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PROJECT RISK RANKING BASED ON PRINCIPAL COMPONENT ANALYSIS – AN EMPIRICAL STUDY IN MALAYSIA-SINGAPORE CONTEXT

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Abstract. *Information Technology (IT) remains a robust and sustainable industry, resulting in high demand for IT project practitioners. Nevertheless, the high failure rate of IT projects has resulted in significant losses for many companies. This crucial issue needs immediate attention. One of the focusing points should be adopting a practical and proactive project risk management approach. This study aims to determine whether Principal Component Analysis (PCA) can be used in project risk management. The survey was conducted on targeted project managers in the Malaysia-Singapore region. Underlying trends and patterns were analyzed based on an intrinsic risk ranking study. PCA was performed to isolate highly associated key risks from less associated lower-ranked risks. As a result, PCA effectively removed weakly correlated risk factors while identifying significant components and retaining the data information. The results showed that combining PCA with established risk management approaches provides a credible risk assessment based on criticality.*

Keywords: Project risk, Ranking, Assessment, Analysis, Principal component analysis

1. **Introduction.** Global competition requires organizations to be nimble, agile, and responsive in dealing with rapid changes. Organizations view projects as "powerful strategic weapons", generating economic value and competitive advantage. As a result, project managers have expanded into strategic leadership roles that include full accountability for project business outcomes [1]. Thus, project management is an extraordinary business skill set for the industry and has been seen as the contemporary form of organizational general management practice [2]. Project teams are foreseen to work more effectively than functional teams, and their unique hierarchical structures enable organizations to respond quickly to changes [3]. Nonetheless, the iron triangle model-based measurement of the overall project success rate remains low [4].

Project risk management involves the required techniques and processes in identifying, mitigating, or avoiding potential problems proactively. Project managers are expected to acquire risk management knowledge and be competent in dealing with risk management planning, monitoring, tracking, and execution. Progressive risk management practice ensures that high-priority risks are dealt with aggressively. It enables project governance

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bodies such as the Project Management Office (PMO) and Steering Committees (SC) to have the necessary, updated information to make informed decisions.

Principal Component Analysis (PCA) is a dimensionality reduction technique successfully adopted in many areas such as data analytics, machine learning, pattern finding and recognition in finance, data mining, bioinformatics, psychology, sociology, marketing, and quality control. In recent studies, Bélanger and Picard implemented the PCA approach to improve the volatility index fear factor-level prediction in venture risk management [5]. The PCA application was developed to delete redundant input indicators in financial risk management analysis [6]. PCA directly indicates each bank's systemic risk contribution to banking supervision and preventing financial crises [7]. Hefaidh and Mébarek [8] applied the PCA method to aggregating data associated with industrial risks as principal factors to classify risks according to their criticality. These findings inspire the research interest in adopting PCA in project risk management practices.

This study aims to evaluate PCA application in project risk management practice. In large and complex projects, conventional risk management practices have limitations in tracking, monitoring, and planning, especially when the number of identified risks increases significantly. Combining PCA with traditional project risk assessment methods may provide a viable solution to the constraints in which PCA is applied to separating the most significant risk factors from a more extensive collection of project risk items.

This paper discusses a literature review of relevant failure studies and an adopted quantitative survey research strategy for sampling, data collection, and analysis. The next step is to disclose each descriptive statistical data, risk exposure analysis and PCA analysis results. Discussion of the findings is shared and ends with a conclusion.

2. **Literature Review.** Risk perceptions refer to people's subjective judgments about the likelihood of potential harm/benefit or the possibility of a loss or gain about the characteristics and severity of risk [9]. Risk perception moderates the relationship between personal norms and individual voluntourism behaviour [10]. In the opinion of Pang et al., risk perception and assessment depend on the number of years of experience acquired [11]. Individual characteristics, such as psychological and demographic characteristics, affect risk perception and management decisions [12]. An experienced project manager will perform risk analysis using a methodology that eliminates the distortions caused by risk perception [13].

All projects are a temporary effort (with a start and end date) to create value through a unique product, service or result. Project management uses specific knowledge, skills, tools and techniques to deliver project value to people [14]. Several theories are associated with project management. First, the theory of the project includes the transformation view (transform of inputs to outputs), flow view (eliminate waste from flow processes) and value generation view (deliver the business purpose). Second, the management theories comprise the theory of planning (translate the resultant plan into action), theory of execution (dispatching tasks) and theory of control (performance correction) [15].

A total of 17 risk factors [16-27] have been documented and identified in research studies from 1998 to 2020 based on a systematic content analysis approach comprising the following steps. The first step was identifying and narrowing the area of interest. The second step was to define explicit inclusion and exclusion criteria and the search target year range, including the keywords defined in step 1. In the third step, the authors identified the resources to be searched, such as online journal article databases, academic search engines and academic-related social networks. Advanced search features refine search keywords and Boolean operands to retrieve the closest relevant articles. Step four was constructing and running the searches based on the search criteria defined in step 2, removing the duplicates, and executing the search on resources defined in step 3. Step five was to retrieve the full text of relevant studies and read the full selected papers capturing and extracting the key concepts, study's aims and objectives, data collection, data analysis method, findings, or metaphors.

This iterative content synthesis helps summarize the findings of the studies, relationships among the studies, and its theory of how the intervention works. This repetitive process began with a target of 50 papers in an initial cycle. Through similar grouping types of risk factors and the elimination of two irrelevant, non-critical risks, the total number of risk factors was reduced to 11 for the development and fine-tuning of the survey questionnaires as follows.

The risk factor, **R1** – *Change in Project Scope*, is considered to elevate risk and can often be critical if changes are made at the end of a waterfall project [16].

Other essential factors concern the inability to discover and correct a deflated budget or impractical timetable and the routine underestimation of workloads. In the cost and schedule dimension, the risk factor, **R2** – *Underestimated Costs and Time*, includes root causes such as underfunding (insufficient budget), the inadequate definition of timescales, and unrealistic deadlines. If this risk is not mitigated during the project's life cycle, it could have disastrous repercussions [17].

From the perspective of project governance, the risk factor, **R3** – *Lack of Top Management Governance and Sponsorship*, is related to the lack of a mechanism and/or strategy for steering a project, which is strongly related to the skills of the steering committee. Some established Project Management Offices (PMOs) frequently play a crucial role in the policies, processes and steering of project realization [20, 28].

Large and complex projects are distinguished by their extended duration, increased risk, cost, high complexity, and large team size, requiring superior communication and coordination. The risk factor, **R4** – *Project is Too Large and Complex*, is associated with failures directly resulting from a project's size and complexity. Poor delivery strategies can have fatal consequences [21].

Unlike the risk factors described above, the risk factor, **R5** – *Poor Management of Requirements*, is primarily caused by failures resulting from the insufficient definition of requirements or lack of information regarding them after project initiation. This risk often becomes a systematic risk, consistently increasing in scope and impacting the entire project life-cycle [22].

R6 – *Poor Stakeholder Management* is a significant risk factor due to conflict among stakeholders with varying interests. Undesirable stakeholder behaviours include the project team being unwilling to execute changes, customers or users being reluctant to accept changes to a system, processes, or project deliverable, and constantly being resistant to change, resulting in a lack of stakeholder involvement and participation [23].

When viewed from the perspective of project methodology, the risk factor, **R7** – *Lack of a Methodology for Project Management*, is related to the choice of project methodology. Usually, this choice falls into two major categories: "agile" or "waterfall". Many organizations tailor their methodology of project practitioner experience in risk ranking analysis in alignment with organizational processes. Omissions of critical guidelines, lack of an integrated methodology, and selection of an inappropriate method may adversely affect project success [24].

The risk factor, **R8** – *Poor Business Plan and Feasibility Study* during the evaluation stage, usually appears due to an unclear description of the project scope due to an improper feasibility study conducted during the evaluation stage. The benefits of a project are not clearly or adequately explained, resulting in the project budget being wrongly estimated. This risk results in the inability to develop a quality business plan, poorly defined goals and objectives, unanswered questions about the scope of a solution and the gap between the specifications of the final product according to different shareholders [25].

The risk factor, **R9** – *Insufficient Communication between Stakeholders*, includes ineffective internal communication among project stakeholders resulting in adverse outcomes. A lack of communication that causes mismatched user and developer requirements leads to a catastrophe [16, 26].

The risk factor, **R10** – *Lack of Requisite Knowledge, Training and Skills* amongst team members, is related to a project team lacking technical, leadership, and project management skills. This risk may be due to a lack of training, knowledge in a specific domain and/or relevant experience [16, 27].

A project's duration significantly impacts team performance and members' willingness to become involved and remain committed to a project. The risk factor, **R11** – *Weak Commitment of Project Team*, is also related to human resources, particularly staff turnover, a lack of commitment or motivation in the project team, and performance issues. Such risks increase the cost of re-hiring and onboarding and the probability of issues regarding the competency of teams [18, 19].

The contributory risk factors appear at different stages in the Project Management Lifecycle (PMLC). Some risk factors could be mitigated with additional funding from project sponsors or implement a corrective plan in the early planning phase; many others could be situational and incidental; triggered by different stakeholder groups. Hermanns et al. [29] argued that the risk classification does not automatically spot project failures. It is a risk management support tool that helps prioritize, decide, monitor, and follow up.

3. **Methodology.** A quantitative survey research strategy was adopted by structuring a questionnaire based on the 11 critical project contributory factors highlighted in the literature review section. These factors were presented to respondents. A survey form was created online [30] with respondents (target population) who were experienced Project Managers (PM), program managers, project directors, and other comparable project practitioners from various organizations.

There were three sections on the survey form. Profiles of respondents were captured in the first section. The second and third sections used the Likert scale for assessing the severity and likelihood of occurrence of 11 IT risk contributory factors. Based on their experiences, respondents were asked to select the most appropriate rating for each extracted question.

3.1. **Sampling.** In this investigation, a random snowball sampling technique was applied to leveraging informants to recruit similarly qualified project practitioners to participate in the survey. Purposive sampling ensures that the investigator collects the genuine views of the target population. This procedure is appropriate when members of homogeneous groups are difficult to locate and compiling a list of the population is challenging [31]. The sampling size was computed based on the z-scores to reduce the risk of sampling bias [32]. The authors selected the initial batch of target respondents or potential subjects using expert judgment based on available qualified social networked resources. The potential subjects were encouraged to use their expert judgment to recruit other similar profiled participants for the survey. These steps were repeated until the required sample size was obtained.

3.2. **Data collection.** The survey received 115 complete responses, reflecting a 72.7% response rate. Respondents are mainly project practitioners with many years of project management experience. 60% of respondents have more than ten years of project management experience, and 79% have more than five years of project management experience.

Other than IT projects, 8% of respondents have other industry project management experience. 113 valid samples after bias reduction are regarded as appropriate and representative compared to other risk management research. For example, 57 responses were collected in Liu et al.'s study [33]; Rahman and Kumaraswamy [34] received 92 survey responses on cooperative risk management research; in El-Sayegh's risk assessment study [35], 70 responses were obtained. The survey respondents' profiles are summarized in Table 1.

TABLE 1. Survey respondent's profiles

Category	**Respondents**	
	Frequency	**%**
Role		
President CEO	1	.9
Vice President	4	3.5
Director	14	12.4
Senior Manager/Manager/PM	54	47.8
Department Head	9	7.9
Supervisor	2	1.8
Executive	8	7.1
Professional Consultant	15	13.3
Staff	5	4.4
Others	1	.9
Project type		
IT	104	92.0
Non-IT	9	8.0
PM experience level		
10 years or more	68	60.2
5-10 years	22	19.5
Less than 5 years	23	20.3

3.3. **Analytical techniques.** The current study attempted to develop a three-step data analysis approach for risk assessment, as shown in Figure 1. Statistical Package for Social Sciences (SPSS) 26.0, Microsoft Excel 2019, and JASP version 0.14.1.0 were used to perform PCA. In the first step, descriptive statistics of the risk factors were outlined. Next, the mean risk exposure scores were applied to ranking the various risk variables in descending order. According to the respondents, each risk factor was perceived in terms of likelihood and impact. In the final step, a dimensional reduction method is employed for extracting the top key risk factors using PCA.

FIGURE 1. Three-step analysis framework

3.3.1. *Risk Exposure score (RE).* Collected quantitative survey data gives an aggregate image of different respondents expectations in terms of risk exposure. Firstly, data has to be reviewed to validate its completeness. Each risk factor RE is calculated based on the Likert scale defined in the survey form and averaged using the mean risk exposure equation (1), where n is the total number of risk responses i. A risk is the possibility that an outcome will be unsatisfactory (a.k.a. "risk impact"). The average product of each risk probability and its associated risk impact is the mean risk exposure score [36]. **Risk Probability** is the likelihood of a risky event or condition. Respondents were requested to rate the likelihood (frequency of occurrence) of a seven-point Likert scale where '1' denoted "extremely low", and '7' denoted "extremely high". Likewise, respondents were asked to rate the severity (degree of impact) of the situation in the first set of surveys of each risk factor on a 5-point Likert scale from '1' meant "very low" and '5' meant "very high".

$$Mean\ Risk\ Exposure\ (RE) = \sum_{i=1}^{n} \frac{Risk\ Probability_i * Risk\ Impact_i}{n} \tag{1}$$

3.3.2. *Principal Component Analysis (PCA).* PCA is a multivariate exploratory analysis method. Its dimensionality reduction capability separates systematic variation from noise and retains the most amount of information [37]. Kaiser-Meyer-Olkin tests determine whether the data are suitable for factor analysis by sampling adequacy for each variable in the model. KMO values between .8 and 1 indicate adequate sampling. KMO values less than .6 indicate insufficient sampling, and corrective action should be taken [38].

4. Data Analysis and Results.

4.1. **Descriptive statistics.** The mean risk exposure score ranges are $15.01 \leq M \leq 21.61$, with individual scores varying from 2 to 35 ($N = 113$), with a range of $15 \leq Mdn \leq 20$ for the median exposure score. The standard deviation range is $5.70 \leq SD \leq 7.40$. The p-value associated with the Shapiro-Wilk for normality was $< .05$, indicating that the risk exposure score was not normally distributed due to the data being ordinal. However, further data analysis conducted for each risk factor indicated that the distribution of the risk exposure score is reasonably similar to a normal univariate distribution since the value of the symmetry and kurtosis measures were between 2 [39] (Table 2).

TABLE 2. Risk exposure scores descriptive statistics

Descriptive statistics	**R1**	**R2**	**R3**	**R4**	**R5**	**R6**	**R7**	**R8**	**R9**	**R10**	**R11**
Valid	113	113	113	113	113	113	113	113	113	113	113
Missing	0	0	0	0	0	0	0	0	0	0	0
Median	20.00	20.00	20.00	15.00	20.00	20.00	16.00	18.00	20.00	16.00	20.00
Mean	19.97	21.61	19.28	15.01	21.20	19.73	16.12	18.98	20.64	17.15	19.60
Std. Dev	6.45	5.80	7.40	5.99	6.88	6.76	6.09	6.62	6.87	5.70	6.05
Kurtosis	−.08	.23	−.41	−.08	−.65	−.30	.05	−.16	−.26	−.26	.06
Std. Error of Kurtosis	.451	.451	.451	.451	.451	.451	.451	.451	.451	.451	.451
Shapiro-Wilk	.964	.950	.957	.967	.951	.964	.952	.957	.959	.962	.957
Shapiro-Wilk p-value	.004	$< .001$	.001	.007	$< .001$	.004	$< .001$	.001	.002	.003	.001
Minimum	5.00	8.00	4.00	2.00	8.00	6.00	5.00	4.00	5.00	4.00	8.00
Maximum	35.00	35.00	35.00	30.00	35.00	35.00	35.00	35.00	35.00	30.00	35.00

4.2. **Risk ranking.** The widely accepted approach of risk ranking is based on the value of the average risk exposure calculated using Equation (1). The risk factor ranking was organized in descending order based on the average value of the risk exposure scores in Table 3. Among the whole set of respondents, the three contributory risk factors with the highest exposure scores were: **R2** (*underestimated costs and time*), **R5** (*poor management of requirements*), and **R9** (*insufficient communication between stakeholders*). The p-value of the Shapiro-Wilk was significant, indicating that the risk exposure score was not normally distributed. For this reason, non-parametric testing was selected.

TABLE 3. Risk contributory factor ranking

ID	Risk contributory factor	Median	Mean	Rank
R2	Underestimated costs and time	20.00	21.478	1
R5	Poor requirement management	20.00	21.283	2
R9	Insufficient communication between stakeholders	20.00	20.434	3
R1	Change in project scope	20.00	19.876	4
R6	Poor stakeholder management	20.00	19.717	5
R11	Weak commitment of project team	20.00	19.628	6
R3	Lack of top management governance and sponsorship	20.00	19.460	7
R8	Poor business case and feasibility study during evaluation stage	18.00	18.858	8
R10	Project team members lack the requisite knowledge, training, and skills	16.00	17.389	9
R7	Lack of project management methodology	16.00	16.150	10
R4	The project is too large and complex	15.00	14.929	11

Risks levels were categorized using a risk matrix (Figure 2). A mean risk exposure value 18 or greater is considered "high". Values between ten and above and below 18 are categorized as "medium", and values below ten are classified as "low". Eight risk factors were considered to be "high" and three to be "medium". Typically, "high" category risks require developing a response plan, and "low" category risks are placed on a "watch list". Table 4 illustrates eleven risk factors being categorized in the risk matrix framework.

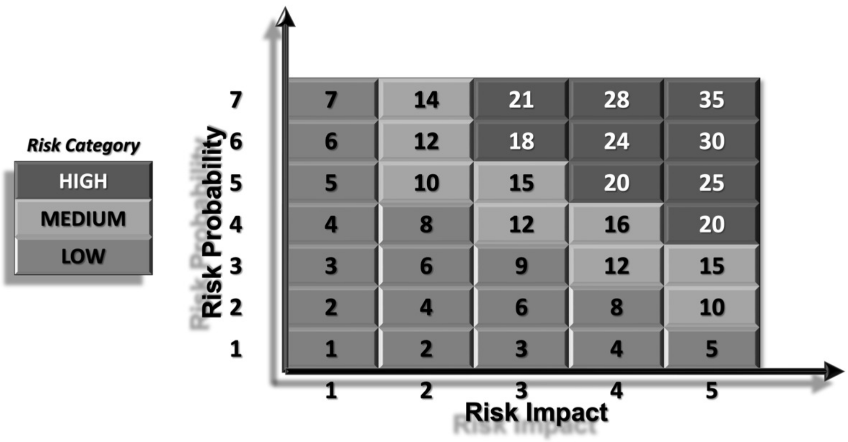

FIGURE 2. Risk matrix

TABLE 4. Contributory risk factor matrix

Impact-Prob	**Low**	**Medium**	**High**
Low	N/A	N/A	▷ Poor business case and feasibility study during evaluation stage ▷ Project team members lack the requisite knowledge, training, and skills
Medium	N/A	▷ Lack of project management methodology ▷ The project is too large and complex	▷ Insufficient communication between stakeholders ▷ Poor stakeholder management ▷ Lack of top management governance and sponsorship
High	N/A	▷ Change of project scope ▷ Weak commitment of project team	▷ Underestimated costs and time ▷ Poor requirement management

4.3. **Principal component analysis.** PCA was conducted using SPSS to identify the less associated risk factors. The Scree plot's eigenvalue distribution showed that just one factor should be extracted. Both the KMO sampling adequacy metric with a computed value of .855 and the Bartlett's test of sphericity was significant ($p < .001$), indicating that the data were suitable for factor analysis [40]. $\chi^2(55, N = 113) = 521.001$, $p < .001$ (Table 5).

TABLE 5. KMO and Bartlett's test, reliability statistics 1

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.855
Bartlett's Test of Sphericity	Approx. Chi-Square (χ^2)	521.001
	Degree of Freedom (df)	55
	Level of Significance (p)	.000
Cronbach's Alpha (α)		.884
N of Items		11

In Figure 3, a single component was extracted from the PCA. All 11 items in this construct belong to that component that was reported on a 5-point and 7-point Likert scale product that explained 46.73% of the variance with factor loadings from .547 to .750 based on the computed eigenvalue > 1.0. Table 7 indicates that all components or dimensions belong to one component. The factor loading of most items is greater than .6 or higher ($> .547$). The results in Table 6 show that one dimension or component emerged from the PCA procedure. The internal reliability test (Cronbach's Alpha test) was .884 (higher than .7), which means that these items (risk factors) were reliable (Table 5).

PCA was then repeated to reduce its dimension while preserving as much of the data's variation as possible. The factor analysis was re-conducted by removing **R4** (*project is too large and complex*) and **R10** (*project team members lack requisite knowledge, training, and skills*). The KMO and Bartlett's test sampling adequacy remained at .851. Bartlett's test of sphericity remained statistically significant $\chi^2(36, N = 113) = 433.481$, $p < .001$ (Table 8). Respondents' views of these two risk factors were less associated with the critical component risk factors that could be made redundant in isolation.

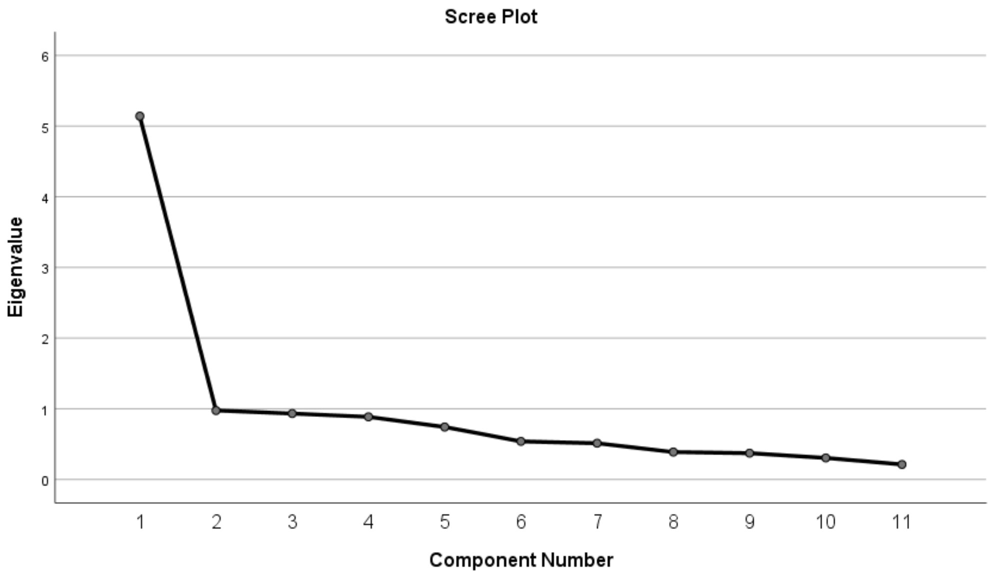

Figure 3. Scree plot 1

Table 6. PCA variance 1

Comp	Initial eigenvalues			Extraction sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	5.140	46.729	46.729	5.140	46.729	46.729
2	.975	8.865	55.594			
3	.932	8.470	64.064			
4	.885	8.050	72.114			
5	.742	6.742	78.856			
6	.538	4.894	83.750			
7	.512	4.657	88.407			
8	.387	3.522	91.929			
9	.371	3.376	95.305			
10	.304	2.766	98.071			
11	.212	1.929	100.000			

The Scree plot in Figure 4 shows that only one component was extracted from the PCA. All nine items in this construct belong to that component; reported based on a 5-point and 7-point Likert scale product that accounted for 51.25% of the variance, with factor loadings from .624 to .827 based on the computed eigenvalue > 1.0. Table 10 indicates that all components or dimensions belong to one component. As a result of the factor loading for every item exceeding .624, the total average variance explained is acceptable since it exceeds the minimum of 60% [38]. The results in Table 9 show that one dimension or component emerged from the PCA procedure. The internal reliability test (Cronbach's Alpha test) was .879 (higher than .7), which means that these items (risk factors) were reliable (Table 8).

5. **Discussion.** An online quantitative survey has conducted a study to rank the eleven key project contributory risk factors. In total 115 responses were collected from a target population of 150 project managers in the Malaysia-Singapore region using a snowball data collection strategy. The survey included section A demographics, section B risk factors,

Table 7. Component loading matrix 1

ID	PC1	Uniqueness
R1	0.621	0.615
R2	0.670	0.551
R3	0.660	0.564
R4	0.563	0.683
R5	0.795	0.368
R6	0.725	0.474
R7	0.747	0.443
R8	0.750	0.437
R9	0.686	0.529
R10	0.547	0.701
R11	0.710	0.496

Table 8. KMO and Bartlett's test, reliability statistics 2

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.851
Bartlett's Test of Sphericity	Approx. Chi-Square (χ^2)	433.481
	Degree of Freedom (df)	36
	Level of Significance (p)	.000
Cronbach's Alpha (α)		.879
N of Items		9

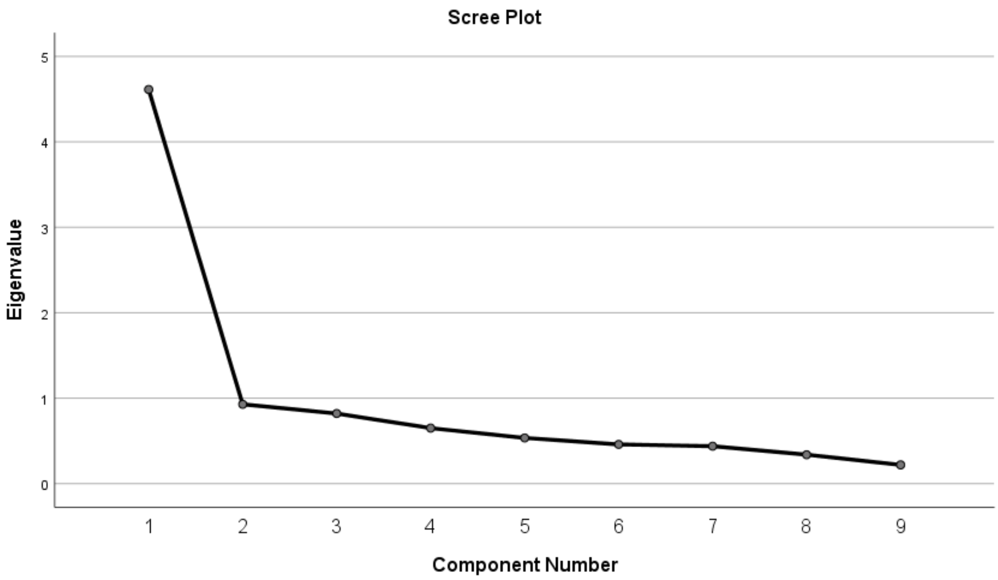

Figure 4. Scree plot 2

and section C frequency of occurrence. Collected responses were put through a quality check to remove fake, improper, and inconsistent responses. 2 out of 115 responses were deleted. The rest of the responses were subjected to risk exposure scoring computation, followed by ranking. PCA was applied to validating the possibility of extracting principal components from the eleven risk factors.

TABLE 9. PCA variance 2

Comp	Initial eigenvalues			Extraction sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	4.613	51.252	51.252	4.613	51.252	51.252
2	.928	10.316	61.568			
3	.820	9.115	70.683			
4	.650	7.218	77.900			
5	.535	5.943	83.844			
6	.495	5.097	88.940			
7	.438	4.865	93.805			
8	.338	3.760	97.565			
9	.219	2.435	100.000			

TABLE 10. Component loading matrix 2

ID	PC1	Uniqueness
R1	0.624	0.611
R2	0.675	0.544
R3	0.674	0.546
R5	0.827	0.316
R6	0.734	0.461
R7	0.718	0.485
R8	0.758	0.426
R9	0.711	0.495
R11	0.704	0.504

The primary objective of obtaining an overall ranking of risk exposure and PCA based on the collected data was achieved. The following are the key findings of this study.

1) The three most prominent risk factors exposure scores based on the survey were: **R2** (*underestimated costs and time*), **R5** (*poor requirement management*), and **R9** (*insufficient communication between stakeholders*).

2) PCA removed two risk factors: **R4** (*the project is too large and complex*) and the **R10** (*project team members lack the requisite knowledge, training, and skills*) could be made redundant and yet preserve the data's variation.

3) **R4** (RE = 14.929) and **R10** (RE = 17.389) were ranked in the 11th and 9th positions, respectively. The finding indicated that PCA could remove less critical risks from highly crucial associated risks.

Results indicated that PCA successfully extracted top key risks leaving less significant risk factors removed from the initial project risk contributory factor list. PCA can benefit from a highly complex, large-scale project with massive risk. Project practitioners can use PCA to withdraw key project risk factors (principal components) from their risk log. Focusing on monitoring and tracking high-risk exposure items and developing a risk response plan accordingly, the remaining less significant risks are put under the "watch list".

The study was conducted in the Malaysia-Singapore region, both of which share a homogeneous social makeup and cultural background. Thus, the minor potential social-cultural impact is negligible. However, the other dimensions, such as political, economic, technological, legislative, and environmental ones, remain significant and cannot be ignored. Furthermore, from an organizational perspective, attributes such as corporate culture, processes, maturity, policy, commercial product success, and stakeholder satisfaction impact are excluded from this study.

There is a possibility of showing different results if similar research was conducted in countries and regions with strong cultural influences on corporate governance and project management maturity. This study is limited to IT projects. The proposed method might result in different outcomes if a comparable study was executed in other projects such as product development, manufacturing, and construction. Besides, in the opinion of Pang et al., the experience level of project stakeholders influences the risk assessment outcomes [11].

The study explores how PCA can enhance project risk management practice by removing second-order dependencies by applying a linear transform to principal components having zero covariances. It is possible, however, that higher-order dependencies could provide opportunities for future research.

6. **Conclusion.** Studying contributory risk factors is essential to delivering a successful project in meeting the triple constraint model. This study has revealed the top three most significant IT project key inherent risks in descending order starting from risk factors **R2**, **R5**, and **R9**. The project success rate is expected to improve if these top-ranked risks are appropriately managed. A proficient PM in risk management practice tends to have better control over project outcomes by addressing potential issues in advance.

This study aims to determine the PCAs dimensional reduction potentiality in separating high-risk items from less significant ones. This analysis is particularly useful for dealing with massive risk items in highly complex and large-scale projects, allowing PMs to prioritize their effort in focusing on higher-risk items. PCA found risk factors **R4** and **R10** to be weakly related and removed from critical components. This finding demonstrated that PCA was a practical, lossless, reliable dimensional reduction technique that helps to prioritize and differentiate critical risk components. Therefore, it is helpful in project risk management practice to improve overall project performance and control.

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