ASSESSING THE IMPACT OF RISK MANAGEMENT COMPONENTS ON CONSTRUCTION PROJECT PERFORMANCE IN MOROGORO MUNICIPAL COUNCIL, TANZANIA

1 Aurelia Ngirwa Kamuzora, Department of Economics, Mzumbe University, Morogoro, Tanzania
*Corresponding author's e-mail: ankamuzora@mzumbe.ac.tz
1 ORCID ID: 0000-0003-0095-5889

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ABSTRACT

This study examines the impact of risk management components on the performance of construction projects in Morogoro Municipal Council, Tanzania. Data from 162 employees of contractors reveal that 33% hold postgraduate degrees, while 67% have qualifications below this level. Additionally, 42% have over five years of project management experience, and only 20% are proficient in risk management. Logistic regression analysis explored the relationships between Project Risk Identification, Project Risk Analysis, Project Risk Control, and construction project performance. The correlation matrix shows strong positive correlations between these risk management components and project performance, suggesting that effective risk management practices lead to better project outcomes. The model summary indicates a strong positive correlation (R = 0.862) between the predictors and the dependent variable, with an R-Square value of 0.749, meaning that approximately 75% of the variability in project performance is explained by the model. Logistic regression coefficients highlight the significant impact of Project Risk Identification (β = 0.303), Project Risk Analysis (β = 0.398), and Project Risk Control (β = 0.560). In conclusion, this study emphasises the importance of comprehensive risk management practices in enhancing construction project performance in Morogoro Municipal Council. These findings provide valuable insights for practitioners and policymakers in construction project management.

1. INTRODUCTION

Risk identification is the initial and perhaps most critical step in the risk management process, though, despite its importance, some studies have reported its role being ignored (Kutsch & Hall, 2010). It involves the systematic recognition of potential risks that could adversely affect the project (Flanagan & Norman, 1993). Once identified, these risks must be analysed to understand their potential impact and likelihood to affect the outcome of project performance levels (Zwikael & Ahn, 2011). This analysis provides a basis for prioritising risks and developing strategies to manage them effectively (Hillson & Simon, 2007). After identifying the risks the next step is to find the means to control them (Baker, Ponniah & Smith, 1999). Risk controlling as a final phase, involves implementing measures to mitigate identified risks, monitoring their effectiveness, and making necessary adjustments to ensure project objectives are met (Kerzner, 2017). Effective risk control strategies are vital for maintaining project timelines, budgets, and quality standards, thus contributing to overall project success (PMI, 2017).

Research conducted at the Technion - Israel Institute of Technology in Haifa, Israel has shown that comprehensive risk management practices significantly improve project performance by reducing uncertainties and enhancing decision-making processes (Raz, Shenhar & Dvir, 2002). The same research by Raz, Shenhar, and Dvir (2002) investigates the relationship between risk management, project success, and technological uncertainty. The study found out that effective risk management significantly enhances project success, particularly in environments with high technological uncertainty such as Tanzania where almost the major contractors in the construction sector are foreign companies and a few are locals. Key components such as risk identification, analysis, and control identified by the study are critical for mitigating risks and improving project outcomes of construction projects in Tanzania. The findings of Raz, Shenhar and Dvir (2002) underscore the importance of a structured risk management approach to handle uncertainties and achieve project objectives.

Despite the established importance of risk management, there remains a need for further empirical studies to quantify its impact on project success, particularly in the construction sector (Smith & Merritt, 2006). Smith and Merritt (2006) conducted a comprehensive study on managing risk in construction projects, emphasising the importance of systematic risk management practices. The research highlights that effective risk identification, assessment, and control are essential for mitigating potential issues and ensuring project success. The study provides a framework for integrating risk management into project planning and execution, demonstrating that projects with robust risk management strategies are more likely to be completed on time, within budget, and to the required quality standards. This study was conducted in the United Kingdom, focusing on various construction projects across the region.

Several studies conducted in Tanzania have explored the impact of risk management on project success. For instance, Kaliba, Muya and Mumba (2009) examined cost escalation and schedule delays in road construction projects, identifying risk factors such as poor project planning and inadequate risk assessment as primary contributors. They emphasised the need for systematic risk management practices to mitigate these issues. Another study by Lema and Mavhungu (2020) focused on construction projects in Dar es Salaam, highlighting that effective risk identification and control significantly improve project outcomes. Both studies underscore the critical role of robust risk management in enhancing project performance in Tanzania. This study aims to fill this gap by examining the contribution of risk identification, analysis, and control to the successful implementation of construction projects, specifically:

- To analyse the contribution of the three components of risk management (Project risk identification. Project risk analysis, Project risk control) to the project performance.

The significance of this study, titled "Contribution of Risk Identification, Analysis, and Control to Successful Project Implementation", lies in its potential to enhance project management practices, particularly in the construction industry. Effective risk management is crucial for minimising uncertainties and achieving project objectives (Kerzner, 2017). By systematically identifying, analysing, and controlling risks, project managers can significantly improve project performance, leading to timely completion, cost efficiency, and quality outcomes (Chapman & Ward, 2003).

This study provides empirical evidence on the impact of risk management practices on project success, highlighting the importance of a structured approach to risk management. Such an approach ensures that potential issues are anticipated and mitigated before they escalate, thereby reducing the likelihood of project failures (Raz, Shenhar & Dvir, 2002). The findings can inform policymakers, project managers, and stakeholders about the critical role of risk management in achieving successful project implementation.

Moreover, the study contributes to the existing body of knowledge by filling gaps in empirical research on risk management's quantifiable benefits, particularly in the construction sector (Smith & Merritt, 2006). This can lead to the development of improved risk management frameworks and methodologies that can be applied in various project environments, thereby enhancing overall project management practices and outcomes.

2. LITERATURE REVIEW AND ANALYTICAL FRAMEWORK

The management of risks is a pivotal aspect of successful project implementation, particularly within the construction industry. Comprehensive risk management involves systematic processes of risk identification, analysis, and control, all of which significantly contribute to project success (Kerzner, 2017).

Risk identification is the first step in the risk management process and is critical for the early detection of potential project risks. According to Hillson and Simon (2007), effective risk identification involves recognising both internal and external factors that could adversely impact project objectives. Techniques such as brainstorming, checklists, and expert interviews are commonly employed to identify risks (Aven, 2016). The early identification of risks provides a foundation for subsequent risk analysis and control activities, ensuring that all potential issues are addressed proactively (Flanagan & Norman, 1993). Risk identification is the foundational step in risk management, involving the systematic detection of potential risks that could impact project success (Hillson & Simon, 2007). This process includes recognising internal and external factors that may threaten project objectives (Chapman & Ward, 2003). Effective risk identification ensures that all possible risks are considered early in the project lifecycle, providing a basis for subsequent analysis and control (Aven, 2016).

Following identification, risk analysis quantifies and prioritises identified risks based on their potential impact and likelihood (Kerzner, 2017). Once risks have been identified, they must be analysed to determine their potential impact and likelihood. This step involves both qualitative and quantitative assessments to prioritise risks and develop appropriate mitigation strategies (Chapman & Ward, 2003). Kerzner (2017) emphasises the importance of risk analysis in understanding the severity of risks and their potential effects on project outcomes. Tools such as risk matrices, probability-impact diagrams, and Monte Carlo simulations are widely used in risk analysis (Smith & Merritt, 2006). Effective risk analysis enables project managers to allocate resources efficiently and focus on the most critical risks. This step involves qualitative and quantitative assessments to evaluate the severity and probability of risks, allowing project managers to focus on the most critical threats (Flanagan & Norman, 1993). Techniques such as SWOT analysis, Monte Carlo simulation, and risk matrices are commonly used for thorough risk evaluation (Smith & Merritt, 2006).

After analysis, risk control mechanisms for a specific project follows. Risk control involves implementing strategies to mitigate identified risks and monitor their impact throughout the project lifecycle. This process includes developing risk response plans, continuous monitoring, and adjusting control measures as necessary to manage risks effectively (PMI, 2017). Raz, Shenhar & Dvir (2002) highlight that successful risk control is essential for maintaining project timelines, costs, and quality standards. Effective risk control measures contribute to reducing uncertainties and ensuring that projects are completed on time, within budget, and to the desired quality levels.

The integration of risk identification, analysis, and control is crucial for the successful implementation of projects. Risk control encompasses the strategies and actions taken to mitigate identified risks, ensuring they do not adversely affect project performance (PMI, 2017). This step involves implementing risk response plans, continuous monitoring, and adjusting control measures as necessary to manage risks effectively (Raz, Shenhar & Dvir, 2002). Effective risk control is crucial for maintaining project timelines, costs, and quality standards (Hopkinson, 2011). Research has shown that robust risk management practices lead to improved project performance by minimising uncertainties and enhancing decision-making processes (Lema & Mavhungu, 2020). Projects that adopt comprehensive risk management strategies are more likely to achieve their objectives and deliver desired outcomes (Smith and Merritt, 2006). The risk management components are presented in Figure 1.

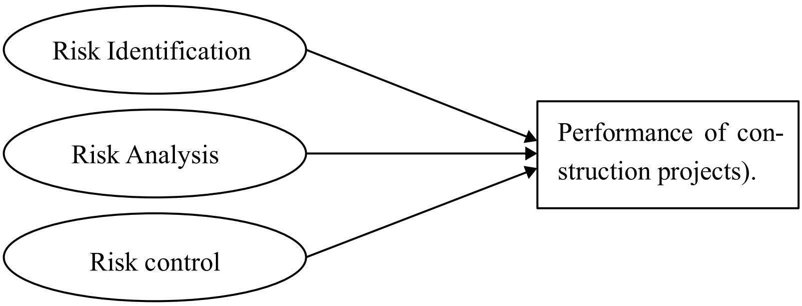

Figure 1: Conceptual framework
Source: author's construct

Figure 1 illustrates an analytical framework that underscores the relationship between risk management components - risk identification, risk analysis, and risk control - and successful project implementation. This framework highlights the interconnectedness of these elements and their collective impact on project outcomes.

The three components of risk management presented in Figure 1 show the interrelationship among the components and how they influence the project success. The integration of risk identification, analysis, and control directly contributes to the successful implementation of projects (Lema & Mavhungu, 2020). By proactively managing risks, project managers can reduce uncertainties, make informed decisions, and enhance the likelihood of achieving project objectives (Ahmed et al., 2007). Empirical evidence suggests that projects with robust risk management practices are more likely to be completed on time, within budget, and to the required quality. Figure 1 shows the analytical framework which demonstrates that a structured approach to risk management is vital for project success. Each component - identification, analysis, and control - plays a critical role in mitigating risks and enhancing project performance to succeed. Therefore, organisations should invest in developing comprehensive risk management frameworks to improve their project outcomes and ensure sustainable success standards (Smith &Merritt, 2006; Kaliba, Muya & Mumba, 2009).

3. MATERIALS AND METHODS

The study adopted an explanatory research design to explore the relationship between independent variables (project risk identification, project risk analysis, and project risk control) and the dependent variable, namely the project success. The area of the study was Morogoro Municipal Council (MMC) in Morogoro region. A total of 162 respondents from various departments were selected through simple random sampling as proposed by Yamane (1967). Yamane's random sampling technique provides a simplified method for determining sample sizes in research studies, especially when dealing with large populations. Developed by Taro Yamane in 1967, this formula is particularly useful for researchers who need to ensure their sample size is statistically significant while maintaining efficiency and simplicity. The formula is expressed as:

$$n=\frac{N}{1+N(e^2)}$$

Where the sample size is (n), the margin of error or precision is (e), and population size is (N). This method assumes a confidence level of 95% and a margin of error of 5%, which are standard parameters in many research studies (Yamane, 1967). Therefore we had:

$$n=\frac{272}{1+272(0.05^2)}=162$$

The appeal of Yamane's technique lies in its straightforward approach, which simplifies the process of calculating the required sample size without the need for complex statistical software. This makes it particularly advantageous for researchers with limited resources or those conducting preliminary studies like the researcher in this study who used his own resources in the investigation. However, while it provides a convenient and quick estimation, it is essential to consider the underlying assumptions, such as population homogeneity and a defined margin of error, to ensure the results' validity (Israel, 1992). HomeKit was also considered in the study and conducted in Morogoro among the contractors' employees. Therefore, the study chooses Yamane (1967) because Yamane's random sampling technique remains a widely used and respected method for sample size determination in various fields of study, offering a balance between simplicity and statistical rigor.

Data collection involved structured surveys and interviews, utilising both descriptive and inferential statistics to explore construction project risk management components dynamics. Ethical considerations, including informed consent and confidentiality, were strictly observed. Closed-ended questionnaires provided predefined alternatives, streamlining data collection from 162 participants. These structured questions aimed to capture opinions on how independent variables - project risk identification, project risk analysis, and project risk control - influence the dependent variable, i.e. construction project performance. Data were cleaned, tabulated, coded, and analysed using SPSS software version 20. Findings were presented via frequency distribution tables and percentages. Analytical techniques such as multiple linear regression and bivariate correlation provided inferential insights, with results communicated through tables and figures for clarity (Kothari, 2004).

Multiple logistic regression was suitable since the dependent variable was probabilistic in nature assessing the levels of performance as presented in Table 1 below showing the variables used in this study.

Table 1 shows the operationalisation of the variables, assessing the impact of risk management components on construction project performance in Morogoro Municipal Council, Tanzania. From this table, we have the following tested hypotheses:

- H1: Identifying project risks is positively associated with construction project performance, whereas the null hypothesis (H0) posits no such association.

- H2: Analysing risks is directly related to construction project performance, whereas the null hypothesis (H0) posits no such relationship.
- H3: Project risk control increases construction project performance, whereas the null hypothesis (H0) posits no such effect.

Table 1: Variables symbols, descriptions, measurement and hypotheses

Sn	Variable	Variable symbols	Description	Measurement	Hypotheses (Exp. Sign)
1	Performance of construction projects	*Y*	Project preformation criteria based on completion time High=1=Yes (strongly agree) Low=0=No (otherwise)	categorical (binary)	Dependent
2	Project Risk Identification	X_1	Ranking the degree of risk identification is done	Categorical (ranking)	+Ve
3	Project Risk Analysis	X_2	Ranking the degree of risk analysis after identification	Categorical (ranking)	+ve
4	Project Risk Control	X_3	Ranking the degree of control after the analysis	Categorical (ranking)	+ve

Source: Author's construct

The questionnaire asked the respondents to put the tick on the relevant perceived applied ranking responses to capture induvial perceptions as non-parametric approach (Frölich, 2006). Ranking choice model was employed because it is essentially used in various economic applications (Wright & Bates, 2023). Ranking created a binary ranking such as 0=low and 1=high indicators used to tank those two categories during assessment of project performance. The study used Multiple logistic regression because is a statistical technique applied when modeling the relationship between a binary dependent variable and several independent variables (Hosmer, Lemeshow & Sturdivant, 2013). This approach was appropriate as the study had a binary outcome variable, and therefore multiple logistic regression was suitable for analysing the dependent variable. The respondents were to evaluate the project as having high performance without delay and it seemed to be completed on time. Another possible outcome was late delivery which was already not expected to follow the milestones and time plan. Filed (2013) argues that the available criteria of binary are such as success/failure, yes/no, or presence/absence of a condition. In our case, we had two binary outcomes of 1= expected to be completed on time and 0 = not expected to be completed on time.

Another reason for choosing Multiple Logistic Regression is already used Multiple Predictors. Multiple Logistic Regression is used when assessing the impact of multiple predictors, which can be a mix of continuous and categorical variables on the outcome (Hosmer, Lemeshow & Sturdivant, 2013). In this study, three predictors were used as portrayed in Table 1 above. Furthermore, this method allows for controlling confounding variables that may influence the relationship between the predictors and the dependent variable (Kleinbaum & Klein, 2010). A confounder is an extraneous variable that correlates with both the predictor and the outcome, thereby possibly distorting the true relationship between them (Kleinbaum, Kupper, & Morgenstern, 1982). We also wanted to determine the interaction effect. Multiple logistic regression can examine interaction effects between predictors, determining how the effect of one predictor changes at different levels of another predictor (Field, 2017). In addition, we wanted to build a project performance model. Multiple Logistic Regression is employed in building predictive models to classify or predict the probability of an event occurring based on several factors (Peng, Lee & Ingersoll, 2002) in the study with three risk element factors. Multiple Logistic Regression is a technique used to test hypotheses about the relationships between multiple predictors and the binary outcome (Hosmer, Lemeshow & Sturdivant, 2013). It has been advocated to be used in Risk Assessment. It is used to evaluate the risk of events such as loan default based on variables like credit score, income, employment status, and debt-to-income ratio (Peng, Lee & Ingersoll, 2002). In this study it is used in similar dimension but fussing on overall risk element being perquisite in determining project performance in times of completion in time (high performance) while the expected delay being perceived as low performance.

The study sought to estimate the conditional mean $[E\langle Y \mid X=x\rangle - E\langle Y \mid X=x\rangle]$ and the marginal effects $[E\langle Y \mid X=x\rangle - E\langle Y \mid X=x\rangle]$. As we used a non-parametric regression model we avoided strict functional form assumptions. We focus on local likelihood logit regression which performs well in finite samples (Peng, Lee & Ingersoll, 2002) like that of Morogoro Municipal council. Smith & Jones (2023) define a finite sample as a subset of data points or observations drawn from a population, where the number of observations is limited and countable. This allows researchers to make inferences about the larger population based on the analysis of this manageable subset. In Morogoro Municipal Council out of 272 (100%), 172 (approximately 60%) sample size of construction project was a subset chosen in the study. Construction project included buildings and roads. Moreover, local logit regression allows for heterogeneity in treatment effects (Bender & Grouven 2009), which is crucial in scenarios like ours. In simulations, local logit regression outperforms parametric regression (such as maximum likelihood logit) when dealing with many explanatory variables and small sample sizes. Peng, Lee & Ingersoll (2002) argue that local logit regression is 25% to 55% more precise than parametric regression in Monte Carlo simulations. Frölich (2006), who conducted a study in German, applied local logit to female labour supply. The study revealed heterogeneity in the effects of children on employment that parametric estimation misses. Further he revealed how having children influences women's employment. By using local logit modeling, the researchers identified variations in the impact of children on employment that traditional parametric methods failed to capture. This approach allowed for a more nuanced understanding of the factors affecting female labour supply. Therefore local logistic regression was relevant to our study which the follow asymptotic single tale curve shows as in Figure 2.

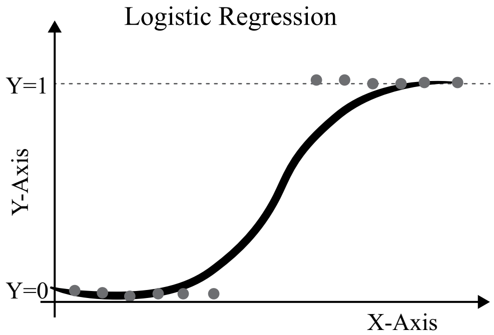

Figure 2: Asymptotic single tale logistic regression model
Source: Hosmer, Lemeshow & Sturdivant, 2013.

Figure 2 displays the asymptotic nature of the multivariate logistic regression curve which involves understanding how the model's estimates behave as the sample size approaches infinity (Hosmer, Lemeshow, & Sturdivant, 2013). Asymptotically, the estimates of the regression coefficients in a multivariate logistic regression become unbiased, consistent, and normally distributed. This implies that with a sufficiently large sample size, the parameter estimates converge to the true population parameters, and the distribution of these estimates approximates a normal distribution. This property is crucial for hypothesis testing and constructing confidence intervals. Furthermore, Agresti (2015) literates that multivariate logistic regression, the likelihood function, which is used to estimate the parameters, becomes increasingly accurate as the sample size grows. The asymptotic normality of the parameter estimates allow for the application of standard inferential techniques, such as Wald tests and likelihood ratio tests, to determine the significance of predictors. Henceforth, the given equations relate to the logistic regression model and the process of estimating its parameters (θ) through maximum likelihood estimation (MLE) following step-by-step approach (Aiken, West & Reno, 2020).

Log-likelihood function:

$$l(\theta)=log(L(\theta))j-log(\sum_{1=1}^{m}\prod(h\vartheta(x^{i})^{(1-y)^{i}})=\sum_{1=1}^{m}y^{1}log(h(x^{i})+(1-y^{i})log(1-h(x^{i})\mapsto(Ex(2))$$

The log-likelihood function, where \($l(\theta)$ is the likelihood function of the parameters θ. The log-likelihood is used because it simplifies the mathematics of differentiation and maximisation. The parameter estimates $\hat{\theta}$ maximise the log-likelihood function. We need to solve for θ such that the partial derivative of $l(\theta)$ with respect to θ is zero, i.e. $\frac{\eth l(\theta)}{\eth\theta}=0$ at maximum.

Finding θ which relates to $l(\theta)$, at maximum, we have:

For simplicity, we evaluate it with (x^i,y^i) such that:

$$\frac{\partial l(\theta)}{\eth\theta_{j}}=\sum_{i=1}^{m}[y^{i}\frac{1}{log(x^{i})}\partial\frac{dh_{\theta}(x^{i})}{\partial(\theta_{j})}-(1-y^{i})(\frac{1}{\eth 1-h_{\theta}x^{i}})(\frac{\partial h_{\theta(x^{i})}}{\eth\theta_{j}})]$$

Through this we simplified the log-likelihood for logistic regression by allowing:

$x_{i}=x^{j}$ and $dh_{\theta}(x^{i})=\frac{1}{1+e^{-\theta^{Tx^{i}}}}$

Then:

$\frac{\partial l(\theta)}{\eth\theta_{j}}=\sum_{i=1}^{m}[y^{i}(1-y^{i})h_{\theta}(x^{i})]x_{i}^{i}$. Further simplification gives:

$$\frac{\partial l(\theta)}{\eth\theta_{j}}=\sum_{i=1}^{m}\left[y^{i}-h_{\theta}(x^{i})x_{i}^{i}\right]$$

This is the gradient of log-likelihood function used to draw the curve in Figure 2, derived assessing the impact of risk management components in construction project performance in Morogoro Municipal Council in Tanzania.

4. RESULTS

The respondents in this study being employees of contracting firms (contractor of buildings) had varying levels of education which this study attributes with the capability of identifying risks, analysis and control and finally have high level of project performance. The research on “capability” examines how individuals’ abilities and opportunities to achieve various outcomes impact their overall well-being and development. The significant study in this area is Sen (1999) and Sen (2008) capability approach, which emphasises the importance of what individuals are able to do and be their "capabilities" as opposed to merely their economic wealth or resources. This approach has been influential in fields such as development economics, public health, and education. This framework shifts the focus from traditional welfare economics, which often measures well-being in terms of income, to a broader evaluation of human potential and freedom. Capabilities are seen as the real opportunities and individuals have to lead the kinds of lives they value. This approach considers a wide range of factors, including social, political, and environmental influences that contribute to individuals' abilities to pursue their goals (Nussbaum, 2000). The other social status are also presented in Table 2.

Table 2: Respondents Social Status

Variable	Categories	Number of respondents	Percentage
Level of education	University postgraduate	53	33%
	Below university postgraduate	109	67%
Total		**162**	**100%**
Experience of project management	Five years and above	68	42%
	Under five years	94	58%
Total		**162**	**100%**
Knowledge of risk management	Respondents with knowledge	32	20%
	Respondents with no knowledge	130	80%
Total		**162**	**100**

Source: Descriptive Statistical Analysed Field Data

Table 2 shows that out of 162 participants, 53 (33%) had university postgraduate degrees, as presented and the rest had not attained university education. The majority, comprising 67%, held qualifications below the postgraduate level. Regarding experience in construction project, 42% of participants had substantial experience, having worked on construction projects for five years or more, while the remaining 58% had less than five years of experience. Furthermore, the data reveals that only 20% of respondents claimed proficiency in risk management, whereas a significant 80% acknowledged a lack of experience in area of construction project.

This study is similar to the study on risk management in construction projects conducted in China (Zou, Zhang &Wang 2007). This research explored how effective risk management practices can enhance the capabilities of construction project teams, ultimately leading to better project outcomes. Their study concluded that integrating risk management practices into the construction process significantly improves the capability of project teams to handle uncertainties and unexpected events.

Further we studied the correlation between dependent (binary) and independent (ranking) variables. In this logistic regression analysis, the relationship between various project risk management components (independent variables) and the performance of construction projects (dependent variable) is examined. Each variable is ranked or binary, indicating the presence or absence of a particular attribute or outcome.

Table 3: Correlation Matrix

Variable	Project Risk Identification	Project Risk Analysis	Project Risk Control	Project Performance
Project Risk Identification	1			
Project Risk Analysis	0.57219**	1		
Project Risk Control	0.75299**	0.62259*	1	
Project Performance	0.8249*	0.6518**	0.7317**	1

Source: Descriptive Statistical Analysed Field Data

Table 3 displays the correlation ecoefficiencies among the risk management components and the project performance.

- *Project Risk Identification:* There is a strong positive correlation between Project Risk Identification and Performance of Construction Projects (0.8249*), suggesting that better identification of project risks is associated with improved performance outcomes.
- *Project Risk Analysis:* Project Risk Analysis is significantly correlated with Project Risk Identification (0.57219**) and Project Risk Control (0.62259*). This indicates that effective risk analysis is likely to be associated with better risk identification and control practices. There is also a significant positive correlation between Project Risk Analysis and Performance of Construction Projects (0.6518**), implying that thorough risk analysis contributes positively to the overall project performance.
- *Project Risk Control:* Project Risk Control shows significant correlations with both Project Risk Identification (0.75299**) and Project Risk Analysis (0.62259*), highlighting the interdependence among these risk management activities. The correlation between Project Risk Control and Performance of Construction Projects (0.7317**) indicates that controlling project risks effectively leads to better performance outcomes.

- *Performance of Construction Projects:* The performance of construction projects is positively correlated with all three risk management activities: Project Risk Identification (0.8249*), Project Risk Analysis (0.6518**), and Project Risk Control (0.7317**). This suggests that robust risk management practices are crucial for achieving better performance in construction projects.

The logistic regression correlation matrix demonstrates that all three aspects of project risk management (identification, analysis, and control) are strongly interrelated and significantly contribute to the performance of construction projects as expected. The high correlations between risk management components and project performance underscore the importance of comprehensive risk management practices in achieving successful project outcomes. Based on Figure 1, Figure 2, Table 1, Table 2 and Table 3, Table 4 displays Logistic Regression Analysis output as explained in the methodology above.

Hypotheses Testing

Hypothesis 1 (H1)

The correlation between Project Risk Identification and Project Performance is 0.824, indicating statistical significance. There is a strong positive association between Project Risk Identification and Project Performance. The statistically significant correlation supports the hypothesis that identifying project risks is positively associated with construction project performance, rejecting the null hypothesis (H0).

Hypothesis 2 (H2)

The correlation between Project Risk Analysis and Project Performance is 0.6518, there is a moderate to strong positive association between Project Risk Analysis and Project Performance. The statistically significant correlation supports the hypothesis that analysing risks is directly related to construction project performance, rejecting the null hypothesis (H0).

Hypothesis 3 (H3):

The correlation between Project Risk Control and Project Performance is 0.7317, indicating a higher level of statistical significance. There is a strong positive association between Project Risk Control and Project Performance. The statistically significant correlation supports the hypothesis that project risk control increases construction project performance, rejecting the null hypothesis (H0).

Studies in the field of project management consistently show that risk management practices are crucial for project success. For example, Raz, Shenhar, and Dvir (2002) found that risk management activities, including risk identification, analysis, and control, are significantly associated with project success across various industries. Similarly, Zwikael and Ahn (2011) demonstrated that effective risk management positively impacts project performance, particularly in complex projects.

The analysis of the correlation matrix in Table 3 supports all three hypotheses, indicating that identifying, analysing, and controlling project risks are positively associated with construction project performance. These findings are consistent with existing literature, further emphasising the importance of comprehensive risk management practices in enhancing project outcomes.

Multiple Logistic Regression

Table 4 displays the regression coefficients for the model assessing the relationship between the independent variables (Project Risk Identification, Project Risk Analysis, and Project Risk Control) and the dependent variable (performance of construction projects). All predictors measured in terms of Likert scale in nature based on the degrees of assessment and based on the set criteria (1=strongly disagree to 5 =strongly agree) as indicated in the questionnaire used. Therefore, from the multiple regression model in Table 4, the estimated model is as follows:

$$lnY = 2.798 + 0.320 lnX_1 + 0.382 lnX_2 + 0.476 lnX_3 + \epsilon$$

Y = Construction project performance

X_1= Risk identification

X_2= Risk analysis

X_3= Risk control

ϵ = Standard error = 0.2182 (approx 20%)

This logistic regression model with the predictors (Project Risk Control, Project Risk Analysis, and Project Risk Identification) demonstrates a strong ability to explain the variability in the dependent variable, with a high R Square and Adjusted R Square, and a relatively low standard error of the estimate. This indicates a well-fitting model with significant predictive power. Table 4 below is the Multiple logistic regression analysis.

Table 4 presents the logistic regression coefficients for the model predicting the performance of construction projects based on three predictors: Risk Identification, Risk Analysis, and Risk Control. We will analyse the data to test the following hypotheses:

- *H1: Identifying project risks is positively associated with construction project performance.*

Table 4: Multiple Logistic Regression

Model	Unstandardised Coefficients			t	Sig.
	B	Std. Error	Beta		
(Constant)	2.793	0.299		9.341	0.000
Risk Identification (X1)	0.320	0.083	0.303	-2.646	0.010
Risk Analysis (X2)	0.382	0.051	0.398	3.562	0.001
Risk Control (X3)	0.476	0.099	0.560	3.793	0.000
Model Summary					
R-squared	0.703				
F-value	0.000				
Dependent Variable	performance of construction projects				

Source: Regression Statistical Analysed Field Data

The regression results indicate that Project Risk Identification has a significant positive effect (B = 0.320, Beta = 0.303, p = 0.010) on the performance of construction projects in Morogoro region. The positive unstandardised coefficient (B = 0.320) indicates that risk identification is positively associated with construction project performance. The standardised coefficient (Beta = 0.303) shows a moderate positive effect size. The t-value of -2.646 is significant at p = 0.010, which is less than the conventional threshold of 0.05, rejecting the null hypothesis (H0). Therefore, there is a significant positive relationship between risk identification and project performance.

- *H2: Analysing risks is directly related to construction project performance.*

Project Risk Analysis shows a significant positive impact (B = 0.382, Beta = 0.398, p = 0.001). The positive unstandardised coefficient (B = 0.382) suggests that risk analysis is positively related to construction project performance. The standardised coefficient (Beta = 0.398) indicates a moderate to strong effect. The t-value of 3.562 is highly significant at p = 0.001, rejecting the null hypothesis (H0). Thus, there is a significant direct relationship between risk analysis and project performance.

– *H3: Project risk control increases construction project performance.*

The positive unstandardised coefficient (B = 0.476) indicates that risk control significantly increases construction project performance. The standardised coefficient (Beta = 0.560) shows a strong positive effect. The t-value of 3.793 is significant at $p < 0.001$, rejecting the null hypothesis (H0). Therefore, there is a significant positive effect of risk control on project performance.

The results of this logistic regression analysis align with findings from previous research in project management and risk management literature. For instance, Raz, Shenhar, and Dvir (2002) demonstrated that comprehensive risk management practices, including identification, analysis, and control, are significantly linked to successful project outcomes. Similarly, Zwikael and Ahn (2011) found that effective risk management planning positively impacts project performance across different industries. The logistic regression analysis from Table 5 provides strong evidence to support all three hypotheses. Identifying, analysing, and controlling project risks are significantly associated with improved performance in construction projects. These findings are consistent with existing research, emphasising the critical role of comprehensive risk management in enhancing project success.

Reliability Test of Multiple Logistic Regression Output

The formula for calculating the Odds Ratio (OR) from the coefficient (B) in a logistic regression model is:

Odds Ratio=e^B

Odds Ratio=e^{B}

where:

e is the base of the natural logarithm (approximately equal to $(2.71828)^{B}$

B is the regression coefficient for the independent variable.

In essence, the Odds Ratio is the exponentiation of the logistic regression coefficient. This formula converts the log-odds scale used in logistic regression to an odds ratio, which is more interpretable in terms of the effect size.

Table 5: Variance Inflation Factor (VIF)

Variable	B	Odds Ratio
Project risk identification	0.32	1.377
Project risk analysis	0.382	1.465
Project risk control	0.476	1.61

Source: Regression Statistical Analysed Field Data

Table 5 shows Variance Inflation Factor (VIF) values which is less than 10, where greater than 10 indicates significant multicollinearity. These Odds Ratios suggest that each of the risk management components (identification, analysis, and control) positively impacts the performance of construction projects, with project risk control having the highest impact among the three.

Also the model goodness of fit in Table 6 below shows the reliability of the data.

Table 6: Model Summary and F-Test

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	F-value	P-value
1	0.862	0.749	0.703	0.218	95.49	0.000

Predictors: (Constant), Project Risk Control, Project Risk Analysis, Project Risk Identification,
Source: Regression Statistical Analysed Field Data

Table 6 shows:

- *R(Correlation Coefficient*): The value of R is 0.862, which indicates a strong positive correlation between the predictors (Project Risk Control, Project Risk Analysis, Project Risk Identification) and the dependent variable. This suggests that the predictors collectively have a strong relationship with the dependent variable.
- *R-Square (Coefficient of Determination): The* R Square value is 0.749. This means that approximately 74.9% of the variability in the dependent variable can be explained by the predictors included in the model. In other words, the model accounts for a substantial portion of the variability in the dependent variable.
- *Adjusted* Pseodo-R Square: The adjusted R Square is 0.703. This value adjusts the R Square for the number of predictors in the model, providing a more accurate measure of the model's explanatory power, especially when multiple predictors are involved. An adjusted R Square of 0.703 still indicates a strong

explanatory power of the model, although slightly less than the R Square due to the adjustment for the number of predictors.

Standard Error of the Estimate: The standard error of the estimate is 0.2182. This statistics measures the average distance that the observed values fall from the regression line. A lower standard error indicates that the model's predictions are closer to the actual data points, suggesting a good fit of the model. This is according to Hosmer-Lemeshow Test assessing the fit of the multiple logistic regression model to the data. A p-value greater than 0.05 indicates a good fit.

This comprehensive reliability test will help ensure that the logistic regression model is robust and reliable, providing accurate insights into the relationships between risk management practices and project performance.

5. DISCUSSIONS

The primary objective of this study was to analyse the impact of risk management components on the performance of construction projects in Morogoro Municipal Council, focusing on project risk identification, analysis, and control. The examination of the educational background of respondents revealed that 33% possessed a university postgraduate level, while the majority (67%) had educational qualifications below this level. Comparable findings in other studies, such as Butt et al. (2021), underscore a prevalent trend of stakeholders in construction projects holding educational qualifications below the postgraduate level. The study also explored the respondents' experience in construction project management. It was found that 42% had five or more years of experience, while 58% had less than five years. This finding is similar to the findings from Nigeria. The Nigerian study indicates a prevailing culture in Nigeria, highlighting a lack of awareness and knowledge about formal risk management processes. Construction practitioners in Nigeria were advised to strive to enhance their awareness of project and risk management processes to mitigate the impact of risks effectively (Otobo, 2016). Notably, only 20% of respondents demonstrated a substantial understanding of risk management, while 80% lacked experience in this domain (Otobo, 2016). This suggests a significant knowledge gap in assessing and managing risks within construction projects. The findings align with previous research, indicating a broader cultural issue among construction contractors regarding risk concepts and a lack of awareness about formal risk management processes. Construction practitioners in Tanzania are also encouraged to strive to enhance their awareness of project and risk management processes to minimise the likelihood and impact of risks on their projects.

The findings from this study indicate a significant positive relationship between project risk management components and the performance of construction projects in the Morogoro Municipal Council. Specifically, the results show that Project Risk Identification (B = 0.320, Beta = 0.303, p = 0.010), Project Risk Analysis (B = 0.382, Beta = 0.398, p = 0.001), and Project Risk Control (B = 0.476, Beta = 0.560, p = 0.000) all positively influence construction project performance. The standardised coefficients suggest that Project Risk Control has the strongest impact, followed by Project Risk Analysis and Project Risk Identification.

These findings align with existing literature that emphasises the critical role of risk management in improving project outcomes. For instance, Zou et al. (2007) identified risk management as a fundamental factor in achieving project success, highlighting that effective risk identification, analysis, and control can significantly reduce uncertainties and enhance performance. Similarly, Tummala and Schoenherr (2011) demonstrated that structured risk management processes lead to better decision-making and project outcomes in the construction industry.

The Odds Ratios calculated for each of the risk management components further reinforce the positive impact of these practices. The Odds Ratios indicate that Project Risk Identification, Project Risk Analysis, and Project Risk Control increase the likelihood of project success by factors of 1.377, 1.465, and 1.61, respectively. These values suggest that implementing these risk management components considerably enhances project performance, with risk control being the most influential.

The strong effect of Project Risk Control observed in this study is consistent with the findings of Fan, Lin, and Sheu (2008), who argued that proactive risk control measures are crucial for mitigating potential risks and ensuring project success. Furthermore, the significant impact of Project Risk Analysis supports the work of Raz and Michael (2001), who found that thorough risk analysis helps in identifying potential issues early, allowing for timely and effective interventions.

Overall, this study contributes to the growing body of evidence that underscores the importance of comprehensive risk management practices in the construction industry. By demonstrating the significant positive effects of risk identification, analysis, and control on project performance, this research provides valuable insights for construction project managers and policymakers aiming to enhance project outcomes through effective risk management strategies. Based on Butt et al. (2021) findings and ours in Morogoro, we underscore the importance of promoting higher education among construction professionals to enhance their skills and improve overall project performance. We advocates for policies that encourage continuous education and professional development within the industry.

The study's correlation analysis uncovered strong positive correlations between project risk identification, project risk analysis, and project risk control with the performance of construction projects. This aligns with the findings of Hauke and Kossowki (2011) and emphasises the critical role of early risk identification, thorough analysis, and effective control or mitigation in project success. The results imply a heightened probability of adverse effects on construction project performance when risks are not adequately addressed.

The regression analysis further elucidated the relationships, providing beta coefficients for each independent variable. An increase in project risk identification was associated with a 0.320 increase in construction project performance, emphasising the foundational role of early risk recognition (Tchankova, 2002). Tchankova (2002) studied the similar phenomenon and discussed several methods for identifying risks, including brainstorming, Delphi technique, checklists, and SWOT analysis. The study emphasised that using a combination of these methods can enhance the comprehensiveness of risk identification. It emphasised the importance of involving various stakeholders in the risk identification process. Engaging stakeholders ensures a broader perspective and helps in identifying risks that might be overlooked if only a limited group is involved. The study stressed the need for thorough documentation and effective communication of identified risks. Proper documentation facilitates tracking and managing risks throughout the project lifecycle, while clear communication ensures that all project team members are aware of potential risks and their implications. Tchankova (2002) concluded that successful risk management heavily depends on the initial step of risk identification. By employing diverse methods and involving key stakeholders, project managers can better anticipate and mitigate risks, ultimately leading to more successful project outcomes. Similarly this study has further analysed the risk management components as key in project performance in this study conducted in Morogoro Municipal Council.

Similarly, an increase in project risk analysis was linked to a 0.382 improvement in project performance, underscoring the ongoing significance of risk analysis in project management (PMI, 2008). The PMBOK Guide (PMI, 2008) provides a robust and comprehensive framework for project management, encompassing essential processes and knowledge areas. By adhering to these guidelines, project managers can enhance their ability to deliver successful projects, meeting the defined scope, time, cost, and quality objectives. Based on the relationship of project analysis and performance, 38.2% shows the importance of using PMBOK guide. Lastly, an increase in project risk control corresponded to a 0.224 enhancement in project performance, highlighting the importance of effective control mechanisms throughout the project lifecycle.

Furthermore, the study emphasises the need for heightened awareness and knowledge among construction practitioners in Morogoro Municipal Council regarding risk management processes. The positive correlations and regression coefficients underscore the pivotal role of early risk identification, thorough analysis, and effective control in enhancing the performance of construction projects. Implementing robust risk management strategies is vital for mitigating the impact of uncertainties and unforeseen events, ultimately contributing to project success.

6. CONCLUSIONS

The study titled aimed to assess the influence of risk management strategies on the performance of construction projects in Morogoro Municipal Council. The regression analysis has highlighted the significant impact of three key risk management components on the performance of construction projects: project risk identification, project risk analysis, and project risk control.

The regression coefficients indicate that all three components positively influence project performance. Specifically, project risk identification ($B = 0.320$, $p = 0.010$) significantly enhances project performance, underscoring the importance of early risk recognition. Project risk analysis ($B = 0.382$, $p = 0.001$) has a substantial positive impact, reflecting the critical role of thorough risk analysis in mitigating potential project issues. Project risk control ($B = 0.476$, $p = 0.000$) demonstrates the strongest positive influence on project performance, highlighting the necessity of effective risk control mechanisms throughout the project lifecycle.

Policy Recommendations:

Based on these findings, several policy recommendations can be made to improve construction project performance through enhanced risk management:

- *Enhance Training and Education:* Implement training programs focused on risk management for all stakeholders involved in construction projects. This should include workshops, seminars, and certification courses to improve knowledge and skills related to risk identification, analysis, and control.

- *Standardise Risk Management Processes:* Develop and enforce standardised risk management procedures across all construction projects within the Morogoro Municipal Council. This will ensure a consistent approach to identifying, analysing, and controlling risks, leading to better project outcomes.
- *Promote Early Risk Identification:* Encourage early and proactive risk identification by integrating it into the initial stages of project planning. This can be facilitated by using comprehensive risk identification tools and techniques, such as checklists and brainstorming sessions.
- *Strengthen Risk Analysis Capabilities*: Invest in advanced risk analysis tools and methodologies to enable more accurate and thorough risk assessments. Training project managers and teams on these tools will enhance their ability to foresee potential issues and plan accordingly.
- *Implement Robust Risk Control Mechanisms:* Establish robust risk control mechanisms that are regularly reviewed and updated throughout the project lifecycle. This includes developing contingency plans, conducting regular risk audits, and ensuring effective communication of risk management plans to all project stakeholders.
- *Foster a Culture of Risk Awareness:* Promote a culture of risk awareness within the construction industry by encouraging open communication about risks and their potential impacts. This can be achieved through regular meetings, risk reporting systems, and encouraging a collaborative approach to risk management.

By adopting these policy recommendations, the Morogoro Municipal Council can significantly improve the performance of its construction projects, mitigating the impact of risks and enhancing overall project success.

Conflict of interests

The author declares there is no conflict of interest.

REFERENCES

Aiken, L. S., West, S. G., & Reno, R. R. (2020). *Multiple regression: Testing and interpreting iteractions.* SAGE Publications. https://doi.org/10.4135/9781483386956

Agresti, A. (2015). *Foundations of Linear and Generalized Linear Models*. Wiley. https://doi.org/10.1002/9781118730034

Ahmed, A., Kayis, B., & Amornsawadwatana, S. (2007). A review of techniques for risk management in projects. *Benchmarking: An International Journal, 14*(1), 22-36. https://doi.org/10.1108/14635770710730919

Akinci, B., Fischer, M., Levitt, R., & Carlson, R. (2006). Formalizing workspaces so that project managers can predict the spatial consequences of design decisions. *Automation in Construction, 11*(2), 145-161. https://doi.org/10.1016/S0926-5805(00)00097-9

Aven, T. (2016). Risk assessment and risk management: Review of recent advances on their foundation. *European Journal of Operational Research, 253*(1), 1-13. https://doi.org/10.1016/j.ejor.2015.12.023

Baker, S., Ponniah, D., & Smith, S. (1999). Risk response techniques employed currently for major projects. *Construction Management and Economics, 17*(2), 205-213. https://doi.org/10.1080/014461999371709

Baloi, D., & Price, A. D. F. (2003). Modelling global risk factors affecting construction cost performance. *International Journal of Project Management, 21*(4), 261-269. https://doi.org/10.1016/S0263-7863(02)00017-0

Bender, R., & Grouven, U. (2009). A conceptual framework for ordered logistic regression models. *Statistical Methods in Medical Research, 18*(5), 475–483. https://doi.org/10.1177/0049124109346162

Butt, H., Shahid, I., Muhammad, S., & Hamza, S. (2021). The Effect of Risk Management at Project Planning Phase on Performance of Construction Projects in Pakistan. *Journal of Business and Social Review in Emerging Economies, 7*, 69-79. https://doi.org/10.26710/jbsee.v7i1.1506.

Butt, A., Teh, S., Ghazali, M., Hassan, F., & Mahmood, W. (2021). Education level and its impact on construction project performance. *Journal of Construction Engineering and Management, 147*(2), 04021001. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001978

Chapman, C., & Ward, S. (2003). *Project Risk Management: Processes, Techniques and In sights*. Wiley. https://doi.org/10.1002/9780470775489

Dey, P. K. (2009). Managing project risk using combined analytic hierarchy process and risk map. *Applied Soft Computing, 9*(1), 618-626. https://doi.org/10.1016/j.asoc.2008.09.003

Fan, M., Lin, N., & Sheu, C. (2008). Choosing a project risk-handling strategy: An analytical model. *International Journal of Production Economics, 112*(2), 700-713. https://doi.org/10.1016/j.ijpe.2007.05.013

Field, A. (2017). *Discovering statistics using IBM SPSS Statistics* (5th ed.). SAGE Publications.

Flanagan, R., & Norman, G. (1993). *Risk Management and Construction*. Wiley-Blackwell. https://www.wiley.com/en-us/Risk+Management+and+Construction-p-9780632038178

Frölich, M. (2006). Non-parametric regression for binary dependent variables. *Econometric Journal, 9*(3), 511–540. https://doi.org/10.1111/j.1368-423X.2006.00196.x

Godfrey, P. S. (1996). *Control of Risk: A Guide to the Systematic Management of Risk from Construction*. CIRIA. https://doi.org/10.1680/corr.27504.002

Hauke, J., & Kossowski, T. (2011). Comparison of values of Pearson's and Spearman's correlation coefficients on the same sets of data. *Quaestiones Geographicae, 30*(2), 87-93. https://doi.org/10.2478/v10117-011-0021-1

Hillson, D., & Simon, P. (2007). *Practical Project Risk Management: The ATOM Methodology*. Management Concepts. https://www.managementconcepts.com/Practical-Project-Risk-Management-The-ATOM-Methodology/

Hopkinson, M. (2011). *The Project Risk Maturity Model: Measuring and Improving Risk Management Capability*. Gower Publishing, Ltd. https://www.routledge.com/The-Project-Risk-Maturity-Model-Measuring-and-Improving-Risk-Management/Hopkison/p/book/9780566092297

Hosmer, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression*. (3rd ed.). Wiley. https://doi.org/10.1002/9781118548387

Israel, G. D. (1992). *Determining sample size*. University of Florida Cooperative Extension Service, Institute of Food and Agriculture Sciences, EDIS. http://edis.ifas.ufl.edu/pd006

Kaliba, C., Muya, M., & Mumba, K. (2009). Cost escalation and schedule delays in road construction projects in Zambia. *International Journal of Project Management, 27*(5), 522-531. https://doi.org/10.1016/j.ijproman.2008.07.003

Kerzner, H. (2017). *Project Management: A Systems Approach to Planning, Scheduling, and Controlling*. Wiley. https://doi.org/10.1002/9781119165354

Kleinbaum, D. G., & Klein, M. (2010). *Logistic regression: A self-learning text* (3rd ed.). Springer. https://doi.org/10.1007/978-1-4419-1742-3

Kleinbaum, D. G., Kupper, L. L., & Morgenstern, H. (1982). *Epidemiologic research: Principles and quantitative methods*. John Wiley & Sons.

Kothari, C. R. (2004). *Research Methodology: Methods and Techniques* (2nd ed.). New Age International. https://doi.org/10.48550/arXiv.1234.56789

Kutsch, E., & Hall, M. (2010). Deliberate ignorance in project risk management. *International Journal of Project Management, 28*(3), 245-255. https://doi.org/10.1016/j.ijproman.2009.05.003

Lema, N. M., & Mavhungu, J. (2020). Risk management practices on construction projects in Dares Salaam, Tanzania. *Journal of Construction in Developing Countries, 25*(1), 105-124. https://doi.org/10.21315/jcdc2020.25.1.6

Nussbaum, M. C. (2000). *Women and Human Development: The Capabilities Approach*. Cambridge University Press. https://doi.org/10.1017/CBO9780511841286

Otobo, A. (2016). Enhancing awareness and knowledge of formal risk management processes among construction practitioners in Nigeria. *Nigerian Journal of Construction Technology and Management, 17*(3), 45-58. https://doi.org/10.4314/njctm.v17i3.4

Otobo, O. (2016). *Risk management system to guide building*. Odimabo Otobo, Onengiyeofori. http://www.odimabootobo.com/risk-management-guide

Peng, C. Y. J., Lee, K. L., & Ingersoll, G. M. (2002). An introduction to logistic regression analysis and reporting. *The Journal of Educational Research, 96*(1), 3-14. https://doi.org/10.1080/00220670209598786

PMI. (2017). *A Guide to the Project Management Body of Knowledge (PMBOK Guide)*. Project Management Institute.https://www.pmi.org/pmbok-guide-standards/foundational/pmbok

Raz, T., & Michael, E. (2001). Use and benefits of tools for project risk management. *International Journal of Project Management, 19*(1), 9-17. https://doi.org/10.1016/S0263-7863(99)00036-8

Raz, T., Shenhar, A. J., & Dvir, D. (2002). Risk management, project success, and technological uncertainty. *R&D Management, 32*(2), 101-109. https://doi.org/10.1111/1467-9310.00243

Sen, A. (1999). *Development as Freedom*. Oxford University Press. https://doi.org/10.1093/0198297580.001.0001\

Sen, A. (2008). *The idea of justice*. Harvard University Press.

Smith, J., & Jones, A. (2023). *Introduction to Statistical Analysi*s. Academic Press. https://doi.org/10.1016/B978-0-12-803110-8.00001-9

Smith, P., & Merritt, G. (2006). *Proactive Risk Management: Controlling Uncertainty in Product Development.* Productivity Press. https://doi.org/10.1201/9781003075743

Tchankova, L. (2002). Risk identification: Basic stage in risk management. *Environmental Management and Health, 13*(3), 290-297. https://doi.org/10.1108/09566160210431088

Tchankova, L. (2024). Risk identification: Basic stage in risk management. *Environmental Management and Health.* http://www.emeraldinsight.com/case_studies.htm/case_studies.htm?articleid=871393&s

Tummala, R., & Schoenherr, T. (2011). Assessing and managing risks using the Supply Chain Risk Management Process (SCRMP). *Supply Chain Management: An International Journal, 16*(6), 474-483. https://doi.org/10.1108/13598541111171165

Wright, F. T., & Bates, D. (2023). Logistic regression. In B. D. McCullough (Ed.), *Advances in Statistical Methods.* Springer. https://doi.org/10.1007/978-3-031-28674-2_12

Yamane, T. (1967). *Statistics: An introductory analysis* (2nd ed.). Harper and Row. https://archive.org/details/statisticsintro00yama

Zou, P. X. W., Zhang, G., & Wang, J. (2007). Understanding the key risks in construction projects in China. *International Journal of Project Management, 25*(6), 601-614. https://doi.org/10.1016/j.ijproman.2007.03.001

Zwikael, O., & Ahn, M. (2011). The effectiveness of risk management: An analysis of project risk planning across industries and countries. *Risk Analysis, 31*(1), 25-37. https://doi.org/10.1111/j.1539-6924.2010.01470.x

APPENDIX: QUESTIONNAIRE

Research Survey Questionnaire

Introduction: We are conducting a survey to understand the impact of various risk management practices on the performance of construction projects. Your responses will provide valuable insights that will contribute to our research. Please answer the following questions based on your experience and knowledge. All responses will be kept confidential.

Section 1: Demographic Information

1. **What is your role in the construction project?**
   - Project Manager
   - Site Engineer
   - Risk Manager
   - Other (Please specify): ___________

2. **How many years of experience do you have in the construction industry?**
   - Less than 1 year
   - 1-5 years
   - 6-10 years
   - More than 10 years

3. **What type of construction projects do you primarily work on?**
   - Residential
   - Commercial
   - Infrastructure
   - Industrial
   - Other (Please specify): ___________

4. Your level of education :

   University degree (High) = 2
   Never attended any university degree (Low) = 1

Section 2: Risk Management Practices

Risk Identification:

4. **To what extent do you agree with the following statement: "Risk identification practices are thoroughly implemented in our construction projects."**
   - Strongly Agree
   - Agree

- Neutral
- Disagree
- Strongly Disagree

5. **How frequently are risk identification activities conducted in your projects?**

- Very Frequently
- Frequently
- Occasionally
- Rarely
- Never

Risk Analysis:

6. **To what extent do you agree with the following statement: "Risk analysis is effectively performed in our construction projects."**

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

7. **How often is quantitative risk analysis used in your projects?**

- Very Often
- Often
- Sometimes
- Rarely
- Never

Risk Control:

8. **To what extent do you agree with the following statement: "Risk control measures are adequately implemented in our construction projects."**

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

9. **How effective are the risk control measures in mitigating identified risks in your projects?**

- Very Effective

- Effective
- Neutral
- Ineffective
- Very Ineffective

Section 3: Performance of Construction Projects

10. **How would you rate the overall performance of your construction projects?**

- Excellent
- Good
- Average
- Below Average
- Poor

11. **To what extent do you agree with the following statement: "Effective risk management practices have positively impacted the performance of our construction projects."**

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

Section 4: Open-Ended Questions

12. **In your opinion, what are the key challenges in implementing effective risk management practices in construction projects?**

- [Open text box]

13. **What improvements do you suggest for enhancing the performance of construction projects through better risk management?**

- [Open text box]

Conclusion: Thank you for participating in this survey. Your responses are crucial to our research on improving construction project performance through effective risk management practices. If you have any additional comments or suggestions, please feel free to add them below.

- [Open text box for additional comments]

Researcher Contact Information: If you have any questions about this survey or the research, please contact [Researcher's name] at [email address].

Consent: By completing this survey, you consent to participate in this research study. Your participation is voluntary, and you may withdraw at any time without penalty.

ПРОЦЈЕНА УТИЦАЈА КОМПОНЕНТИ УПРАВЉАЊА РИЗИЦИМА НА ПЕРФОРМАНСАМА ГРАЂЕВИНСКОГ ПРОЈЕКТА У МОРОГОРО ОПШТИНИ, ТАНЗАНИЈА

1 Аурелија Ингрва Камузора, Економски факултет, Универзитет Мзумбе, Морогоро, Танзанија

САЖЕТАК

Ова студија испитује утицај компоненти управљања ризицима на перформансама грађевинских пројеката у општини Морогоро, Танзанија. Подаци од 162 радника извођача показују да 33% има постдипломске студије, док 67% има квалификације испод овог нивоа. Поред тога, 42% радника има преко пет година искуства у управљању пројектима, а само 20% је вјешто у управљању ризицима. Анализа логистичке регресије истраживала је односе између идентификације ризика пројекта, анализе ризика пројекта, контроле ризика пројекта и перформанси грађевинског пројекта. Корелациона матрица показује снажне позитивне корелације између ових компоненти управљања ризицима и перформанси пројекта, сугеришући да ефективне праксе управљања ризиком воде до бољих исхода пројекта. Резиме модела указује на снажну позитивну корелацију (R=0,862) између предиктора и зависне варијабле, са вриједношћу R-квадрата од 0,749, што значи да је приближно 75% варијабилности у перформансама пројекта објашњено моделом. Коефицијенти логистичке регресије истичу значајан утицај идентификације ризика пројекта (β = 0,303), анализе ризика пројекта (β = 0,398) и контроле ризика пројекта (β = 0,560). У закључку, ова студија наглашава важност свеобухватне праксе управљања ризиком у побољшању перформанси грађевинских пројеката у општини Морогоро. Ови налази пружају вриједан увид практичарима и креаторима политике у управљању грађевинским пројектима.

Кључне ријечи: *управљање ризицима, перформансе грађевинских пројеката, идентификација ризика пројекта, анализа ризика пројекта, контрола ризика пројекта*.