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The Strategic JOURNAL of Business & Change MANAGEMENT
ISSN: 2312-9492 www.strategicjournals.com
Vol. 10, Iss.2, pp 1279 – 1294. June 10, 2023. www.strategicjournals.com, ©Strategic Journals

DEVELOPMENT OF A MODEL FOR TRANSPORT INFRASTRUCTURE PROJECTS MONITORING: A CASE OF TANZANIA

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Accepted: June 1, 2023

ABSTRACT

Clients, stakeholders, and customers in the construction industry around the world have long been concerned about project success. Despite massive financial investments in construction and the related economic advantages, road construction projects in Tanzania are plagued by cost overruns, time delays, and failure to meet required quality and stakeholders' expectations. Even though prior studies have produced models and frameworks to improve project success, researchers have not considered in depth in put factors affecting project success in developing countries particularly Tanzania. Hence, this study developed a model for monitoring of road projects in Tanzania. The relationship between three dimensions of project monitoring, namely practices, enabling factors, and tools, and three attributes of project success, as assessed by time, cost, and quality, was established. The SMART PLS 4 statistical software was employed for analysis and model development. The model developed revealed a strong, positive, and significant relationship between monitoring attributes and project success. The findings backed up the model, implying that understanding the attributes from monitoring practices, enabling factors as well as tools are necessary for enhancing project success in road construction projects. The study recommended the adoption of a model and that the model may be applied by government and private parties in road construction projects.

Keywords: *Road projects, Monitoring, SMART PLS, Project success, Model*

CITATION: Matívila, H., Kundi, B. A., Mwaluko, G., Kafuku, J., Mbumba, M. T., John, G. R., & Chang'waro, S. K. (2023). Development of a model for transport infrastructure projects monitoring: A case of Tanzania. *The Strategic Journal of Business & Change Management,* 10 (2), 1279 – 1294.

INTRODUCTION

Monitoring focuses on the implementation process and raises the main question, whereas assessment examines the implementation process (Hussein et al. 2023). Evaluation appraises the amount to which project outcomes can be linked to project objectives, as well as the quality and efficacy of the program by recording the impact on participants and the community (Maulana 2017)

The formulation of a well-planned project schedule, as well as an awareness of the important success elements, are required for project success. Project mission, top management support, project schedule, plan, client consultation, personnel, technology to support the project, client acceptance, monitoring, feedback channels of communication, and troubleshooting skill are the most prevalent predictors of project success that are recognized by the research community (Oh and Choi 2020). In both for-profit and non-profit organizations, monitoring procedures have been a mainstay and a major activity over many decades. Within their limited resources and abilities, these organizations have improved and used strategies to better understand issues that they cannot control but have a substantial impact on their survival and success (Thi & Swierczek, 2010).Through successful monitoring procedures, it was predicted that a firm may exercise some positive influence over market forces, establish competitive advantages, improve organizational effectiveness, and increase performance (Leonidou et al. 2017). As a result, new concepts, and tools in an aspect of development program management within the development sector have been developed and introduced throughout time to provide formality and uniformity to project management practices in the development sector (Sundqvist, 2020). Monitoring functions have been established by public sector organizations around the world to improve their sustainability outcomes. Because of the relevance of monitoring around the world, many clients have recognized the benefits and are attempting to use it in their operations (Bakr 2018). Over the last five years, government programs have assumed the role of primary service providers. The indicators for monitoring were key instruments for project management and influencing policy and practices at the national and international levels. Monitoring is vital for analyzing the success of projects at the regional and sub-regional levels, and it can also be a useful tool for management planning in non-government enterprises (Kusek and Rist 2004). Monitoring operations consume a significant portion of a development program's annual budget (2 to 15%). Publishing proposals, establishing programs, and establishing frameworks are examples of such activities, as are assembling action plans, gathering data, writing reports, and maintaining information systems through monitoring studies.

Developing countries conduct regular monitoring initiatives, which range from sophisticated national assessment systems in nations like India and Malaysia to simple monitoring of chosen projects in many African and Middle Eastern countries (Edmunds and Marchant 2008). It is critical to concentrate and improve monitoring and evaluation capabilities across all government areas. Similarly, project sustainability is a big issue in many developing countries, with a significant number of projects completed at high expenditures frequently encountering difficulties. All major donors, including the World Bank, Asian Development Bank, and bilateral aid agencies, have expressed concern over the situation (Nehru 2014). In the African context, during its third term in office since democracy, the South African government has prioritized monitoring (Wotela 2016). Several studies have been conducted to look at the elements that influence project performance in developing countries.

According to Durdyev and Hosseini, (2019), project delays are caused by a lack of competent staff, poor supervision and site management, inadequate leadership, and a shortage and breakdown of equipment due to insufficient monitoring techniques. Quality and attitude of service are significant elements constraining good monitoring procedures on project delivery (Habtemariam 2019). Time, budget, quality, and stakeholder satisfaction are all measures used to measure performance (Suckling et al. 2009). The performance measurement can also be defined as a comparison between desired and actual performance. It is measured and assessed using performance indicators that can be related to many aspects of scope, time, cost, quality, client happiness, customer changes, business performance, health, and safety. However, the most important performance monitoring criteria are time, cost, and quality. In the global endeavor to achieve environmental, economic, and social sustainability, monitoring has become an increasingly significant instrument in Spain (Alyson 2019).

For the sake of clarity, the evolution of monitoring in France has been divided into several separate phases, which helps to demonstrate how concepts have evolved and expectations have grown through time (Pramod and Chudasama 2020). The Monitoring and Evaluation (M&E) function has grown in importance in recent years, partly because it aids management in compensating for the loss of control that comes with increased organizational complexity, but more importantly, it aids management in detecting and managing risks, which is an important part of the governance process (Alyson 2019). Government initiatives in developed nations, particularly those funded by the Organization for European Cooperation and Development (OECD), have had 20 years or more of M&E experience, but many developing countries are only getting started with this important public management tool. The experiences of developed countries are instructive and can teach developing countries valuable lessons. Countries like the United States of America have been able to accomplish successful development because they have implemented effective and efficient mechanisms for tracking development goals (Pramod and Chudasama 2020).

In the early 1980s, when governments and non-governmental organizations around the world were grappling with internal and external demands for greater accountability and transparency, monitoring and evaluation concepts and practices were introduced as part of global trends on the adoption of results-based management practices under the umbrella of new public management. In the early 1990s, the Tanzanian government implemented Monitoring and Evaluation concepts and methods as part of the aforementioned global trends (Yambesi 2014).

Tanzania embarked in construction of roads using her own funds in early 2000's (Nyakundi 2018). As the number of road projects increased, there has been a public outcry regarding success of projects in terms of timely completion, high-cost overruns, poor quality of completed road projects and low satisfaction to stakeholders. The cause of all issues of poor success of the road projects is being linked to improper monitoring of the road projects during planning and implementation stages.

By providing corrective action for deviations from the expected norm, the Project Monitoring and Evaluation practices provide value to the overall efficiency of project planning, management, and implementation (Alyson, 2019). Tanzania's monitoring and evaluation of projects is lacking due to lack of institutional structures. Most public organizations lack trained M&E specialists who are capable of developing relevant tools, resulting in inadequate M&E systems (Nyakundi 2018).

So far, most studies conducted to date have addressed the topic of monitoring and assessment in tandem; further, this study contends that current monitoring procedures are ineffective in meeting the stated aim. Furthermore, few researches have been done specifically on the development of a model for monitoring road projects (Alyson 2019; Habtemariam 2019; Maulana 2017; Vähämäki 2018). The study's primary goal is to close this gap. The three most significant parts of monitoring in project success, according to studies in the literature examined, are monitoring practices, tools, and approaches. The researcher was unable to locate any studies that included the enabling criteria listed in the suggested framework for project success. This is the second gap addressed by this study. Previous studies were largely conducted in the United States, Malaysia, Iran, India, Nigeria, the United Kingdom, and other countries. From a Tanzanian perspective, very few studies have been conducted on project success monitoring. Monitoring has not been emphasized as a crucial project success component in the handful that has been carried out. As a result, another knowledge gap that was addressed by this study to contribute to the body of knowledge is the inclusion of a Tanzanian perspective in the research. Thus, this study was carried to cover the identified gaps by the development of a model for monitoring road projects in Tanzania.

METHODOLOGY

The design of this study focused on the development of a model for monitoring transport infrastructure projects. Data were collected in two phases depending on their purposes. The first phase involved use of questionnaires and interviews data collection methods and the data were used as variables and parameters necessary for developing a model for monitoring transport infrastructure projects and the second phase was to test the model. Furthermore, during validation, the model results were compared to actual monitoring findings of five projects obtained by using existing monitoring practices. A total of 281 sample sizes for the survey was used in this study to represent the population. Responses were used as inputs for SMART PLS-version 4 which was used for developing a model.

RESULTS & DISCUSSION

In this section, the two-stage model building process for data analysis was first discussed. The measurement and structural models' adequacy were assessed using the criteria from the data collection tools as summarized in Table 1. Second, the Importance-Performance Matrix Analysis was used to discover which endogenous components in the model had the most important constructs. Furthermore, the results were compared with previous studies' findings. Finally, the final model is presented, based on the findings.

Table 1: Variables used

Variables	Factors
Monitoring practices	Time monitoring (TM)
	Bill of Quantities (BoQ) monitoring
	Technical audit (TA)
	Earned value monitoring (EVM)
	Contract monitoring (CM)
	Site meeting (SM)
	Activity monitoring (AM)
	Work safety monitoring (WSM)
	Environmental compliance monitoring (ECM)
	Construction material specification monitoring (CMSM)
	Construction methods monitoring (CMM)
	Check list monitoring (CLM)
	Equipment monitoring (EM)
	Employee competence monitoring (ECM)
	Compliance with specification monitoring (CSM)
	Cost monitoring (COM)
	On site monitoring (OSM)
	Process monitoring (PM)
Monitoring enabling factors	Availability of project design document (APDD)
	Political will (PW)
	Competent monitoring personnel (CMP)
	Existence of a monitoring guide (EMG)
	Availability of resources (AR)
	Availability of monitoring personnel (MP)
	Availability of a monitoring plan (AMP)
	Technical competence of project manager (TCM)
	Managerial competence of project manager (CPM)
	Technical competence of project team (TCT)
Monitoring tools	Work breakdown structure (WBS)
	Result framework (RF)
	Project scope statement (PSS)
	Cost variance (CV)
	Time variance (TV)
	BoQ
	Activity tracking matrix (ATM)
	Indicator tracking matrix (ITM)
	Activity checklist (AC)
	Log frame matrix (LFM)
	Work plan (WP)
	Risk register (RR)
	Construction contract (CC)
	Project charter (PC)
Project success	Time (T)
	Cost (C)
	Quality (Q)

Monitoring practices, enabling factors, monitoring tools and project success were considered during model development. This model was used to identify and explain the various aspects that can affect project success. The structure of the model is developed as shown in figure 1.

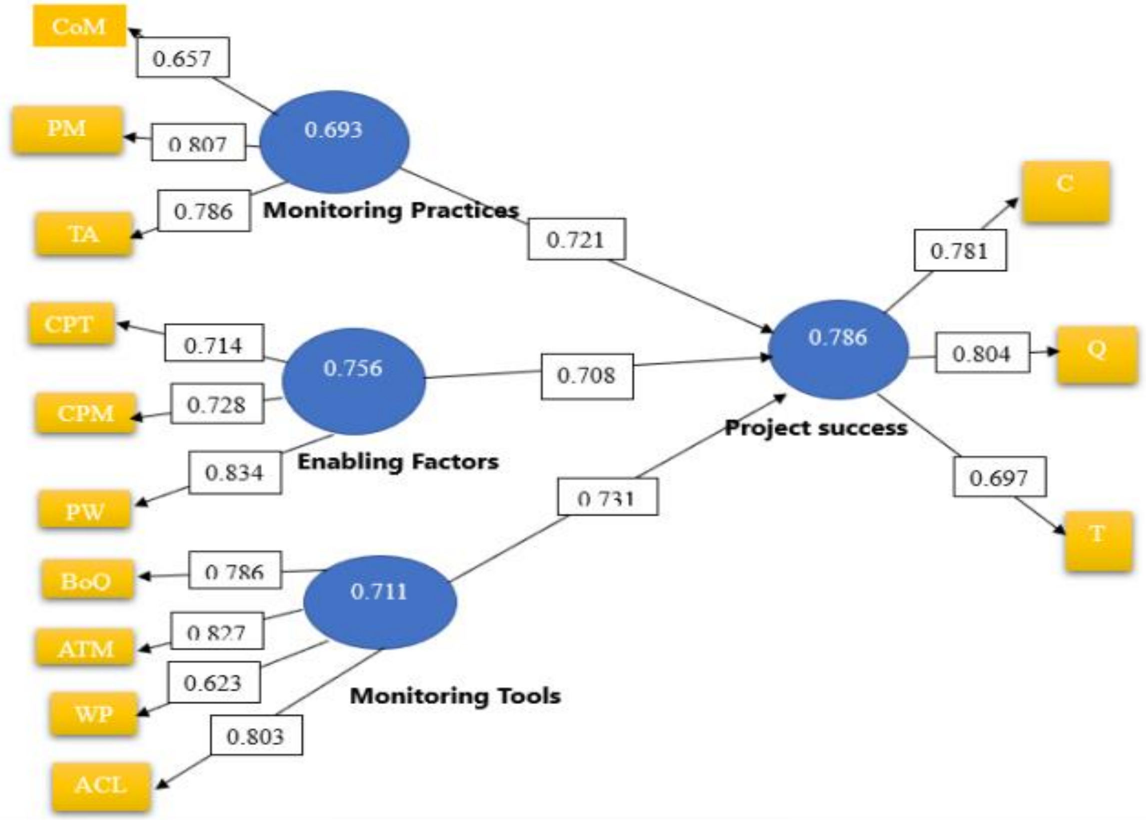

Figure 1. Initial model

SEM Analysis

In this case, the measurement model was assessed, and reliability and validity tests were performed based on predefined criteria adopted as in Table 2 (Hooper, Coughlan, and Mullen 2008)**.**

Table 2: Assessment of measurement Model (Hooper et al. 2008)

Analysis	Test	Criteria	Sources
Internal Consistency	Composite Reliability	≥ 0.6 Acceptable > 0.7 Satisfactory > 0.95 Redundancy	(Hair *et al.*, 2014)
	Cronbach's Alpha	0.6 – 0.7 Acceptable 0.7-0.9 Satisfactory	(Hair *et al.*, 2014)
Indicator reliability	Factor loadings	≥ 0.7 Acceptable	(Hair *et al.*, 2014)
Convergent Validity	Factor Outer loadings	≥ 0.7 Acceptable	(Hair *et al.*, 2014)
	Average Variance Extracted (AVE)	≥ 0.5 Desired	(Hair *et al.*, 2014)
Discriminant Validity	Fornell and Larcker Criteria	AVE of construct should be > than correlation between constructs	(Hair *et al.*, 2014)
	Heterotrait – Monotrait Ratio (HTMT)	HTMT.85 HTMT .90	(Kline, 2011) (Gold *et al.*, 2001)

Internal Consistency

Internal consistency was the first measurement to be performed. Cronbach's Alpha (CA) and Composite Reliability were the two most regularly employed tests in this evaluation (CR). According to Table 2, Cronbach's alpha of 0.6 or above is considered acceptable in this study (Khidzir, Ismail, and Abdullah 2018). Other scholars advise alternative levels of acceptance that an alpha between 0.50 and 0.60 should be accepted (Taber 2018; Ursachi, Horodnic, and Zait 2015). The second test was composite reliability, which determined that any construct with a value greater than 0.6 should be kept for further investigation. However, according to literature, a composite reliability value greater than or equal to 0.95 is referred to be poor (Taber 2018). Both tests on this study, as can be seen in Table 3 as generated from the SMART PLS-4 software, have shown the study's internal consistency reliability values in the range hence are acceptable as factors that may influence success of road project success.

Table 3: Analysis for Reliability and Convergent Validity

Variables	Indicators	Item loading	Alpha	CR	AVE
Monitoring practices	CoM	0.657	0.712	0.789	0.604
	PM	0.807			
	TA	0.786			
Monitoring Enabling factors	CPT	0.714	0.803	0.827	0.731
	CPM	0.728			
	PW	0.834			
Monitoring tools	BoQ	0.786	0.653	0.718	0.573
	ATM	0.827			
	WP	0.623			
	ACL	0.803			
Project Success	C	0.781	0.789	0.836	0.713
	Q	0.804			
	T	0.697			

Indicator Reliability

The indicator reliability is assessed by the loading factor. From the selection criteria in Table 3, the item loadings from 0.7 or above, implies the reliability indicator is satisfactory (Khidzir et al. 2018). In this case, the items with loading below 0.7 may be removed from the scale. Furthermore, when eliminating items that impair the AVE and/or composite reliability, item loadings between 0.4 and 0.7 should be eliminated solely (Khidzir et al. 2018). to remove the items on AVE and composite reliability, the PLS – Algorithm must be re-run for these loadings until there is an improvement on the AVE and/or composite reliability. Figure 2 displays the measurement model with all elements loaded with Coefficient of Determination (R^2) values after eliminating all items which did not comply with the reliability indicator selection criteria.

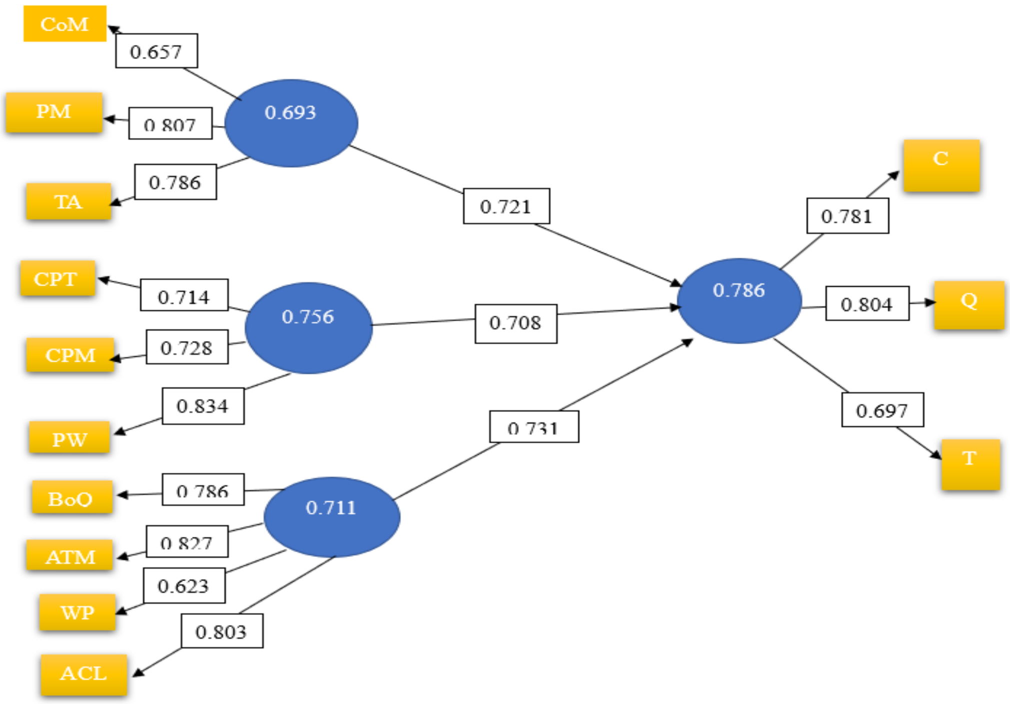

Figure 2: Measurement Model

Convergent Validity

This is the degree to which the items together measure the variables (Wang, French, and Clay 2015). The study used Average Variance Extracted (AVE) and factor outer loadings test to determine convergent validity. From the results, convergent validity is acceptable when the AVE value starts from 0.5. The study lists AVE values obtained from each variable, which were found exceeding the recommended value of 0.5. Another test looked at factor outer loadings, where all items were greater than 0.7, as recommended from Table 3. In this study, all elements were kept for additional investigation.

Likewise, all the elements were found with factor outer loadings greater than the recommended value of 0.7, as shown in Table 4. This finding indicates that the variables in the study had good convergent validity. This implies that Monitoring practices, Monitoring enabling factors and monitoring tools have an influence on the road project success as seen in table 4.

Table 4: Discriminant Validity Results by Cross loading

Items	Monitoring practices	Enabling factors	Monitoring tools	Project success
CoM	**0.657**	0.573	0.136	0.655
PM	**0.807**	0.46	0.001	0.661
TA	**0.786**	0.45	-0.093	0.521
CPT	0.147	**0.714**	0.091	0.172
CPM	0.336	**0.728**	-0.043	0.104
PW	0.92	**0.834**	-0.045	0.151
BoQ	-0.28	-0.198	**0.786**	0.191
ATM	-0.533	-0.19	**0.827**	0.209
WP	-0.49	-0.187	**0.623**	-0.149
ACL	0.238	0.191	**0.803**	-0.212
C	0.313	0.091	0.452	**0.781**
Q	0.133	-0.043	0.716	**0.804**
T	0.231	-0.029	0.613	**0.697**

Discriminant Validity

Discriminant validity was determined and assessed by Heterotrait – Monotrait Ratio (HTMT) and Fornell and Larcker criteria. From the analysis, all the variables were found to have a square root greater than their correlation as seen in Table 5. Literatures argue that there is no discriminant validity when the Fornell-Larcker values are approaching to one (Wang et al. 2015). Normally, discriminant validity between variables exists when the Fornell-Larcker value is less than 0.9 (Henseler et al., 2015). Table 5 depicts the discriminant validity results obtained by the Fornell-Larcker technique which shows relationships between variables, making the discriminant valid.

Table 5. Discriminant validity results

Variables	Monitoring practices	Enabling factors	Monitoring tools	Project success
Monitoring practices	**0.751**			
Enabling factors	0.469	**0.759**		
Monitoring tools	0.276	0.523	**0.782**	
Project success	0.677	0.019	0.713	**0.761**

Note: The bolded numbers are the AVE scores

Assessment of Structural Model

The model assessment is accomplished by the criteria which include significance of the path coefficient, level of coefficient determinant (R^2) of variables, the effect size (f^2) of independent Vs dependent variables, the predictive relevance (Q^2), the Model Fit as well as Importance-Performance values as summarized in Table 6. These criteria have been used in other related studies (Manley et al. 2021; Mohamed, Ubaidullah, and Yusof 2018)

Table 6: Structural Model assessment criteria (Manley et al. 2021)

Analysis	Test	Criteria
Collinearity	Variance Inflator Factor (VIF)	VIF ≤ 5 Acceptable
	Tolerance value	> 0.2
Path relationship (β)	t-value	2.57 Significant level =1%
		1.96 Significant level =5%
		1.65 Significant level =10%
	p-value	<0.01 Significant level =1%
		<0.05 Significant level =5%
		<0.1 Significant level =10%
Coefficient of Determination (R^2)	R^2 value	Substantial: 0.26
		Moderate: 0.13
		Small: 0.02
Effect size(f^2)	f^2 value	0.35 Large effect
		0.15 Medium effect
		0.02 Small effect
Predictive Relevance (Q^2)	Q^2 value	Q^2 value large than 0 indicate Predictive relevance
Model Fit	GoF	0.1 Small, 0.25 Medium, 0.36 Large
	RSRM	< 0.08 Acceptable
Importance-Performance Matrix Analysis	IPMA	NA

Assessment of Collinearity Issue

When two or more independent variables measure the same thing, collinearity occurs. Using both variables in the same model is considered redundant, and the answer is to remove one component from the model. When evaluating a structural model, this is crucial. Assessment of collinearity requires each set of variable predictors to be analyzed independently for each part of the structural model. In this study, the tolerance and the value of the Variance Inflation Factor (VIF) were determined as in Table 7. The VIF found were all less than five (5) and their tolerance greater than 0.2. This implied that collinearity has not reached the critical threshold in any of the variables, and therefore the study can proceed with other steps of structural model estimation without difficulty.

Table 7: Collinearity assessment summary

Variables	Indicators	VIF
Monitoring practices	CoM	1.357
	PM	1.825
	TA	1.602
Monitoring Enabling factors	CPT	1.618
	CPM	1.745
	PW	1.472
Monitoring tools	BoQ	1.417
	ATM	1.356
	WP	1.539
	ACL	1.157
Project Success	C	2.716
	Q	3.231
	T	1.896

Path Coefficient (β)

The latent variables in the model to have an influence, the path coefficient value should be at least 0.1 (Dabi et al. 2018). The path coefficient is responsible for showing the relationships between the variables as well as their significance between the variables in the model (Wong 2016). When the path coefficient is closer to 1, it suggests that the variables have a strong positive relationship; when the path coefficient is closer to -1, it shows that the variables have a strong negative relationship. In Figure 3, all the pathways were found to have a path coefficient above 0.1, indicating influence between the latent variables.

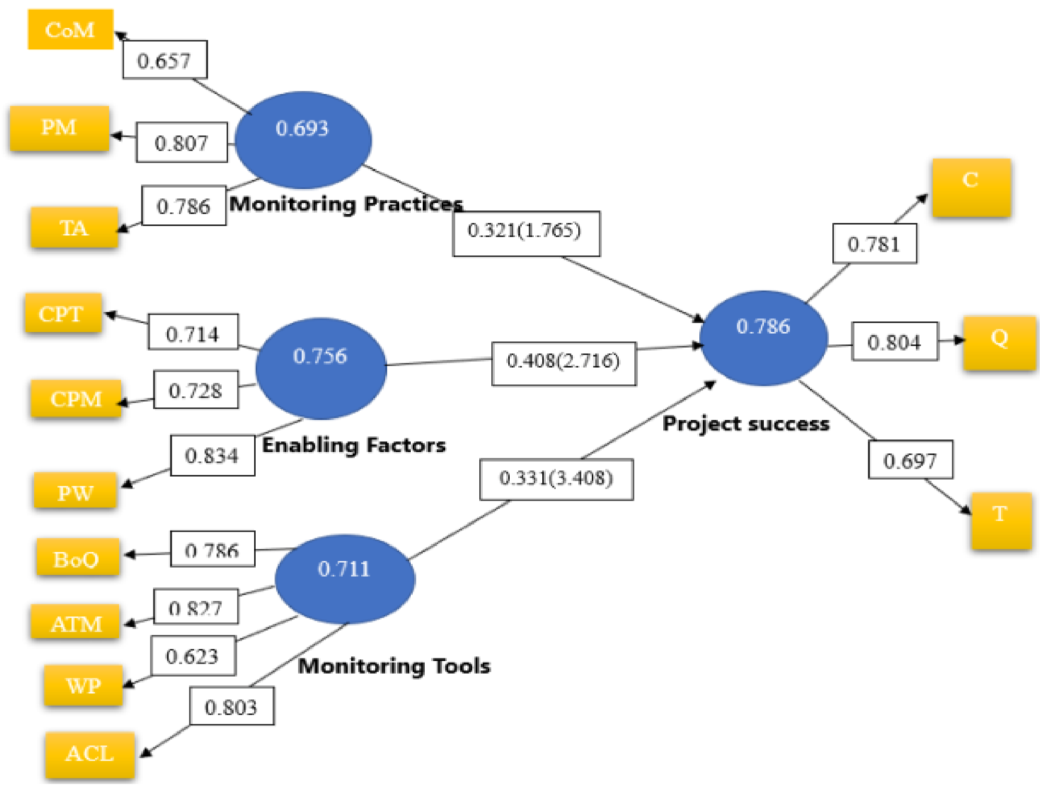

Figure 3: Path Coefficient Values with t-value in the Structural Model

Coefficient of Determinants (R^2)

The coefficient of determination is a typical criterion for assessing the structural model's prediction capacity (R^2). The squared correlation between certain independent factors and dependent variables is used to compute the R^2 value. This coefficient depicts how all connected independent factors explain a dependent variable (Chicco, Warrens, and Jurman 2021). The R^2 value is a number that varies from 0 to 1. The value of R^2 must be sufficiently high to have a high level of predictive power. Previous studies proposed that values of roughly 0.26 be considered considerable, 0.13 be considered moderate, and 0.02 or less be considered tiny (Dabi et al. 2018; Mohamed et al. 2018). The structural model's prediction power improves as the R^2 value rises. The results from this study show a significant value of R^2, which depicts a high prediction of the structural model. The findings of all R^2 values in the model are shown in Table 8.

Table 8: Summary of R^2 Value

Dependent/Independent Variable	R Square (R^2)	Decision
Monitoring practices	0.789	substantial
Enabling factors	0.802	substantial
Monitoring tools	0.454	substantial
Project Success	0.506	substantial

Hypotheses Testing

The bootstrapping approach was used to compute the significance relationship of the path coefficient (ß) value by analyzing t value and p-value using the 95% confident interval to validate the given hypotheses in the structural model (Paiva 2010). To accept the hypotheses, the path coefficient value must be at least 0.1 so it is considered to have an influence (Mohamed et al. 2018). Table 9 shows the path coefficient (ß), t-value, p-value, determined from the hypotheses testing.

Table 9. Results of hypotheses testing

Hypotheses	Relationships	ß-values	t-values	p-values	Decision
H1	Monitoring practices Vs project success	0.321	1.765	0.000	Supported
H2	Enabling factors Vs project success	0.408	2.716	0.000	Supported
H3	Monitoring tools vs project success	0.331	3.408	0.000	Supported

Assessment of Effects Size (f^2)

The structural model was also evaluated using the effect size criterion presented in Table 6 where the effect sizes of 0.02, 0.15, and 0.35 were classified in terms of the contribution as small, medium, and large. When the stated constructs are excluded from the model, the f^2 values are used to evaluate the effect on the endogenous construct (Manley et al. 2021). Table 10 presents the f^2 values for each exogenous construct to its corresponding endogenous construct. According to Taber (2018)'s classification of effect size values, among the factors influencing monitoring practices vs project success, enabling factors vs project success to have a large effect with a value range above 0.35, whereas monitoring tools vs project success was found with a medium effect with a value range between 0.15 and 0.35. These findings show that the f^2 value of each endogenous construct has a significant influence towards project success.

Table 10: Effects Size (f^2) Values

Determinant of Coefficient (R^2)	Path	f^2	Decision
Monitoring practices	monitoring practices-success	0.449	Large effect
Enabling factors	enabling factors-success	0.736	Large effect
Monitoring tools	Tools-success	0.274	Medium effect

Assessment of Predictive Relevance (Q^2)

To assess the model's predictive relevance, the Stone-Geisser's (Q^2) was examined (Geiser, 1974; Stone, 1974). The value of Q^2 is approximated by running a blindfolding procedure, which is a resampling technique that systematically deletes and predicts every data point of the items in the reflective measurement model (Mohamed et al. 2018). Two conditions were considered before blindfolding was conducted: identification of endogenous reflective construct; and set the omission distance (D) value whereby the D=7 was selected to ensure the number of valid observations divided by omission distance is not a whole number. The value was selected based on the standard range which is used by much previous research where the value of D ranges between five (5) to 10 (Dabi et al. 2018). When the value of Q^2 is greater than zero for a reflective endogenous construct it shows the path model's predictive relevance for the specified construct (Hooper et al. 2008). After running the blindfolding procedure, the values of Q^2 were 0.311, 0.274, 0.482 and 0.287 for the monitoring practices, enabling factors, monitoring tools and project success respectively as in Table 11. These values indicated the model's predictive relevance for endogenous constructs.

Table 11: Q^2 Values summary

Constructs	Summary of Q^2 values
Monitoring practices	0.406
Monitoring enabling factors	0.171
Monitoring Tools	0.482
Project success	0.287

Model Fit

In this study, the Goodness-of-Fit (GoF) approach was used to test the model fit (Hooper et al. 2008). The GoF approach defined values of 0.1, 0.25, and 0.36 as small, medium, and large respectively as indicated in Table 6. literatures, further advise using 0.50 as the cut-off value for communality, and different effect sizes of R^2 since it is deemed adequate and large for the model's GoF (Taber 2018). The GoF values were obtained by multiplying the square root of the average R^2 of respective constructs with an average AVE of 0.763. as in Table 12. After determination of the GoF, it was found that the value accepts the range which indicates that the model fits.

Table 12. Summary of GoF

Construct	AVE	R^2 for Monitoring practices	0.789
Monitoring practices	0.751	R^2 for Enabling factors	0.802
Enabling factors	0.759	R^2 for Monitoring tools	0.454
Monitoring tools	0.782	R^2 for Project success	0.506
Project success	0.761		
Total AVE	3.053	Total R^2	2.551
Average of AVE	0.763	Average R^2	0.638
	GoF	0.487	

Importance Performance Matrix Analysis

By assessing the performance of latent variables, the Importance-Performance Matrix Analysis (IPMA) was used to expand the results of the measurement and structural model. IPMA is used in Smart PLS 4 to identify potential areas that need to be addressed and improved through management activities. It estimates the cumulative effects in molding a certain target construct to provide information on the relative importance of the research constructs (Wang et al. 2015). Their index value, on the other hand, represents performance as determined by rescaling all data to a range of 0 to 100 (Mohamed et al. 2018). When it comes to structural model criteria, the IPMA then extends the structural model evaluation by evaluating the actual importance and performance of each exogenous variable in relation to the model's endogenous variables. The IPMA should first determine the target construct and then the entire effect during this measurement. After that, the IPMA function would be used to generate the performance value. The importance and performance of latent constructs were evaluated in this study. The outcome is shown in Table 13. The results suggest that monitoring enabling factors as well as monitoring practices are the most important performance value in terms of latent construct in the success of transportation infrastructure projects.

Table 13: Importance Performance (IPMA) for Project Performance

Variables	Importance (Total Index)	Performance (Index Value)	Ranks based on performance
Monitoring practices	0.684	67.318	2
Enabling factors	0.871	72.265	1
Monitoring tools	0.763	57.114	3

The developed Model

The study's main objective was to develop a model that provides sufficient explanation based on the factors that drive in transport infrastructure projects success in Tanzania. The results from the survey have provided empirical evidence to the overall research model. There were four construct factors from which three hypotheses were developed to explain the project success in Tanzanian context. The finding shows that all hypotheses were supported and have significant positive relationships. Hence, the final model is represented in Figure 4.

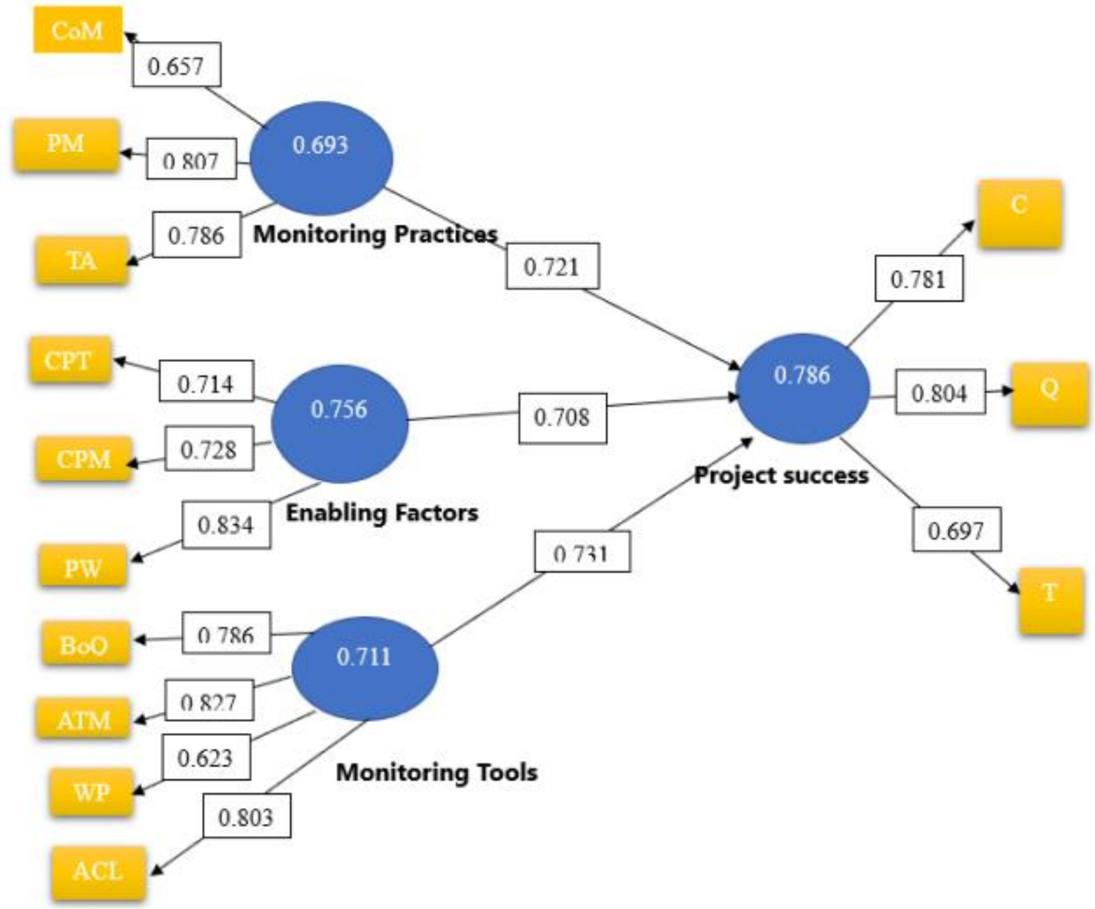

Figure 4: Final model

CONCLUSION

Model development for monitoring of road projects was accomplished by extrapolating from the collected data. For the model development, the results enlightened the researcher on the traits with a higher potential for project success, which were grouped into input, contextual, and output themes. The model focuses on areas that construction professionals should revisit to improve road project success. The developed model, on the other hand, included concerns that were previously well-known in the literature as well as issues unique to the Tanzanian transport infrastructure projects.

Conflict of Interest

There are no conflicts to declare.

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