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Predicting Software Analysis Process Risks Using Linear Stepwise Discriminant Analysis: Statistical Methods

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***Abstract*—The aim of this work is to introduce the linear stepwise discriminant analysis model to predict software risks in software analysis development process. These methods were used to measure and predict risks by using control techniques. Furthermore, we predict risks to three levels (high, medium, low). In addition, these risk control techniques were used to mitigate and predict risk model in software analysis development process looking at Table 31.**

Index terms -Predictive Risk Model, Software Analysis Risks, Risk Controls, Stepwise Discriminant Analysis Methods.

I. INTRODUCTION

Despite much research and progress in the area of software project management, software development projects still fail to deliver acceptable systems on time and within budget. Risk management is a practice of controlling risk and practice consists of processes, methods, and tools for managing risks in a software project before they become problems [1]. The purpose of software risk management is to analyze possibility risks before they occur, so which risk mitigating strategy may be used and planed as needed during the software development lifecycle to mitigate software risks [2]. Today, software risk management has become a common principles and practices amongst leading software companies [3]. In the increasing effort to improve software development processes and software quality, recent the studies have pointed out to an area of software project risk [4]. However, many of the software projects are risky and are often considered runaway, because they do not meet expectations of budgets and schedules. Therefore, an effective software risk management is extremely important to mitigate risks [5]. Risk management helps project manager and team to make better decisions, communication and to mitigate risk in project [6]. Many authors defined risk management, but complex practice to measure the likelihood of impact of software risks and determine appropriate risk management techniques, especially in software development projects [7]. Indeed, risk management for software projects is now a common practice, so software managers should choose a proactive approach and techniques to manage software risks in software projects [8], [9]. In addition, risk management of software projects is highly relevant to the social and cultural context of the development activities. Thus, it is an important to use software risk management to mitigate software project failure as reported that [10].Risk management methodology that has five phases: Risk identification, risk analysis and evaluation, risk treatment, risk controlling, risk communication and documentation relied on three categories or techniques as risk qualitative analysis, risk quantitative analysis and risk mining analysis throughout the life of a software project to meet the goals [11].**The objective of this work is**: To predict and model the software analysis risks in the software development organizations.

II. LITERATURE REVIEW

We used new methods which are the regression test and effect size test proposed to manage the risks in a software project with software process improvement [12]. Khanfar et al. [13], the new technique used the chi-square ($\chi 2$) test to control the risks in a software project. Also we improved quality of software projects of the participating companies while estimating the quality–affecting risks in IT software projects. The results show that there were 40 common risks in software projects of IT companies in Palestine [14]. Furthermore, we used the new stepwise regression technique to manage the risks in a software implementation project [15]. In addition, we proposed the new mining technique that uses the fuzzy multiple regression analysis techniques to manage the risks in a software design project [16]. The paper was introduced the new techniques to determine if fuzzy and stepwise regression are effective in mitigating the occurrence software risk factor in the software implementation process [17]. Additionally, we proposed artifact model of the software risk management for mitigating risks. It has the five levels to mitigate risks through software project [18]. Previous studies had shown that risk mitigation in software projects are classified into three categories[19]– namely, qualitative, quantitative and mining approaches. Firstly, quantitative risk is based on statisticalmethods that deal with accurate measurement about risk or lead to quantitative inputs that help to form a regression model to understand how software project risk factors influence project success. Furthermore, qualitative risk techniques lead to subjective opinions expressed or self-judgment by soft-ware manager using techniques, namely scenario analysis, Delphi analysis, brainstorming session, and other subjective approaches to mitigate risks.

III. Linear Stepwise Discriminant Analysis methods and Empirical Analysis Strategy

Data collection was achieved through the use of a structured questionnaire for estimating the quality of software through determine risks that were common to the majority of software projects in the analyzed software companies. Ten software risks in software analysis process [20], [21] and thirty risk controls were presented to respondents [22]–[24]. The method of sample selection referred to as distribution personal regular sampling was used. This procedure is appropriate when members of homogeneous groups as software project managers are difficult to locate. The seventy six software project managers have participated in this work. In this paper, weusedthe linear stepwise discriminant analysis methods to predict software risks in software analysis development process with risk control techniques.

A. Risk Control Techniques:

We listed risk controls that considered that are important in mitigating in analysis software development[20]–[22], [25]–[28]:

C1: Using of requirements scrubbing, C3: Assessing cost and scheduling the impact of each change to requirements and specifications, C4: Develop prototyping and have the requirements reviewed by the client, C6: Implementing and following a communication plan, C7: Developing contingency plans to cope with staffing problems, C10: Reviewing and communicating progress to date and setting objectives for the next phase, C11: Dividing the software project into controllable portions, C12: Reusable source code and interface methods, C15: Reusable user documents early, C19: Provide scenarios methods and using of the reference checking, C21:Including formal and periodic risk assessment, C22:Utilizing change control board and exercise quality change control practices, C23: Educating users on the impact of changes during the software project, C25: Avoiding having too many new functions on software projects, C27: Combining internal evaluations by external reviews, C28: Maintain proper documentation of each individual's work.

B. Relationships between risks and risk control techniques:

R1: Risk Of 'Unclear, incorrect, continually and rapid changing software project requirements' Compared To Controls.

Table 1: Wilks' Lambda Test and χ^2Test

module (s)	Wilks' Lambda	χ^2	df	Sig.
1	.793	16.888	2	.000

Table 2: Linear Discriminant model and Classification Coefficients

	Function	R1	
	1	Medium	High
C4	1.148	5.880	7.465
C19	2.345	26.102	29.340
Constant	-9.900	-41.269	-54.284

Table 3: Classification Results and Predicted Group Membership for risk 1

R1		Predicted Group Membership			
		Medium	%	High	%
Original [a]	Medium	8	66.7	4	33.3
	High	14	21.9	50	78.1
Cross-validated [b]	Medium	5	41.7	7	58.3
	High	14	21.9	50	78.1

A Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

a. 76.3% of original grouped cases correctly classified.

b. 72.4% of cross-validated grouped cases correctly classified.

The chi-square values (χ^2 = 16.888) which is a statistics for measuring these tests of significance of the Eigen values. The result shows there is significant relationship between the discriminant function 1 and the independent variables of C4, C19 related groups. The coefficients for the good building classification models are presented in Table 2.

R2: Risk of 'Failure to incomplete or missing detailed requirements analysis' Compared to Controls.

Table 4: Wilks' Lambda Test and χ2 Test

Module(s)	Wilks' Lambda	χ^2	df	Sig.
1 through 2	.354	74.807	6	.000
2	.926	5.569	2	.062

Table 5: Linear Discriminant model and Classification Coefficients

	Function		R2		
	1	2	Low	Medium	High
C1	1.376	1.634	9.651	18.047	18.432
C3	1.686	-1.888	32.578	38.934	41.916
C19	1.938	1.305	-59.150	-101.197	-117.853
Constant	-13.961	-3.111	13.559	17.399	20.033

Table 6: Classification Results and Predicted Group Membership for risk 2

R2		Predicted Group Membership					
		L	%	M	%	H	%
Original a	L	4	80	1	20.0	0	.0
	M	0	.0	9	75.0	3	25.0
	H	0	.0	10	16.9	49	83.1
Cross-validated[b]	L	3	60	2	40.0	0	.0
	M	0	.0	9	75.0	3	25.0
	H	0	.0	10	16.9	49	83.1

a 81.6% of original grouped, b. 80.3% of cross-validated grouped.

The chi-square values (χ^2 = 74.807) which is a statistics for measuring these tests of significance of the Eigen values. The result shows there is significant relationship between the discriminant function 1 and the independent variables of C1, C3, and C19 related groups in Table 5. The coefficients for the good building classification models are presented in Table 6.

R3: Risk of 'Developer software gold-plating' Compared to Controls.

Table 7: Wilks' Lambda Test and χ^2 Test

Module (s)	Wilks' Lambda	χ^2	Df	Sig.
1 through 2	.519	47.239	6	.000
2	.867	10.274	2	.006

Table 8: Linear Discriminant model and Classification Coefficients

	Function		R3		
	1	2	Low	Medium	High
C1	1.617	-1.327	10.615	11.506	15.166
C15	1.658	-.013	14.926	18.956	21.548
C19	1.255	2.873	20.218	29.935	29.415
Constant	-12.756	-4.593	-46.858	-81.803	-96.668

Table 9: Classification Results and Predicted Group Membership for Risk 3

R3		Predicted Group Membership					
		L	%	M	%	H	%
Original [a]	L	2	100.0	0	.0	0	.0
	M	1	10.0	8	80.0	1	10.0
	H	1	1.6	14	21.9	49	76.6
Cross-validated[b]	L	0	.0	1	50.0	1	50.0
	M	1	10.0	6	60.0	3	30.0
	H	1	1.6	14	21.9	49	76.6

a 77.6% of original grouped, b 72.4% of cross-validated grouped.

The chi-square values (χ^2 = 47.239, 10.274) which is a statistics for measuring these tests of significance of the Eigen values. The result shows there is significant relationship between the discriminant function 1, 2 and the independent variables of C1, C15, and C19 related groups in Table 8. The coefficients for the good building classification models are presented in Table 9.

R4: Risk of 'Lack of IT Management' Compared to Controls.

Table 10: Wilks' Lambda Test and χ^2 Test

Module (s)	Wilks' Lambda	χ^2	df	Sig.
1 through 2	.557	42.435	4	.000
2	.995	.383	1	.536

Table 11: Linear Discriminant model and Classification Coefficients

	Function		R4		
	1	2	Low	Medium	High
C3	1.639	-1.755	5.166	10.468	12.095
C6	1.314	2.088	8.128	11.260	13.139
Constant	-8.076	-.963	-11.316	-27.841	-37.165

Table 12: Classification Results and Predicted Group Membership for risk 4

R4		Predicted Group Membership					
		L	%	M	%	H	%
Original a	L	2	66.7	1	33.3	0	.0
	M	1	7.7	8	61.5	4	30.8
	H	0	.0	15	25.0	45	75.0
Cross-validated[b]	L	2	66.7	1	33.3	0	.0
	M	1	7.7	8	61.5	4	30.8
	H	0	.0	15	25.0	45	75.0

a 72.4% of original grouped, c 72.4% of cross-validated grouped.

The chi-square values (χ^2 = 42.435) which is a statistics for measuring these tests of significance of the Eigen values. The result shows there is significant relationship between the discriminant function 1 and the independent variables of C3 and C6 related groups in Table 11. The coefficients for the good building classification models are presented in Table 12.

R5: Risk of 'Software project requirements not adequately identified and mismatch' Compared to Controls.

Table 13: Wilks' Lambda Test and χ^2 Test

Module(s)	Wilks' Lambda	χ^2	Df	Sig.
1 through 2	.723	23.547	4	.000
2	.884	8.930	1	.003

Table 14: Linear Discriminant model and Classification Coefficients

	Function		r5		
	1	2	Low	Medium	High
C3	1.821	-1.279	7.022	5.284	8.205
C11	.499	2.321	6.641	11.083	10.020
Constant	-6.339	-2.931	-15.640	-22.362	-26.765

Table 15: Classification Results and Predicted Group Membership for Risk 5

R5		Predicted Group Membership					
		L	%	M	%	H	%
Original [a]	L	3	75.0	0	.0	1	25.0
	M	1	11.1	5	55.6	3	33.3
	H	12	19.0	6	9.5	45	71.4
Cross-validated[b]	L	2	50.0	0	.0	2	50.0
	M	1	11.1	5	55.6	3	33.3
	H	12	19.0	6	9.5	45	71.4

.a 69.7% of original grouped, b 68.4% of cross-validated grouped.

The chi-square values ($\chi2$ = 23.547, 8.930) which is a statistics for measuring these tests of significance of the Eigen values. The result shows there is significant relationship between the discriminant function 1 and the independent variables of C3 and C11 related groups in Table 14. The coefficients for building the classification models are presented in Table 15. The classification results allow us to determine how well we can predict group membership using a classification functions.

R6: Risk of 'Inadequate knowledge about tools and programming techniques' Compared to Controls.

Table 16: Wilks' Lambda Test and χ^2 Test

Module(s)	Wilks' Lambda	χ^2	df	Sig.
1 through 2	.429	60.874	6	.000
2	.840	12.512	2	.002

Table 17: Linear Discriminant model and Classification Coefficients

	Function		R6		
	1	2	Low	Medium	High
C6	.099	3.015	2.906	-.570	3.645
C7	2.062	-.163	8.927	17.839	17.783
C10	1.254	-2.679	7.408	16.159	12.525
Constant	-9.528	-.296	-16.819	-49.153	-49.613

Table 18: Classification Results and Predicted Group Membership for Risk 6

R6		Predicted Group Membership					
		L	%	M	%	H	%
Original [a]	L	3	75.0	0	.0	1	25.0
	M	0	.0	4	50.0	4	50.0
	H	1	1.6	4	6.3	59	92.2
Cross-validated[b]	L	3	75.0	0	.0	1	25.0
	M	0	.0	4	50.0	4	50.0
	H	2	3.1	4	6.3	58	90.6

a. 86.8% of original grouped,b. 85.5% of cross-validated grouped.

The chi-square values ($\chi2$ = 60.874, 12.512) which is a statistics for measuring these tests of significance of the Eigen values. The result shows there is significant relationship between the discriminant function 1, 2 and the independent variables of C6, C7, and C12 related groups in Table 17. The coefficients for building the classification models are presented in Table 18.

R7: Risk of 'Lack of traceability, confidentiality, correctness and inspection of the software project planning' Compared to Controls.

Table 19: Wilks' Lambda Test and χ^2Test

Module(s)	Wilks' Lambda	χ^2	Df	Sig.
1 through 2	.572	40.257	6	.000
2	.876	9.549	2	.008

Table 20: Linear Discriminant model and Classification Coefficients

	Function		r7		
	1	2	Low	Medium	High
C6	1.191	-1.439	10.682	11.039	13.148
C12	1.374	-.082	6.648	8.878	9.694
C23	1.009	2.069	13.970	18.061	16.478
Constant	-9.766	-1.567	-36.508	-53.442	-56.687

Table 21: Classification Results and Predicted Group Membership for Risk 7

R7		Predicted Group Membership					
		L	%	M	%	H	%
Original [a]	L	5	55.6	2	22.2	2	22.2
	M	1	9.1	6	54.5	4	36.4
	H	3	5.4	13	23.2	40	71.4
Cross-validated[b]	L	5	55.6	2	22.2	2	22.2
	M	1	9.1	6	---------- ---------- -.5	4	36.4
	H	3	5.4	13	23.2	40	71.4

a 67.1% of original grouped, b 67.1% of cross-validated grouped.

The chi-square values (χ2 = 40.257, 9.549) which is a statistics for measuring these tests of significance of the Eigen values. The result shows there is significant relationship between the discriminant function 1, 2 and the independent variables of C6, C12, and C23 related groups in Table 20. The coefficients for the good building classification models are presented in Table 21.

R8: Risk of 'Major requirements change after software project plan phase' Compared to Controls.

Table 22: Wilks' Lambda Test and χ^2Test

Module(s)	Wilks' Lambda	χ^2	df	Sig.
1 through 2	.390	67.294	8	.000
2	.897	7.809	3	.050

Table 23: Linear Discriminant model and Classification Coefficients

	Function		r8		
	1	2	Low	Medium	High
C3	1.736	1.527	5.679	15.482	14.256
C10	1.632	-1.939	8.031	14.329	16.383
C23	1.665	.164	12.001	20.278	20.338
C25	-1.286	.388	4.778	-1.170	-1.705
Constant	-10.308	-.254	-30.359	-70.082	-70.887

Table 24: Classification Results and Predicted Group Membership for Risk 8

R8		Predicted Group Membership					
		L	%	M	%	H	%
Original [a]	L	4	100.0	0	.0	0	.0
	M	0	.0	4	36.4	7	63.6
	H	1	1.6	4	6.6	56	91.8
Cross-validated[b]	L	3	75.0	0	.0	1	25.0
	M	0	.0	4	36.4	7	63.6
	H	2	3.3	3	4.9	56	91.8

b 84.2% of original grouped, c. 82.9% of cross-validated grouped.

The chi-square values (χ^2 = 67.294) which is a statistics for measuring these tests of significance of the Eigen values. The result shows there is significant relationship between the discriminant function 1 and the independent variables of C3, C10, C23, and C25 related groups in Table 23. The coefficients for the good building classification models are presented in Table 24.

R9: Risk of 'Changing software project specifications' Compared to Controls.

Table25: Wilks' Lambda Test and χ^2 Test

Module(s)	Wilks' Lambda	χ^2	Df	Sig.
1 through 2	.164	125.726	16	.000
2	.680	26.827	7	.000

Table 26: Linear Discriminant model and Classification Coefficients

	Function		r9		
	1	2	Low	Medium	High
C3	1.079	.371	11.461	21.551	21.048
C11	1.726	-.618	5.112	19.330	20.696
C15	.604	1.644	15.024	22.945	20.088
C19	2.478	1.672	33.236	57.707	55.081
C21	1.269	-2.778	15.089	21.857	27.029
C22	-1.396	-1.176	-8.474	-22.629	-20.730
C27	2.238	.484	14.932	35.400	34.868
C28	-1.394	.619	-2.821	-14.113	-15.432
Constant	-18.702	-.751	-76.174	-206.378	-206.835

Table 27: Classification Results and Predicted Group Membership for Risk 9

R9		Predicted Group Membership					
		L	%	M	%	H	%
Original [a]	L	3	100.0	0	.0	0	.0
	M	0	.0	8	61.5	5	38.5
	H	0	.0	7	11.7	53	88.3
Cross-validated [b]	L	3	100.0	0	.0	0	.0
	M	0	.0	7	53.8	6	46.2
	H	0	.0	7	11.7	53	88.3

a 84.2% of original grouped, b 82.9% of cross-validated grouped.

The chi-square values (χ^2 = 125.726, 26.827) which is a statistics for measuring these tests of significance of the Eigen values. The result shows there is significant relationship between the discriminant function 1, 2 and the independent variables of C3, C11, C15, C19, C21, C22, C27, and C28 related groups in Table 26. The coefficients for building the classification models are presented in Table 27.

R10: Risk of 'Inadequate value analysis to measure progress' Compared to Controls.

Table 28: Wilks' Lambda Test and χ^2Test

Module(s)	Wilks' Lambda	χ^2	df	Sig.
1 through 2	.658	30.393	4	.000
2	.844	12.295	1	.000

Table 29: Linear Discriminant model and Classification Coefficients

	Function		R10		
	1	2	Low	Medium	High
C11	2.351	-.113	6.440	12.738	12.750
C12	-.351	1.983	9.071	6.526	8.449
Constant	-5.556	-5.012	-18.560	-26.086	-31.052

Table 30: Classification Results and Predicted Group Membership for Risk 10

R10		Predicted Group Membership					
		L	%	M	%	H	%
Original [a]	L	3	100.0	0	.0	0	.0
	M	3	15.8	8	42.1	8	42.1
	H	9	16.7	7	13.0	38	70.4
Cross-validated [b]	L	3	100.0	0	.0	0	.0
	M	3	15.8	8	42.1	8	42.1
	H	9	16.7	7	13.0	38	70.4

a 64.5% of original grouped, b 64.5% of cross-validated grouped.

The chi-square values ($\chi2$ = 30.393, 12.295) which is a statistics for measuring these tests of significance of the Eigen values. The result shows there is significant relationship between the discriminant function 1 and the independent variables of C11 and C12 related groups in Table 29. The coefficients for building the classification models are presented in Table 30.

C. Predictive modelling risks in software analysis development process:

Table 31 illustrates predictive modelling for software analysis risks.

Predictive modelling risk	
Risk	**Risk control techniques**
R1	{C4,C19}
R2	{C1,C3,C19}
R3	{C1,C15,C19}
R4	{C3,C6}
R5	{C3,C11}
R6	{C6,C7,C10}
R7	{C6,C12,C23}
R8	{C3,C10,C23,C25}
R9	{C3,C11,C15,C19,C21,C22,C27,C28}
R10	{C11,C12}

IV. CONCLUSIONS

This paper was predicted and modeled risks of software analysis development. These methods were performed using stepwise discriminant analysis methods, to predict and model risks by using control techniques. Furthermore, the software analysis risks were classified to three level high, medium, low. In addition, these control techniques were used to produce predictive modelling risks looking at Table 31. In the future, we will use combine the optimum methods to predict risks such as logistic regression model, linear stepwise discriminant analysis and artificial neural network model.

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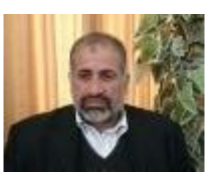

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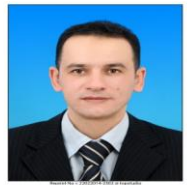

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