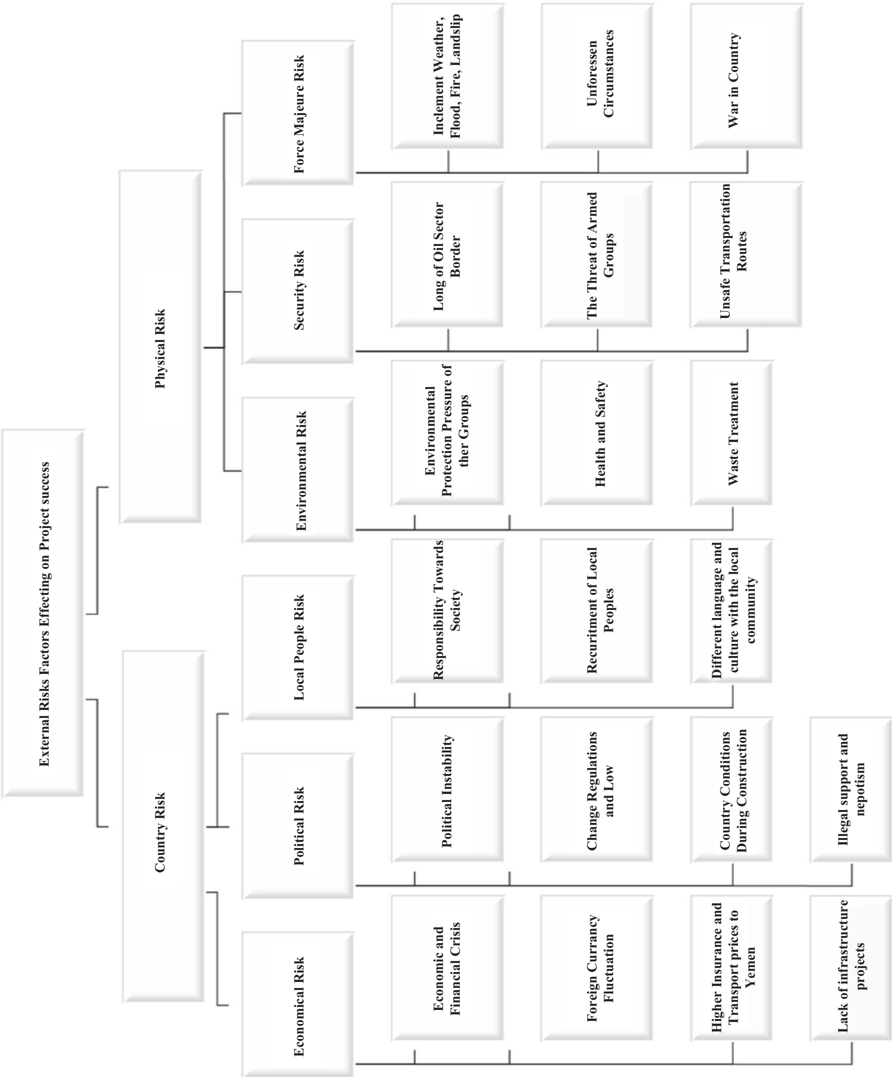

Figure 1.
External risk factors in previous studies (Kassem *et al.*, 2019)

risks, feasibility and design risks, tendering, resource and material supply, contractor, consultant and manage risks as well as their effects on project success. This section consisted of questions that solicited the perceived agreement of the risk factors that influencing project success and the indicators of project success in a five-point Likert scale (1 = very Low, 2 = Low, 3 = Moderate, 4 = High, and 5 = Very High). Krabbe (2017) reported, in Likert scaling, each item is scored on a five-point categorical scale, ranging from one extreme to the other (e.g. strongly disagree, disagree, undecided, agree, strongly agree), with these categories scored from one to five and the reason they make the response phase aggregate is why Likert-style scales are easier to work with than Thurstone scales and the scores can be summed by definition, resulting in a summary ranking. A five-point Likert scale also was used in similar area of study by Acharya *et al.* (2006). A Likert scale is never an individual item; it is always a collection of multiple items with specific features of the system. The answers to these items are added or combined to create a total score or measurement. Data were analyzed by using a PLS-SEM (partial least squares structural equation modeling) by Smart PLS software package.

There are two types of SEM, covariance-based SEM (CB-SEM) is primarily used to confirm or reject theories. Alternatively, in other words, a set of systematic relationships between multiple variables that can be tested empirically, this will be done by determining how well a proposed theoretical model can estimate the covariance matrix for sample data set, in contrast, PLS-SEM – also called PLS path modeling – is primarily used to develop theories in exploratory research by focusing on explaining the variance in the dependent variables when examining the model. PLS-SEM objective is to maximize the explained variance of the endogenous latent constructs (dependent variables) and evolving as a statistical modeling technique, and while there are several published articles on the method based on Hair *et al.* (2012). PLS is a modeling approach to SEM using SmartPLS program with no assumptions about data distribution (Vinzi *et al.*, 2010). This research used the PLS-SEM technique using SmartPLS Version 3.0 to test the research model, and this technique was selected as it could analyze a complicated model base on Hair *et al.* (2011). Also, he suggested that the PLS-SEM is the preferable approach compared to the covariance-based SEM (CB-SEM) when the theory is less developed, and the objective of the study is a prediction. As the primary objective of this study was to test the effects of external risk factors on project success, which are exploratory, the PLS-SEM was selected.

The SEM is a statistical technique that combines a measurement model (confirmatory factor analysis) and a structural model in a single statistical test. These equations depicted all the relationships among construct involved in the analysis. In the SEM process, the measurement model must be validated due to capture the structure relationship between latent variables. Scale reliability is the external consistency of a latent variable and is measured most commonly with a coefficient called Cronbach alpha; while a higher Cronbach's coefficient indicates higher reliability of the scale used to measure the latent variable and the minimum value is 0.70. According to Petroleum Exploration and Production Authority (PEPA) registration which confirmed the total population of employees are 4,218. By using Cochran formula based on the work by Cochran (1977), the sample size (n_0) can be adjusted using the equation:

$$n_0 = \frac{z^2 pq}{e^2}$$

Assume there is a large population, but that does not know the variability in the proportion that will adopt the practice; therefore, assume $p = 0.5$ (maximum variability). Furthermore, suppose desire a 95% confidence level and ±5% precision. The resulting sample size demonstrated in equation below:

$$n_0 = \frac{z^2pq}{e^2} = \frac{(1.96)^2(0.5)(0.5)}{(0.5)^2} = 385$$

The sample size (n_0) can be adjusted using the Equation:

$$n = \frac{n_0}{1 + \frac{(n_0 - 1)}{N}}$$

where n is the sample size, and N is the population size.

Also note that the total number of people understudy from the previous table is equal to 4,812 employees in 12 oil and gas production companies, the sample size that would now be necessary shown in equation:

$$n = \frac{n_0}{1 + \frac{(n_0 - 1)}{N}} = \frac{385}{1 + \frac{(385 - 1)}{4812}} = 357$$

A total of 400 questionnaire sets were distributed to randomly selected participants covering all oil and gas companies working in Yemen. Out of this number, 314 responses were returned and considered acceptable; however, some of the surveys were incomplete or partially filled, which were considered invalid and not suitable for further analysis (see Table 1).

Through the demographic table of the participants, the majority has more than ten years of experience in construction projects while the job title is closely related to project management. The study included the top five oil and gas sectors which have mega projects in comparison to the smaller sectors which have an acceptable rate.

According to Chin (1998), among SEM techniques, by far the most well-known is covariance-based methods as exemplified by software such as LISREL, EQS, AMOS, SEPATH, SMART PLS and RAMONA. Too many social science researchers, the covariance-based procedure is tautologically synonymous with the term SEM. However, an alternative and a widespread technique is known as PLS, which is also available for researchers interested in doing SEM-based analysis. Depending on the study objectives and epistemic view of data to theory, properties of the data at hand, or level of theoretical knowledge and measurement development, the PLS approach can be argued to be more suitable. The step of SEN analysis using PLS (PLS-SEM) can be seen in Figure 2:

Experience in the construction industry	Frequency	Job title	Frequency	Oil company	Frequency
Less than five years	45	Construction manager	33	Petro Masila Sector	53
5–10 years	81	Project manager	40	Safer Sector	49
10–20 years	102	Project Coordinator	23	YLNG Sector	74
20–30 years	66	Site Engineer (Civil-Electrical -Mechanical-Petroleum)	121	Total Sector	47
More than 30 years	20	Site supervisor	50	OMV Sector	49
		Others	47	Other Sectors	42

Table 1. Demographic characteristic for participants

Based on the theoretical model in Figure 3, the study has the following six hypotheses:

H1. Country Economic-related risk factors – EC have significant effects on Construction project success.

H2. Country Political- related risk factors – PO have significant effects on Construction project success.

H3. Local Peoples-related risk factors – LP have significant effects on Construction project success.

H4. Environmental and Safety- related risk have significant effects on Construction project success.

H5. Security- related risk factors-SE have significant effects on Construction project success.

H6. Force Majeure-related risk factors-SE have significant effects on Construction project success.

Results and discussion

The theoretical model (Figure 3) analyzed with partial least square estimation approach. Smart PLS 3.0 was used to estimate measurement and structural model parameters using a two-step process, while Henseler *et al.* (2009) were adopted to calculate PLS model criteria.

The PLS-SEM path model assessments steps are:

Outer model (measurement model) evaluation to determine the reliability and validity of the construct (Hulland, 1999). This measurement can be assessed by examining the individual loading of each item, external composite reliability and discriminant validity Chin (1998).

Inner model (structural model) evaluation to assess the relationship between exogenous and endogenous latent variables (independent latent variables and dependent variable) in respect of variance accounted for by Hulland (1999). In the structural model, the hypotheses are tested by assessing the path coefficients "which are standardized betas" based on Rahman *et al.* (2013). According to Shahriar and Hani (2011), non-parametric bootstrapping

PLS-SEM		
	Assessment of Measurements Model (Outer Model)	**Convergent validity** **1-** Individual item reliability **2-** Composite reliability **3-** Average Variance Extracted
		Discriminate validity **1-** Cross loading **2-** Variable correlation (Root square of AVE)
	Assessment of Structural Model (Inner Model)	**1-** The Hypotheses Testing (Path Coefficient) **2-** The Coefficient of determination - R^2 **3-** Effect size - f^2 **4-** Predictive relevance Q^2 **5-** Goodness of Fit of the Model - GoF

Figure 2.
Data analysis using PLS-SEM method

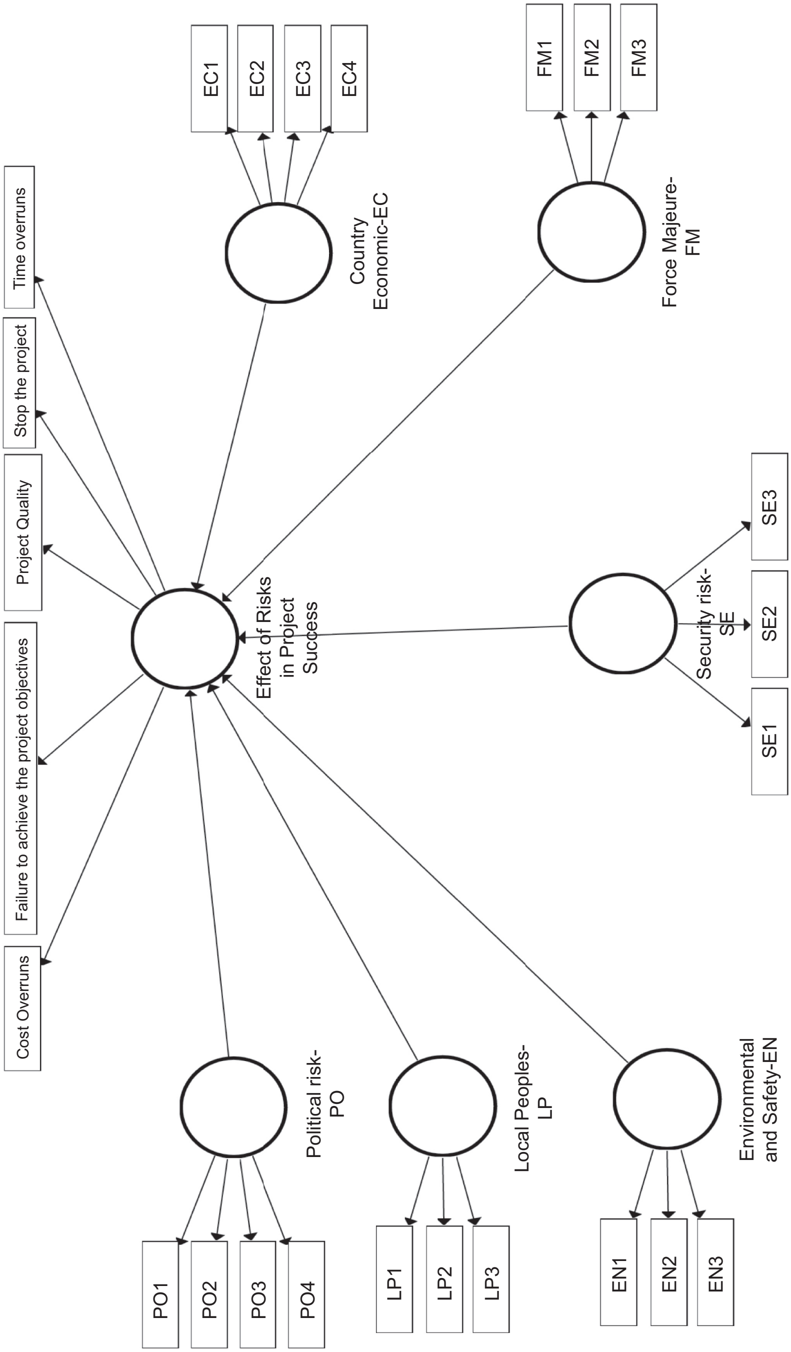

Figure 3.
External risk factors and effects on project success relationship model using PLS-SEMs methodology (research model)

with 5,000 replications was applied to test the hypothesis and obtain the standard errors of the estimates.

Assessment of measurements model

According to Hair *et al.* (2014), the assessment of reflective measurement models contains three necessary tests; composite reliability to evaluate external consistency, individual indicator reliability, and Average Variance Extracted (AVE) to evaluate the convergent validity. The Fornell–Larcker criterion and Cross Loadings are used to assess discriminant validity. In the following sections, we will explain each criterion for the assessment of reflective measurement models.

Step 1: convergent validity

The convergent validity is the extent to which a measure correlates positively with alternative measures of the same construct by using the domain sampling model, and indicators of a reflective construct treated as different approaches to measuring the same construct. Therefore, the items that are indicators (measures) of a specific construct should converge or share a high proportion of variance. Individual item reliability is the extent to which measurements of the latent variables measured with a multiple-item scale reflect mostly the actual score of the latent variables related to the error according to Hulland (1999). To found convergent validity, researchers should consider the outer loadings of the indicators, as well as the average variance extracted (AVE) Sarstedt *et al.* (2017).

The first criterion is evaluating external consistency, known as reliability. It is the traditional standard of Cronbach's external consistency Alpha, providing a reliability estimate based on intercorrelations note indicator variables. In Cronbach's Alpha, all indicators are assumed to be equally reliable; that is, all indicators on external loads are of similar construction. However, the priorities are PLS-SEM indicators according to their reliability. Furthermore, Cronbach's Alpha, for the sensitivity of the number of elements in the table, generally tends to underestimate the reliability of external consistency. This type of reliability considers the different outer loadings of the indicator variables and is calculated using the following formula:

$$\rho_c = \frac{\left(\sum_{k=1}^{k} l_k\right)^2}{\left(\sum_{k=1}^{k} l_k\right)^2 + \sum_{k=1}^{k} \mathrm{Var}(e_k)}$$

where l_k symbolizes the standardized outer loading of the indicator variable k of a specific construct measured with K indicators, e_k is the measurement error of indicator variable k, and var (e_k) denotes the variance of the measurement error, which defined as $1 \_ l_k^2$.

Composite reliability. The limitation of composite reliability varies between 0 and 1, with higher values indicating higher levels of reliability. It is generally interpreted the same way as Cronbach's alpha. Specifically, composite reliability values of 0.60–0. 70 are acceptable in exploratory research, while in more advanced stages of research, values between 0. 70 and 0.90 can be regarded as satisfactory Nunally and Bernstein (1994). Finally, composite reliability values below 0.60 indicate a lack of internal consistency reliability.

Cronbach's alpha. Cronbach's alpha is the second measure of external consistency reliability that assumes the same thresholds but yields lower values than the composite reliability (ρc). This statistic is defined in its standardised form as follows, where K represents the construct's number of indicators and $\bar{r}$ the average nonredundant indicator correlation coefficient (i.e. the mean of the lower or upper triangular correlation matrix):

$$\text{Cronbach's}\, \alpha = \frac{K.\bar{r}}{[1+(k-1).\bar{r}]}$$

According to Sohrabinejad and Rahimi (2015), questionnaires are generally accepted as reliable when Cronbach's alpha is higher than 0.7. In PLS-SEM, Cronbach's alpha is the lower bound, while ρc is the upper bound of external consistency reliability when estimating reflective measurement models with PLS-SEM.

Average variance extracted (AVE). The last step is assessing reflective measurement models under convergent validity, which is the extent to which a construct converges in its indicators by explaining the items' variance. Convergent validity assessed by the average variance extracted (AVE) across all items associated with a construct and referred to as commonality. According to Sarstedt *et al.* (2017), the AVE is calculated as the mean of the squared loadings of each indicator is associated with a construct (for standardized data):

$$\text{AVE} = \frac{\sum_{k=1}^{k} l_k^2}{K}$$

l_k and K were defined earlier.

Hair *et al.* (2014) reported for this issue by using the same logic as that used with the individual indicators. That is, an AVE value of 0.50 or higher indicates that, on average, the construct explains more than half of the variance of its indicators. Conversely, an AVE of less than 0.50 indicates that, on average, more variance remains in the error of the items than in the variance explained by the construct (see Table 2).

The Cronbach's alpha value of the overall model was much higher than 0.7, thereby indicating that all items are reliable and that the whole test is internally consistent. Based on Hulland (1999), the researchers must frequently observe weaker outer loadings in social science studies, mainly when newly developed scales are used, rather than automatically eliminating indicators when their outer loading is below 0.70. Besides, researchers should carefully examine the effects of item removal on the composite reliability as well as on the construct's content validity. However, indicators with outer loadings between 0.40 and 0. 70 should be considered for removal from the scale only when deleting the indicator leads to an increase in the composite reliability or the average variance extracted AVE above the suggested threshold value. Another consideration in the decision of whether to delete an indicator is the extent to which its removal affects content validity. Indicators with weaker outer loadings are sometimes retained based on their contribution to content validity.

The loading of the indicator item of Poor Quality, which measures the endogenous constructs is between 0.4 and 0.7, and when we delete it, the AVE becomes above 0.5, which is acceptable value as Table 3 below.

The indicators with very low outer loadings (below 0.40) should always be eliminated from the scale Hair *et al.* (2011). Figure 4 below shows the outer loading of all external items, which are all above 0.7 and all are acceptable values.

Step 2: discriminant validity

Discriminant validity based on Hair *et al.* (2014) is the extent to which a construct is a correct distinct from other constructs by empirical standards. However, establishing discriminant validity implies that a construct is unique and captures phenomena which are not represented by other constructs in the model.

Exogenous Constructs	Items	Loadings	AVEb	CRa	Alpha
Country Economic -EC	EC1	0.895	0.778	0.934	0.905
	EC2	0.891			
	EC3	0.853			
	EC4	0.889			
Political risk-PO	PO1	0.910	0.792	0.939	0.913
	PO2	0.887			
	PO3	0.890			
	PO4	0.874			
Local Peoples -LPs	LP1	0.882	0.734	0.892	0.819
	LP2	0.900			
	LP3	0.784			
Environmental and Safety-EN	EN1	0.910	0.805	0.925	0.879
	EN2	0.910			
	EN3	0.871			
Security risk -SE	SE1	0.855	0.808	0.926	0.880
	SE2	0.921			
	SE3	0.919			
Force Majeure-FM	FM1	0.868	0.761	0.906	0.845
	FM2	0.866			
	FM3	0.884			

Endogenous constructs	Constructs	Items	Loadings	AVE	CR	Alpha
Effect of risks in project success	Cost Overruns		0.595	0.491	0.826	0.74
	Failure to achieve the project objectives		0.761			
	Stop the project		0.741			
	Time overruns		0.800			
	Poor Quality		0.591			

Note(s): [a] Composite Reliability (CR) = (square of the summation of the factor loadings)/ {(square of the summation of the factor loadings) + (square of the summation of the error variances)}. [b] Average Variance Extracted (AVE) = (summation of the square of the factor loadings)/ {(summation of the square of the factor loadings) + (summation of the error variances)}

Table 2. Results of measurements model – convergent validity

Endogenous constructs	Constructs	Items	Loadings	AVE	CR	Alpha
Effect of risks in project success	Cost Overruns		0.537	0.548	0.826	0.74
	Failure to achieve the project objectives		0.806			
	Stop the project		0.734			
	Time overruns		0.847			

Table 3. Results of measurements model – convergent validity iteration 2

Fornell–Larcker test. The Fornell–Larcker criterion is a second and more conservative approach to assess discriminant validity Hair *et al.* (2014). It compares the square root of the AVE values with the latent variable correlations. Usually, the square root of each construct's AVE should be higher than its highest correlation with any other construct. In other words, this criterion can be mentioned as the AVE should exceed the squared correlation with any other indicators. The dialectics of this method is according to the idea that a construct shares more variance with its associated constructs than with other indicators (see Table 4).

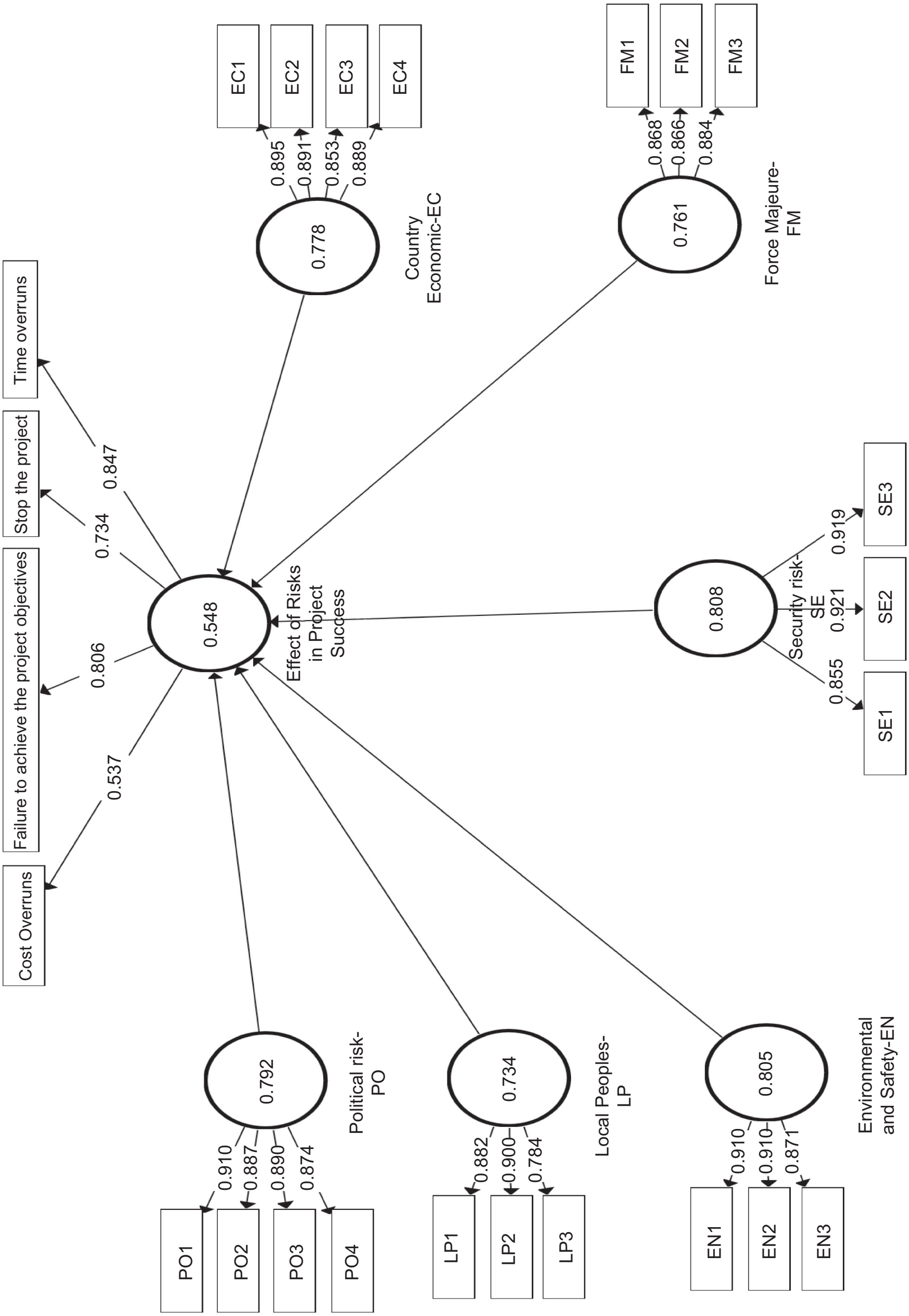

Figure 4.
Convergent validity of measurement model – External Risk Factors (R^2 and Factor loading analysis)

Cross loading. There are two measures of discriminant validity have been proposed. One method for assessing discriminant validity is by examining the Cross Loadings of the indicators. Specifically, an indicator's outer loading on the associated construct should be higher than all its loadings on other constructs. The presence of cross-loadings that exceed the indicators' outer loadings represents a discriminant validity problem. This criterion is generally considered somewhat liberal regarding establishing discriminant validity based on Hair *et al.* (2011). That is, it is very likely to indicate that two or more constructs exhibit discriminant validity (see Table 5).

Assessment of structural model (inner model)

The next stage, when confirming that the construct measures are valid and reliable, is the assessment of the structural model results by examining the inner relations between the dependent variables. It involves examining the model's predictive capabilities and the relationships between the constructs. This stage consists of five steps to examine the structural model, as shown in Figure 5 below.

Step 1: hypotheses testing (path coefficient)

The running of the PLS algorithm in SmartPLS program obtained for the structural model relationships (i.e. the path coefficients), which represent the hypothesized relationships among the constructs. The limit of path coefficients has standardised values between −1 and +1. Estimated path coefficients close to +1 represent strong positive relationships (and vice versa for negative values) that are almost always statistically significant (i.e. different from zero in the population). The closer values of the estimated coefficients are to 0, the weaker the relationships and shallow values close to 0 are usually non-significant (i.e. not significantly different from zero) Hair *et al.* (2014).

Whether a coefficient is significant ultimately depends on its standard error that is obtained using bootstrapping. According to Kushary *et al.* (1997), the bootstrapping routine applied as for the next step, where we used the procedure to assess whether a reflective indicator significantly contributes to its corresponding construct. The bootstrap standard error allows computing the observed t value. For example, to estimate the significance of the path coefficient linking constructs $Y1$ and $Y3$, we would enter the original path coefficient estimate (p_{13}) and the bootstrap of standard error (se^*_{13}) in the following formula:

$$t = \frac{p_{13}}{se^*_{13}}$$

Table 4.
Discriminant validity-Fornell-Larcker-external risk factors

	Country economic-EC	Environmental and Safety-EN	Force Majeure-FM	Local peoples-LPs	Political risk-PO	Security risk -SE
Country Economic -EC	*0.882*					
Environmental and Safety-EN	0.740	*0.897*				
Force Majeure-FM	0.798	0.688	*0.873*			
Local Peoples -LPs	0.770	0.734	0.718	*0.857*		
Political risk-PO	0.873	0.715	0.805	0.780	*0.890*	
Security risk -SE	0.845	0.745	0.807	0.783	0.805	*0.899*

	Country economic -EC	Environmental and Safety-EN	Force Majeure-FM	Local peoples-LPs	Political risk-PO	Security risk -SE
EC1	*0.895*	0.655	0.717	0.692	0.809	0.757
EC2	*0.891*	0.631	0.694	0.639	0.742	0.732
EC3	*0.853*	0.599	0.702	0.634	0.711	0.723
EC4	*0.889*	0.719	0.706	0.745	0.808	0.769
EN1	0.655	*0.910*	0.590	0.631	0.652	0.650
EN2	0.676	*0.910*	0.604	0.707	0.648	0.703
EN3	0.664	*0.871*	0.672	0.633	0.625	0.651
FM1	0.675	0.602	*0.868*	0.636	0.668	0.656
FM2	0.632	0.557	*0.866*	0.601	0.670	0.691
FM3	0.768	0.637	*0.884*	0.641	0.759	0.756
LP1	0.740	0.626	0.684	*0.882*	0.756	0.713
LP2	0.676	0.585	0.616	*0.900*	0.690	0.702
LP3	0.548	0.705	0.536	*0.784*	0.540	0.587
PO1	0.832	0.674	0.745	0.742	*0.910*	0.758
PO2	0.780	0.671	0.708	0.662	*0.887*	0.667
PO3	0.739	0.634	0.723	0.702	*0.890*	0.739
PO4	0.756	0.563	0.686	0.664	*0.874*	0.693
SE1	0.742	0.759	0.677	0.698	0.706	*0.855*
SE2	0.758	0.642	0.716	0.738	0.715	*0.921*
SE3	0.780	0.619	0.782	0.675	0.751	*0.919*

Table 5. Discriminant Validity-Cross Loading for External risk factors

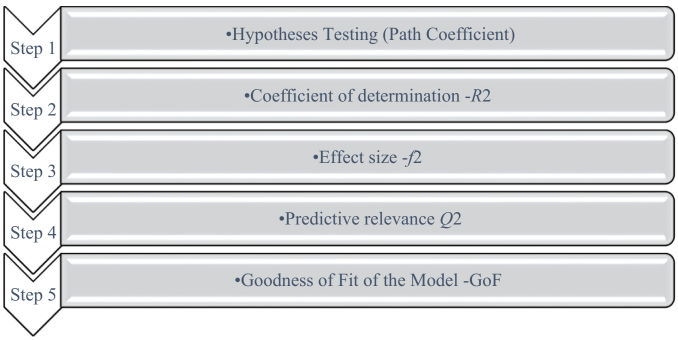

Figure 5. Structural model assessment procedure

The *t* distribution can reasonably be approximated for sample sizes larger than 30. Correspondingly, we can use the quantiles from the normal distribution as critical values to compare the observed *t* value with it. When the empirical *t* value is larger than the critical value, we say that the coefficient is significant at a certain error probability (i.e. significance level). The commonly used critical values for two-tailed tests are 1.65 (significance level = 10%), 1.96 (significance level = 5%), and 2.57 (significance level = 1%). According to Sarstedt *et al.* (2017), researchers in marketing usually assume a significance level of 5%, but this does not always apply; however, consumer research studies sometimes assume a significance level of 1%, especially when experiments are involved. On the other hand, when a study is exploratory, researchers often assume a significance level of 10%. Ultimately, the choice of the significance level depends on the field of study and the study objective.

Figure 6 shows the path of external risk factors in construction projects in the oil and gas sector in Yemen. It includes the most influential tracks, as well as the supported hypotheses.

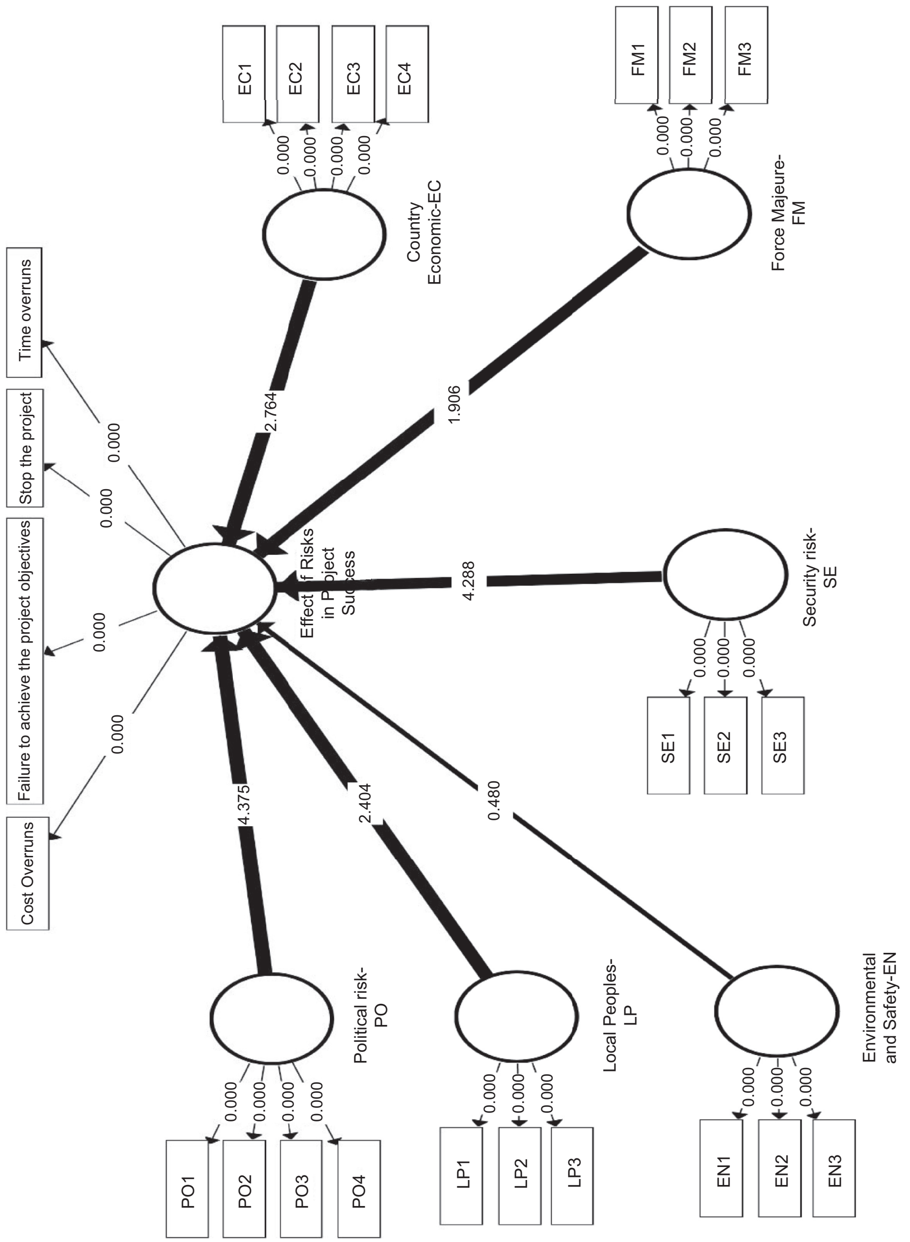

Figure 6.
Path analysis of the research hypotheses-external factor

Step 2: coefficient of determination (R^2 value)

Another important criterion for assessing the structural model in PLS-SEM is the R squared value, which is also known as the coefficient of determination (Hair *et al.*, 2011, 2012; Henseler *et al.*, 2009), and the most commonly used measure to evaluate the structural model is the coefficient of determination (R^2 value). This coefficient is a measure of the model's predictive accuracy and calculated as the squared correlation between the actual and predicted values of a specific endogenous construct. The R-squared value represents the proportion of variation in the dependent variable(s) that can be explained by one or more predictor variable (Elliott and Woodward, 2007; Hair *et al.*, 2010). Although the acceptable level of R^2 value depends on the research context, Hair *et al.* (2010) and Falk and Miller (1992) proposed an R-squared value of 0.10 as a minimum acceptable level. Meanwhile, Chin (1998) suggests that the R-squared values of 0.67, 0.33, and 0.19 in PLS-SEM can be considered as substantial, moderate, and weak, respectively, and any R^2 values less than 0.19 are unacceptable (see Tables 6 and 7).

Step 3: measuring the effect size (f^2)

According to Hair *et al.* (2014), in addition to evaluating the R^2 values of all endogenous constructs, the change in the R^2 value when a specified exogenous construct omitted from the model can be used to evaluate whether the omitted construct has a substantive impact on the endogenous constructs. This measure referred to as the f^2 effect size. The effect size could be expressed using the following formula (Cohen, 1988; Selya *et al.*, 2012; Cohen *et al.*, 2007).

No	Hypotheses	Original sample (O)	Sample mean (M)	Standard Deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
External risk factors							
1	Country Economic-EC → Effect on Project Success	0.235	0.241	0.085	2.762	0.00**	Supported
2	Political risk-PO → Effect on Project Success	0.024	−0.025	0.051	0.479	0.00**	Supported
3	Local Peoples-LPs → Effect on Project Success	0.122	−0.121	0.064	1.909	0.00**	Supported
4	Environmental and Safety-EN → Effect on Project Success	0.142	0.143	0.059	2.391	0.00**	Supported
5	Security risk-SE → Effect on Project Success	0.370	0.365	0.084	4.374	0.00**	Supported
6	Force Majeure-FM → Effect on Project Success	0.308	0.306	0.072	4.289	0.000**	Supported

Note(s): *$p < 0.05$; **$p < 0.01$

Table 6. Path coefficient of the research hypotheses

Constructs relation	R^2	Result
Effect of External Risks in Project Success	0.743*	High

Note(s): * Chin (1998), suggested that the values of R^2 that above 0.67 considered high, while values ranging from 0.33 to 0.67 are moderate, whereas values between 0.19 and 0.33 are weak and any R^2 values less than 0.19 are unacceptable. Falk and Miller (1992) propose an R-squared value of 0.10 as a minimum acceptable level

Table 7. R-Square of the endogenous latent variables

$$f^2 = \frac{R^2_{\text{included}} - R^2_{\text{excluded}}}{1 - R^2_{\text{included}}}$$

It was reported by Hussain *et al.* (2018) that the f^2 is the degree of the impact of each exogenous latent construct on the endogenous latent construct. When an independent construct deleted from the path model, it changes the value of the coefficient of determination (R^2) and defines whether the removed latent exogenous construct has a significant influence on the value of the latent endogenous construct. The f^2 values were 0.35 (strong effect), 0.15 (moderate effect), and 0.02 (weak effect) as per Cohen (1988).

Step 4: blindfolding and predictive relevance (Q2)

It was confirmed by Hair *et al.* (2014) that each data point of the indicators of a selected reflective endogenous latent variable is removed and then predicted. Thus, the blindfolding procedure can compare the original values with the predicted values. If the prediction is close to the original value (i.e. there is a small prediction error), the path model has high predictive accuracy. This prediction errors, calculated as the difference between the right values and the predicted values along with a trivial prediction error (defined as the mean of the remaining data), are then used to estimate the *Q*2 value Chin (1998), and the *Q*2 values larger than 0 suggest that the model has predictive relevance for a specific endogenous construct. In contrast, values of 0 and below indicates a lack of predictive relevance.

According to Hussain *et al.* (2018), the blindfolding pro cedure is only applied to endogenous constructs that have a reflective measurement model specification as well as to endogenous single-item constructs. *Q*2 statistics are used to measure the quality of the PLS path model, which is calculated using blindfolding procedures and cross-validated redundancy performed. The *Q*2 criterion recommends that the conceptual model can predict the endogenous latent constructs.

Step 5: The goodness of fit of the model – GoF

The goodness of Fit of the Model (GoF) applied as an index for the complete model fit to verify that the model sufficiently explains the empirical data. Tenenhaus *et al.* (2005) defined GoF as the global fit measure. It is the geometric mean of both average variances extracted (AVE) and the average of R^2 of the endogenous variables. The purpose of GoF is to account the study model at both levels, namely measurement and structural model with a focus on the overall performance of the model (Vinzi *et al.*, 2010; Henseler and Sarstedt, 2013; Liu *et al.*, 2016). The calculation formula of GoF is as follow:

$$1\text{: GoF For External Risk Factors} = \sqrt{(\bar{R}^2 \times \bar{\text{AVE}}^2)}$$

$$\text{GoF} = \sqrt{(0.743 \times 0.659)} = 0.699$$

The criteria of GoF to determine whether GoF values are no fit, small, medium, or large to be considered as global valid PLS model have been given by (Wetzels *et al.*, 2009). The table below presents these criteria (see Tables 8 and 9):

As reported by Trimestral (2016), concerning the investigation of the structural model, it is essential to understand that the PLS-SEM adjusts the model to the empirical data, in the attempt to obtain the best estimates of the parameters by maximizing the explained variance of the latent endogenous variable. Thus, the detriment of applying goodness-of-fit measures for the model, the structural model in PLS-SEM, is assessed based on heuristic criteria that are determined by the predictive power of the model Hair *et al.* (2014). In this aspect, it assumed that the model is specified correctly, as it predicts the endogenous constructs Rigdon *et al.* (2012). The result of GoF for our model is 0.699 for external risk factors effect on project success, which is larger than 0.36, and considered high value based on Table 10.

Country Economic -related risk factors – EC According to Luo and Yan (2010) the attractiveness of the fiscal terms has a major effect on a project's feasibility and economic benefits of international oil companies, and it is an essential indicator for judging the country's investment environment of the oil industry. Furthermore, in SEM analysis (Table 6) the Hypotheses 1: Country Economic -related risk factors – EC have a significant effect on project success, is supporting. Numerous researchers have identified these risk factors of Country Economic that contributed to the effect of project success (Al-Momani, 2000; Aven, 2009; Berends, 2007; George and Larry, 2004; Perez *et al.*, 2017; Sabri *et al.*, 2015; Xiong *et al.*, 2014) and approved the aforementioned items. Moreover, the economic risk factors group is the second important group among external risk factors. The oil and gas sector has always been concerned with the economic and political decisions taken by governments, and shows an increased sensitivity, improving the state budget, raising the level of income among citizens, or the high level of liquidity of the Monetary Institution or the announcement of large projects, or change Strategy in economic policy such as opening up to other economies, strengthening the relationship with large economies, or entering giant companies to take advantage of the country's capabilities, as well as declaring low inflation, low unemployment, or the decline of poverty and all these decisions reflect positively on the economy the year is eloquently portrayed by the market.

No	Constructs	Effective size f^{2*}	Result
External Risk Factors			
1	Country Economic -EC	0.037	Small
2	Environmental and Safety-EN	0.041	Small
3	Force Majeure-FM	0.066	Small
4	Local Peoples -LPs	0.023	Small
5	Political risk-PO	0.100	Small
6	Security risk -SE	0.076	Small

Note(s): *Interpreting Effect Size (f^2) (Cohen, 1988)
f^2 above 0.35 are considered large effect size.
f^2 ranging from 0.15 to 0.35 are medium effect size.
f^2 between 0.02 and 0.15 considered small effect size.
f^2 values less than 0.02 are considering with No effect size

Table 8. Assessment of effect size (f^2)

Endogenous latent variables	SSO	SSE	Q^2 (=1-SSE/SSO)
Effect of External Risks in Project Success	1,256.00	784.787	0.375

Table 9. Results of Predictive Relevance (Q2) values

GoF less than 0.1	No fit
GoF between 0.1 and 0.25	Small
GoF between 0.25 and 0.36	Medium
GoF greater than 0.36	Large

Table 10. Value of goodness of fit of the model (GoF)

Political-related risk factors-PO In the context of political risk, the threat to the construction could be regarded as possible events which stem from the political system in the host country or its embedded context for the political situation, while the turbulent political environment discourages investment based on Deng *et al.* (2018). Moreover, in SEM analysis (Table 6) the Hypotheses 2: Political -related risk factors - PO have a significant effect on project success, is supporting and factors of this group get highest loading factors among external risk factors. Numerous researchers were identified these risk factors of Political situation that contribute to effect of project success (Adam *et al.*, 2015; Al-Sabah *et al.*, 2014; Alkaf and Karim, 2011; Dehdasht *et al.*, 2015; Khodeir and Mohamed, 2015; Tanaka, 2014) and they confirm the importance of the role of the risks resulting from the political situation of the countries on the success of the construction projects. Also with regard to matters of governance and the country's politics, the announcement of any positive amendment in the general constitution of the country, as well as the announcement of raising the level of transparency, or activating democracy, and the preservation of the rights of citizens, all of this also reflects positively also on the performance of the general economy and the creation of a favorable climate for recovery and A boom that appears clearly in the financial markets and quite the contrary unless the negatives were announced contrary to the above, the low budget of the country, the low level of income of the individual, the low level of liquidity of the monetary institution or the like or the announcement of the death of a president, or influential in decisions It is undoubtedly directly reflected negatively.

The oil and gas sector are also directly responsive to the political decisions in developing countries, where public economies grow only in a stable political climate. The general shock or the stability of the country, they will undoubtedly relax the very negative impact on the performance of the economy and therefore on the financial markets which reflect this quickly.

Local Peoples -related risk factors-LP Based on Ofori (2016) the peoples of the developing countries bear the brunt of social stress as many of them rely on the natural ecosystems for their livelihoods, and they lack the expertise and skills that qualify them to work in oil companies, although there is a specific employment rate imposed on oil and gas companies from the population of the community adjacent to the oil sector and might be a source of risk on the company's future projects. Further, in SEM analysis (Table 6) the Hypotheses 3: Local Peoples -related risk factors-LP have a significant effect on project success, is supporting. Numerous researchers have identified these risk factors of Local Peoples that contribute to the effect of project success (Kamalirad *et al.*, 2017; Pidomson, 2017; Rodhi *et al.*, 2019; Ronza *et al.*, 2009; Tanaka, 2014; Van der Ploeg and Vanclay, 2017).

Environmental and Safety-related risk factors-EN Oil and gas companies faced risks ranging from volatile commodity prices, which are less linked to primary supply and demand but more to global socioeconomic factors, to increased health, safety, and environmental pressures resulting from past and recent significant accidents negatively impacting the environment, industry image, and its social lease regarding to Bigliani (2013). In SEM analysis (Table 6) the Hypotheses 4: Environmental and Safety-related risk factors-EN have a significant effect on project success, is supporting. This result is explained by the stringent procedures in the oil and gas sector that reduce the risk factors in this group and can be considered high challenges. Numerous researchers have identified these risk factors of Environmental and Safety -related risk factors-EN that contributed to the effect of project success (Abdrabou, 2012; Alzahrani and Emsley, 2013; Bigliani, 2013; Dumas, 2011; Kashwani and Nielsen, 2017; Sawacha *et al.*, 1999; Taylan *et al.*, 2014) and approved the aforementioned items.

Security risk -related risk factors-SE According to Hirst *et al.* (2010) the constant security threats, coupled with persistent tribal conflicts, make it a high-risk context within which to operate. Security issues are one of the most influential factors affecting the progress of projects in the oil and gas sector in a troubled country such as Yemen. SEM analysis in

Table 6 shows the Hypotheses 5: Security - related risk factors-SE have a significant effect on project success, is supporting. Numerous researchers have identified these risk factors of Local Peoples that contributed to the effect of project success (Chaher and Soom, 2016; Hirst *et al.*, 2010; Mubin and Mubin, 2008; Sears *et al.*, 2015; Syed and Hirst, 2010; Tixier *et al.*, 2017).

Force Majeure -related risk factors-FM According to Baghdadi and Kishk (2015) the force majeure risk level consists of two sources of risks: natural phenomena and weather issues that are not within any project participants' control. Furthermore, in SEM analysis (Table 6) the Hypotheses 6: Force Majeure -related risk factors-FM have a significant effect on project success, is supporting. Many researchers have identified these risk factors of Force Majeure that contributed to the effect of project success (Alaghbari *et al.*, 2017; Ali *et al.*, 2018; Baghdadi and Kishk, 2015; Myakenkaya *et al.*, 2014; Sultan and Alaghbari, 2018).

Conclusion

The statistical analysis revealed the six external risk factors groups affecting project success that may be grouped in-country economic risks, political risks, Local Peoples risks, Environmental and Safety risks, Security risks, and Force Majeure risks. The results of the structural equation model suggest that the relationship between external risk factors and project success in oil and gas construction projects can be explained by factor loading of all items which are above the value required 0.7. While *R*-squared value represents the proportion of variation in the dependent variable(s), that can be explained by one or more predictor variable equal to 0.743 considered exceeding the high value required 0.67. Moreover, the *Q*2 is 0.375 above than zero, which indicates that the conceptual model can predict the endogenous latent constructs. Thus, the positive relationship suggests that H1, H2, H3, H4, H5 and H6 are supported. The result of the Goodness of Fit of the Model GoF for our model is considered substantial value.

However, the beta coefficient (β) value describes the strength between exogenous and endogenous latent constructs, Path Coefficient of the Research Hypotheses test. Security ($\beta = 0.370$), Force Majeure ($\beta = 0.308$) and economic risk factors ($\beta = 0.235$) are the most external factors related to the effect on project success; these factors need to focus more and develop an effective strategy to respond and mitigate the effects resulting in the cost of the project and the schedule as well as quality. According to (Khodeir and Mohamed, 2015) the process of management of risks also includes risk response strategies that are defined as risk retention, risk transfer, risk reduction and risk avoidance. For the three groups mention above wich are mor effects in project success we have to use risk avoidance response as we can otherwise transfer or reduce risk to mitigate the effect of risk on project success.

The study contributes to three areas: academia, governments/authorities, and the Oil and gas sector. This research contributes to the academic sector by setting out the practical advantages and disadvantages of each risk factor faced in the Oil and gas sector. it has identified and grouped external risk factors to enable focus from the most effecting groups (economic, political, security, etc.). This should help future academic researchers to look at other groups and analyze how these factors and groups influence other sectors.

This study will help governments and authorities to set up guidelines and policies to improve stakeholder collaboration and integration during the project life cycle. The authorities can also help oil companies by developing more infrastructure and road projects to the location of the onshore oil production areas in the desert (all Yemenis oil sectors are onshore in the desert and the construction projects are a part of oil and gas projects stages either upstream, midstream, and downstream), and coordinating to facilitate the flow of materials to and from the company site without hindrance. The study also outlines the measures by which the government can provide support and provide a safe and suitable environment for investment. In addition, the study provides a detailed explanation of the economic and political risk factors related to the government and the recommendations and proposals necessary for the government to contribute to improving the environment suitable for the success of projects in the oil and gas sector in Yemen.

The study stressed that the stakeholders in the construction projects of the oil and gas sector need to develop strategies to respond to external risks and the need to allocate responsibilities between them in order to mitigate these risks as much as possible. Companies operating in the oil sector need to develop plans to follow up the construction project from the feasibility study and the preparation of designs through the stage of tenders and contracts and consider them an essential part in the management of the project, because of their potential effects during the implementation phase of projects. Successful management of risk factors is the way to a successful project without exceeding the cost or time and thus achieving the project objectives as planned.

Recommendations to mitigate the effect of external risk factors on project success:

(1) Providing the right environment for investment and the necessary facilities for the success of oil and gas projects in Yemen as a tributary of the national economy.

(2) Develop the country infrastructure and road projects in Yemen's oil and gas regions.

(3) Create laws that identify policy procedures and deal with and work on reducing red tape in official transactions and tracking bribery in oil and gas sector tenders.

(4) To speed up decisions on projects and their budget and everything related to government supervision of the oil sectors.

(5) To improve the economic and political environment that serves long-term investment in Yemen.

(6) Strengthening security measures in oil and gas areas and coordinating between the various parties responsible for the security of the oil sector to facilitate the procedures and transportation of materials and not to cause any risks as a result of the security failure.

(7) Coordinating with oil and gas companies in training and developing local staff to become more professional and able to manage the sector in the future.

(8) Prepare plans to respond to potential risks that may affect the progress of oil and gas sector projects.

Data availability

All data, models, or code generated or used during the study are available from the corresponding author by request.

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Corresponding author
Mukhtar A. Kassem can be contacted at: mukhtarkas@gmail.com