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Validation of a Model Developed for Value Engineering Approach Performance on Gravel Roads Maintenance Projects in Tanzania

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ABSTRACT: A validated model offers a consistent framework for decision-makers to understand the critical factors influencing performance across different data sets. Gravel roads (GR) are vital in Tanzania, comprising over 75% of the road network, with 65% in poor condition. Value engineering (VE) has emerged as a promising tool to enhance GR maintenance, accounting up to 83.3% of the variance, as demonstrated by a model developed using partial least squares structural equation modeling (PLS-SEM). This paper therefore evaluates the validation of a Model Developed for Value Engineering Approach Performance on Gravel Roads Maintenance Projects in Tanzania using split data methodology and the PLSpredict tool in SmartPLS, which assesses the out-of-sample predictive power of PLS-SEM. The results revealed that the model exhibits medium predictive relevance for the corresponding constructs, with 65.38% and 61.22% of indicators in the PLS-SEM yielding smaller prediction errors compared to the naïve linear regression model (LM) benchmark for training and validation data sets, respectively. These findings validate the model's ability to predict future data effectively, supporting its use for decision-making and strategic planning. The study concludes that adopting a VE approach to enhance GR maintenance projects in Tanzania and other regions is crucial, given the model's predictive relevance across different data sets.

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In Tanzania, significant investments have been made in the development and maintenance of road infrastructure, including gravel roads. Despite these efforts, gravel roads have persistently remained in poor condition, facing numerous performance challenges (NAO, 2023). Given that gravel roads constitute a large proportion of the road network, there is a pressing need for alternative maintenance approaches to improve their condition and performance. Traditional gravel road maintenance practices have not effectively addressed the ongoing performance issues. This necessitates the exploration of innovative solutions such as value engineering (VE). According to Aigbavboa *et al.*, (2016), VE is a method that enhances the value of construction projects by identifying and eliminating unnecessary materials, methods, and processes. Wei *et al.*, (2022) further assert that VE has been successfully used for over 70 years to improve project value by substituting materials and methods with less expensive alternatives without compromising functionality. To address the challenges in gravel roads maintenance, a model that integrates the value engineering principles and activities and gravel roads maintenance performance factors with structural equation modeling (SEM) approach was developed. SEM is a powerful technique for analyzing relationships among variables. In this context, SEM was utilized to identify critical VE phases and associated indicators alongside maintenance performance factors such as cost, quality,

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time, social, relational, and environmental aspects. Any developed model must be validated to examine its performance to give a sanity check by addressing oversights, providing additional insights and verifying that performance is as reported. Model validation is crucial to ensure that the proposed model adequately fits its intended purpose and that the constructs and indicators used are statistically significant and robust. For gravel roads maintenance projects, a valid model assists in the optimal allocation of resources, including materials, personnel, equipment, and plants, and informs policy formulation. Validation also helps identify areas for model improvement by adjusting indicators with abnormal measurement issues or structural model specifications. Harrington (2017) emphasized the importance of using training and validation datasets to estimate the generalization performance of the model accurately. Numerous model validation methods exist in the literature, including Goodness-of-Fit Indices, Reliability Testing, Validity Testing, Predictive Validity, Cross-Validation (data splitting), Diagnostic Checks, Model Modification Indices, and External Validation (Yun *et al.*, 2018). Combining these methods can lead to a more comprehensive validation of the SEM model. This study adopted cross-validation by splitting the data into training and validation subsets and employed predictive validity using the PLSpredict tool in SmartPLS. Shmueli *et al.*, (2022) recommend including PLSpredict in the evaluation of PLS-SEM for its predictive capabilities. Consequently, this paper examines the potential of the data split technique and PLSpredict in validating SEM models since model validation is a critical step in developing effective and sustainable modeling frameworks. For Tanzania, a well-validated SEM model entailing value engineering approach on gravel roads maintenance, will enable more informed decision-making and better policy formulation, leading to organized and reliable maintenance of roads infrastructure. This paper therefore evaluates the validation of a Model Developed for Value Engineering Approach Performance on Gravel Roads Maintenance Projects in Tanzania.

MATERIALS AND METHODS

Data Split Methodology for Validation of a Model: This study adopted the technique of splitting data into training and testing sets, which is a fundamental approach involving the division of data into parts, commonly with an 80:20, 70:30, or 50:50 split (LeewayHertz, 2023). Specifically, this study utilized a 70:30 split, where approximately 70% of the data was used for training the model and 30% for testing its performance. The testing data also included the validation data. The advantage of this technique lies in its ability to evaluate the model's response to new, unseen data. To avoid data sampling bias, the data for this study were randomly selected from the 213 total responses using the Statistical Package for Social Sciences (SPSS) tool. This involved selecting a random sample of cases and applying the 70:30 data split. As a result, 157 records (70%) were used for training data, and 69 records (30%) were used for test or validation data. This distribution allowed the training set to include 70% of the most available dataset, forming the "knowledge" base of the model. The remaining 30% of the dataset was used as the validation and test dataset to fine-tune the model parameters, assess the permissible error, and evaluate the model's predictive performance. The holdout set data technique was not employed because there was no overfitting of hyper parameters Table 1 illustrates the technique of splitting data into training and validation/test data.

Table 1: Splitting data into training and validation/testing sets

Training data (For fitting)	Validation/test data (For evaluating model performance)
70%	30%

The crux of all validation methods is data division, which is crucial for simulating how the model would react when subjected to data it has never encountered before.

Model Validation Using PLSpredict in SmartPLS: Model validation using PLSpredict in SmartPLS is a rigorous process designed to ensure that the Partial Least Squares Structural Equation Modeling (PLS-SEM) model possesses adequate predictive power (Shmueli *et al.*, 2019). This study systematically adhered to the PLSpredict steps for SEM model validation. According to Sharma *et al*., (2023), model validation using PLSpredict involves several steps to assess the predictive power of a PLS-SEM model: Building the PLS-SEM Model was the first step which involved carefully specifying all constructs, indicators, and relationships, including calculating path coefficients, outer loadings, and (R^2) values. Secondly, performing PLSpredict analysis. This step entails navigating the PLSpredict tool in SmartPLS and running the analysis and thirdly evaluating predictive performance which involved assessing metrics such as mean absolute error (MAE), root mean squared error (RMSE), and Q^2_predict, and comparing the predicted and actual values. In interpreting Q^2_predict values; for endogenous constructs, a positive Q^2_predict values indicate predictive relevance. To evaluate the predictive capabilities of the model, PLSpredict should be included in the evaluation of PLS-SEM results as suggested by Hair *et al.*, (2022). Based on the procedures suggested by Shmueli *et al*., (2016), the current PLSpredict algorithm in the SmartPLS software allows researchers to obtain prediction error summaries such as RMSE, MAE, and mean absolute percentage error (MAPE). This study utilized these metrics to interpret findings in conjunction with a naïve linear regression model (LM) benchmark. The LM benchmarks were obtained by running a linear regression of each dependent construct's indicators on the exogenous constructs in the PLS path model. When comparing the RMSE or MAE values with the LM values, Shmueli *et al*., (2019) highlighted the following criteria: That if all indicators in the PLS-SEM analysis have lower RMSE or MAE values compared to the LM benchmark, the model has *high predictive power*, and if the majority (or the same number) of indicators in the PLS-SEM analysis yields smaller prediction errors compared to the LM, this indicates *medium predictive power*. Similarly, if a minority of the dependent construct's indicators produce lower PLS-SEM prediction errors compared to the LM benchmark, the model has *low predictive power* and lastly if the PLS-SEM analysis yields lower prediction errors in terms of RMSE (or MAE) for none of the indicators, the model *lacks predictive power*. This study followed these processes to ensure the development of a robust SEM model with appropriate predictive power. The SEM model being validated portrays the impact of value engineering implementation on the performance of gravel roads maintenance projects in Tanzania.

RESULTS AND DISCUSSION

The analysis employed the PLSpredict tool within SmartPLS for both the training and validation/test datasets, which were split in a 70%:30% ratio as illustrated in Figure 1, detailing the total data split technique. The results obtained from PLSpredict for both datasets provided critical metrics essential for assessing the model's predictive power, with primary emphasis placed on metrics such as root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and Q^2_predict values. These outputs represent the latest advancements in PLSpredict results, crucial for evaluating the model's predictive efficacy (Liengaard *et al*., 2021). Based on findings from the training data (157 records) and the test/validation data (69 records), structural equation models (SEM) were developed depicting the impact of value engineering (VE) implementation on the overall maintenance performance of gravel roads in Tanzania.

These models, illustrated in Figures 4 and 5 for training and test/validation data respectively, integrate five VE phases linked with relevant activities and gravel road maintenance performance factors encompassing cost, time, quality, social and relational factors, and environmental impacts. After excluding statistically insignificant variables with low outer loading values (<0.7 for both models), internal consistency and model fit tests were conducted following the guidelines of Hair *et al*., (2016). Summaries of these results are presented in Tables 1 and 2, affirming the models' acceptability and their suitability for validating the core SEM model developed. Both models demonstrated construct reliability and validity, meeting established thresholds such as Rho_A $\geq$ 0.70, Cronbach's alpha $\geq$ 0.70, composite reliability (CR) $\geq$ 0.70, and average variance extracted (AVE) $\geq$ 0.5, as recommended by Hair *et al*., (2016) and Wong (2013). Model fit was evaluated with the standardized root mean square residual (SRMR), deemed acceptable at $\leq$ 0.08, and the unweighted least squares discrepancy (d_ULS), where lower values indicate better fit. Results of the model fit tests in Table 3 for both training and validation/test datasets met these criteria, confirming the robustness of the models. The overall impact of VE implementation on gravel road maintenance project performance was assessed within the framework of the PLS algorithm, utilizing bootstrapping and blindfolding techniques. Results indicated that the training data yielded a coefficient of determination R^2 of 0.836, while the test/validation data yielded an R^2 value of 0.858, demonstrating excellent model performance as both values exceeded the acceptable threshold of $R^2 \geq 0.20$. This highlights the significance of validation in ensuring the models are robust, acknowledging their potential limitations and assumptions for extrapolation to out-of-sample data (Hair *et al.*, 2022).

Comparing PLS-SEM and LM Benchmark Results using PLSpredict Tool: Model validation using PLSpredict in SmartPLS represents a contemporary and robust process for assessing the predictive adequacy of models (Shmueli *et al.*, 2016). According to Shmueli *et al.*, (2016), the PLSpredict algorithm facilitates the computation of prediction error statistics such as root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). These metrics serve to evaluate the predictive performance of the partial least squares path (PLS-SEM) model for both manifest variables (MV) and latent variables (LV). Notably, RMSE and MAE are applicable to both MV and LV results, whereas MAPE is solely computed for MV results. In this study, the focus was on manifest variables criteria. The results presented in Tables 3 and 4 illustrate the model's constructs or indicators incorporated in the modified model, alongside their respective error metric values (RMSE, MAE, MAPE) and Q^2_predict scores for both PLS-SEM analysis and the naïve linear regression model (LM). Interpretation of these metrics involved comparing each indicator's RMSE, MAE, and Q^2_predict values against the LM benchmark. Emphasis was placed on Q^2_predict values in drawing conclusions due to its critical role as a key metric in PLSpredict, indicating out-of-sample predictive power derived from comparing predicted and actual values.

In all cases, Q^2_predict value is considered to bear substantial predictive relevance when it is positive. This viewpoint aligns with the assertion by Shmueli *et al.*, (2019) that Q^2 in PLSpredict assesses prediction errors using the mean value of the training sample to predict outcomes in the test or validation sample obtained through blindfolding in PLS-SEM. Positive Q^2_predict values indicate that prediction errors in PLS-SEM results are smaller compared to those using mean values of RMSE, MAE, and MAPE alone. Therefore, the presence of a positive Q^2_predict value suggests superior predictive performance of the PLS-SEM model and negative Q^2_predict values calls for model refinement and further adjustments.

Predictive Power of the Model for the Training Data: The execution of PLSpredict involved training the model on a 70% sample and evaluating its performance on a validation sample (Shmueli *et al.*, 2019) to achieve satisfactory performance metrics. The primary objective of the training data was to establish a well-generalizing algorithm model for handling new, unfamiliar data. Figure 1 illustrates the results of the model developed using the training sample data, focusing on quality criteria evaluated through the PLS algorithm.

Notably, the "Creativity" phase of value engineering (VE) emerged as the most influential, with a path coefficient of 0.410. Among its associated activities, "Awareness of value increment techniques" (CP1) stood out significantly with a coefficient of 0.964. Following in importance were the VE phases of evaluation (0.405), information (0.225), development and presentation (0.104), and function (0.016). In terms of hard maintenance factors, the cost construct exhibited the highest coefficient (0.739), with activity C5 "adequate funds allocation considering actual maintenance needs" leading with a coefficient of 0.782, followed by quality (0.721) and time (0.613). Soft performance measures highlighted the social and relational aspects surpassing environmental considerations.

The overall coefficient of determination R^2 was calculated as 0.836, surpassing the threshold criterion of $R^2 \geq 0.20$ as suggested by Hair *et al.*, 2016). Further comparison with the model developed using the entire dataset depicted in developed model showed minor deviations, with an overall R^2 of 0.833, indicating a negligible difference of 0.36%. These discrepancies confirm the accuracy and reliability of the training data model fitting. All model constructs detailed in Table 2 met the established criteria, affirming their reliability and validity through rigorous model fit tests. The SRMR value of 0.176 and d_ULS value of 182.044 for the estimated model (Table 3) both passed the predefined benchmarks. The Heterotrait-Monotrait (HTMT) ratio analysis, as recommended by Hair *et al.*, (2010), indicated that a significant proportion of correlated constructs exhibited ratios below the threshold of ≤ 0.85. Table 4 presents further analysis of manifest variables, detailing RMSE, MAE, MAPE, and Q^2_predict values for both PLS-SEM and naïve linear regression model (LM) benchmarks across 52 indicators. A noteworthy finding was that 65.38% of indicators demonstrated SMSE values lower than those of the naïve LM benchmark, underscoring the model's medium predictive power according to Shmueli *et al.*, (2019). Notably, 59.62% of the indicators in the PLS-SEM model had lower Mean Absolute Percentage Error (MAPE) values compared to those in the naïve Linear Model (LM) benchmark. Specifically, 31 out of 52 indicators/constructs exhibited reduced MAPE values.

Consequently, the Standardized Mean Squared Error (SMSE) emerged as the predominant metric for evaluating the training dataset results. Additionally, the findings revealed that all constructs/indicators in the PLS-SEM model had positive Q^2_predict values, indicating substantial predictive relevance.

In conclusion, the training data model's results, with 65.38% of indicators showing SMSE values below the naïve LM benchmark, indicate *medium predictive power* and suitability for its intended purpose, emphasizing substantial predictive relevance. Additionally, the Importance-Performance Matrix analysis highlighted nearly equal weighting of latent variables' performances for VE implementation and overall gravel road maintenance, validating their interdependency at 21.488% and 21.382%, respectively.

Predictive Power of the Model for the Validation Data: The results from the validation data involved executing PLSpredict on a validation/test sample (30%) to evaluate the performance of the model developed using training sample considerations, as depicted in Figure 2. This process provided an unbiased assessment of the model's fitness on the training dataset while fine-tuning its parameters for final evaluation. In the analysis of quality criteria, the "creativity value engineering phase" emerged as the top performer with a path coefficient of 0.469, followed by the VE phases of evaluation (0.439), information (0.178), development and presentation (0.085), and function (0.002).

The ranking of VE phases maintained consistency across the main model, training, and validation/test data samples, highlighting the predictive performance of the model. Results presented in Table 2 for the validation/test data indicated that all construct reliability and validity tests met acceptable criteria, with the exception of the Cronbach's alpha value for the function VE phase, which slightly fell short at 0.504 (just below the threshold of ≥ 0.70). Despite this, it was deemed appropriate to retain this function phase at the 0.504 Cronbach's alpha value, as adjusting it further could potentially affect other reliability and validity measures, all of which surpassed the required thresholds. The summary of model fit tests in Table 3 indicated an SRMR value of 0.213 and d_ULS value of 256.733, both of which signify a well-fitting model.

Table 2: Construct reliability and validity test results summary

Constructs name	Training data results summary						Validation/Test data results summary			
	Item code	Rho-A	Cronbach's alpha	Composite reliability	AVE		Rho-A	Cronbach's alpha	Composite reliability	AVE
Information	IP	0.925	0.908	0.922	0.501		0.942	0.923	0.934	0.543
Function	FP	1.008	0.667	0.779	0.549		1.153	0.504	0.752	0.621
Creativity	CP	0.983	0.982	0.985	0.877		0.985	0.984	0.986	0.890
Evaluation	EP	0.984	0.984	0.986	0.897		0.983	0.982	0.984	0.887
Development/presentation	DP	0.879	0.823	0.867	0.522		0.943	0.884	0.896	0.523
Time	T	0.784	0.784	0.875	0.700		0.881	0.872	0.921	0.795
Cost	C	0.720	0.700	0.813	0.523		0.720	0.714	0.821	0.534
Quality	Q	0.749	0.745	0.840	0.568		0.746	0.740	0.836	0.562
Relational	R	0.942	0.942	0.963	0.896		0.945	0.944	0.964	0.898
Environment	E	0.977	0.975	0.982	0.931		0.975	0.974	0.981	0.927
VE-implementation	VE-IM	0.980	0.966	0.970	0.516		0.982	0.960	0.965	0.514
Maintenance performance	OMP	1.000	-	-	-		1.000	-	-	-
Acceptable value		≥ 0.70	≥ 0.70	≥ 0.70	≥ 0.50		≥ 0.70	≥ 0.70	≥ 0.70	≥ 0.50

Table 3: Model fit test result summary

Fit test for training model			Fit test for validation/Test model	
Fitness test	Saturated Model	Estimated Model	Saturated Model	Estimated Model
SRMR	0.158	0.176	0.193	0.213
d_ULS	147.307	182.044	212.302	256.733

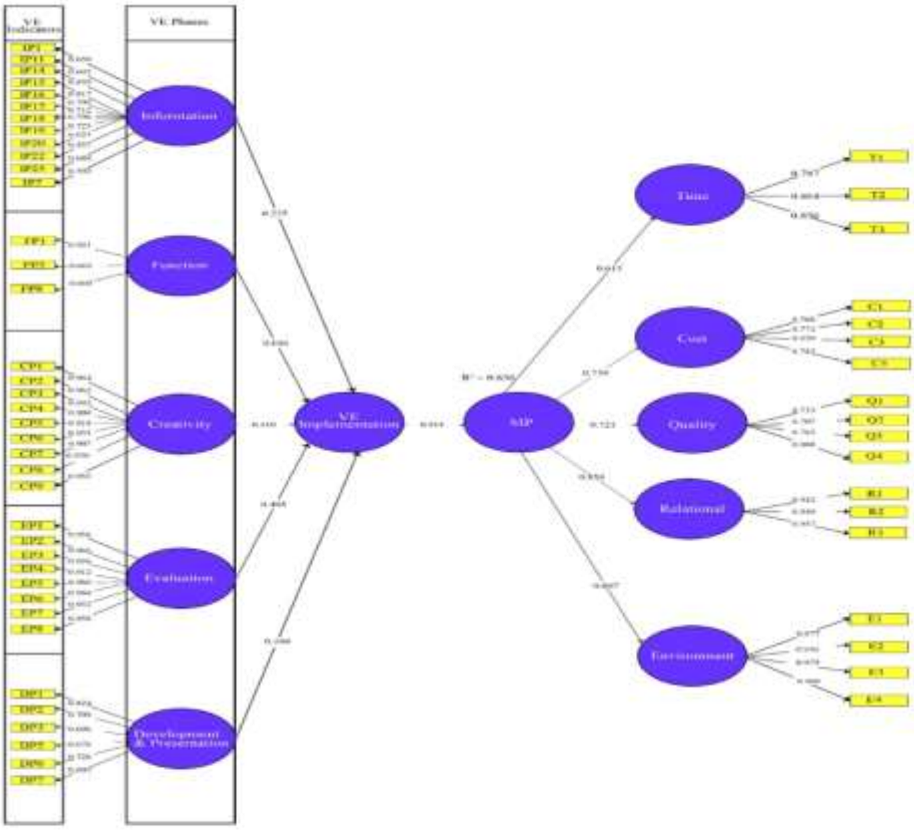

Fig 1: Structural equation model with path coefficients and R^2 for training data

The overall coefficient of determination R^2 was calculated as 0.858, exceeding the threshold of 0.20, indicating that the model meets expectations across different dataset conditions. Discriminatory validity was assessed using the Heterotrait-Monotrait (HTMT) ratio, with substantial proportions of correlated constructs demonstrating ratios below the threshold of ≤ 0.85. Table 5 presents a summary of RMSE, MAE, MAPE, and Q^2_predict values for model validation, comparing the model's predictive performance against a naïve linear regression model (LM). Similar procedural analysis as done on the training data sample was adopted for the validation/test data, with Q^2_predict values serving as the key error metric as it depicts substantial predictive relevance when it is positive. According to Shmueli *et al.*, (2019), if a majority or the same number of indicators in the PLS-SEM analysis yield smaller prediction errors compared to the LM benchmark, the model demonstrates *medium predictive power*. In this study, 61.22% of PLS-SEM indicators exhibited MAPE values lower than the naïve LM benchmark, indicating medium predictive power, consistent with the findings from the training data sample. Results indicated that 53.06% of the model constructs/indicators in the validation data had lower SMSE values in the PLS-SEM model compared to the naïve LM benchmark. This finding, along with the fact that 61.22% of the constructs/indicators exhibited lower MAPE values, underscores the importance of MAPE in determining the model's predictive relevance. These results are pivotal in assessing whether the model possesses high, medium, low, or no predictive relevance. According to Shmueli *et al.*, (2019), the model utilizing validation/test data set exhibits demonstrates medium predictive power.

This comprehensive analysis concludes that the model's predictive performance remains robust across both training and validation/test data samples, obviating the need for further adjustments to constructs, indicators, or relationships. This study navigated the complexities of model validation effectively, culminating in a conclusive assessment of its predictive capabilities as outlined. The developed PLS-SEM model has therefore been validated using both training and validation datasets, demonstrating significant understandings into its predictive capabilities. The results indicate substantial predictive performance and relevance, establishing the model as a reliable tool for analyzing and predicting outcomes in gravel roads maintenance projects.

Table 4: Manifest variables results on RMSE, MAE, MAPE and Q^2_predict for training data

Model Construct/Indicators' Code	**PLS-SEM results summary**				**Linear Regression Model (LM) results**			
	RMSE	**MAE**	**MAPE**	**Q^2_predict**	**RMSE**	**MAE**	**MAPE**	**Q^2_predict**
C1	0.942	0.778	47.411	0.062	1.006	0.784	46.008	-0.058
C2	0.682	0.571	38.343	0.156	0.713	0.559	36.915	0.078
C3	0.884	0.702	39.641	0.009	0.920	0.712	38.880	-0.072
C5	0.707	0.587	38.881	0.224	0.727	0.555	35.598	0.180
E2	0.392	0.278	18.497	0.840	0.470	0.087	4.994	0.970
E4	0.439	0.343	20.751	0.752	0.146	0.092	4.908	0.973
E3	0.498	0.366	21.377	0.688	0.166	0.117	7.066	0.965
E1	0.498	0.358	20.900	0.690	0.102	0.044	2.429	0.987
R1	0.519	0.432	27.649	0.815	0.218	0.159	8.947	0.967
T3	0.797	0.669	44.443	0.006	0.838	0.666	44.242	-0.098
Q1	0.824	0.669	39.391	0.076	0.789	0.645	35.387	0.152
Q4	0.713	0.594	36.461	0.125	0.839	0.649	38.151	-0.211
T2	0.762	0.634	41.930	0.044	0.850	0.642	42.686	-0.189
Q2	0.757	0.625	41.514	0.134	0.831	0.620	39.932	-0.044
R2	0.433	0.346	20.830	0.750	0.196	0.120	6.286	0.949
R3	0.446	0.304	20.214	0.776	0.102	0.045	2.716	0.988
Q3	0.745	0.612	37.856	0.055	0.659	0.522	31.520	0.262
T1	0.748	0.599	37.867	0.079	0.804	0.648	38.671	-0.065
DP7	0.735	0.633	43.293	0.106	0.821	0.684	41.231	-0.098
IP17	0.620	0.517	36.064	1.195	0.623	0.513	32.098	0.134
CP9	0.657	0.505	28.765	0.827	0.936	0.312	24.234	-0.035
IP25	0.710	0.566	36.448	0.130	0.819	0.395	30.902	-0.039
CP4	0.541	0.397	21.332	0.762	0.134	0.645	27.567	-0.347
EP5	0.397	0.315	19.830	0.867	0.673	0.345	25.850	0.650
CP1	0.291	0.234	17.241	0.893	0.378	0.537	24.468	-0.899
CP8	0.434	0.353	19.394	0.856	0.578	0.378	31.234	0.073
IP1	0.829	0.643	42.107	0.251	0.945	0.732	45.000	0.082
EP8	0.364	0.287	17.226	0.835	0.452	0.324	30.200	0.990
EP7	0.421	0.347	20.258	0.773	0.745	0.567	29.450	-0.058
IP15	0.619	0.510	34.471	0.320	0.620	0.547	32.658	0.371
CP5	0.473	0.368	18.872	0.765	0.359	0.458	19.004	0.679
EP6	0.410	0.314	19.018	0.783	0.623	0.528	26.282	0.457
IP11	0.708	0.585	38.263	0.162	0.238	0.578	31.689	0.987
IP14	0.653	0.496	33.239	0.440	0.759	0.450	28.900	-0.067
DP2	0.718	0.607	40.491	0.172	0.650	0.704	45.238	0.185
CP2	0.501	0.408	23.166	0.843	0.509	0.411	25.848	0.812
DP1	0.627	0.491	34.011	0.424	0.452	0.503	33.893	0.345
IP18	0.646	0.533	34.856	0.343	0.648	0.539	29.456	0.335
CP6	0.436	0.309	21.670	0.794	0.463	0.568	24.78	0.048
IP16	0.642	0.534	36.371	0.259	0.499	0.567	42.678	0.288
CP7	0.482	0.347	20.232	0.714	0.364	0.319	23.853	0.780
CP3	0.522	0.431	24.339	0.811	0.637	0.584	31.009	-0.033
DP6	0.758	0.610	40.797	0.077	0.846	0.700	35.345	0.047
EP3	0.412	0.306	18.794	0.681	0.477	0.344	20.234	0.748
DP3	0.879	0.730	47.195	0.086	0.987	0.628	45.763	0.091
IP19	0.667	0.553	36.098	0.257	0.843	0.649	39.345	-0.026
EP1	0.432	0.345	23.158	0.887	0.328	0.435	24.568	0.456
EP4	0.558	0.401	24.288	0.752	0.520	0.403	26.345	0.840
FP1	0.826	0.663	42.375	0.112	0.730	0.744	43.650	0.634
IP20	0.736	0.599	39.514	0.096	0.836	0.523	40.332	0.083
DP8	0.682	0.588	40.280	0.095	0.720	0.571	37.409	-0.009
EP2	0.359	0.272	18.808	0.867	0.430	0.432	0.324	0.849

Table 5: Manifest variables results on RMSE, MAE, MAPE and Q^2_predict for validation data

Model Construct/Indicators' Code	PLS-SEM results summary				Linear Regression Model (LM) results			
	RMSE	MAE	MAPE	Q^2_predict	RMSE	MAE	MAPE	Q^2_predict
C3	0.969	0.741	44.260	-0.050	1.392	1.077	58.801	-1.167
C2	0.785	0.653	45.127	0.054	2.079	1.478	95.633	-5.641
C1	1.068	0.897	55.469	-0.093	2.197	1.627	102.912	-3.623
C5	0.835	0.690	46.863	0.100	1.317	0.982	65.681	-1.237
E4	0.374	0.284	17.069	0.823	0.293	0.192	10.389	0.892
E2	0.373	0.262	18.058	0.849	0.251	0.127	6.754	0.932
E3	0.429	0.314	19.095	0.734	0.302	0.218	13.176	0.868
E1	0.437	0.315	19.427	0.729	0.321	0.256	0.319	0.985
Q3	0.764	0.606	40.028	-0.039	1.022	0.794	47.412	-0.856
Q2	0.942	0.795	53.054	0.053	1.761	1.265	85.804	-2.311
T3	0.911	0.745	49.529	-0.050	1.608	1.149	74.506	-2.273
Q4	0.761	0.616	40.194	-0.065	1.327	0.938	56.453	-2.239
R3	0.420	0.274	18.540	0.806	0.388	0.208	20.45	0.901
Q1	0.868	0.681	39.734	-0.043	1.739	1.245	65.993	-3.190
T2	0.920	0.760	51.448	-0.110	1.768	1.352	94.310	-3.105
R2	0.368	0.288	17.335	0.817	0.358	0.252	14.201	0.827
T1	0.818	0.673	44.325	0.035	1.577	1.170	74.192	-2.631
R1	0.522	0.439	28.091	0.812	0.499	0.317	18.340	0.829
CP9	0.704	0.535	30.123	0.809	0.345	0.238	34.902	0.023
CP5	0.448	0.358	18.240	0.800	0.345	0.436	20.869	0.765
EP1	0.458	0.365	25.840	0.876	0.567	0.567	28.478	0.894
EP11	0.844	0.661	42.842	0.036	1.045	0.749	84.934	-3.493
CP1	0.329	0.247	18.332	0.877	0.439	0.438	23.908	0.045
IP1	0.889	0.711	47.855	0.116	0.946	0.832	46.985	0.123
CP6	0.395	0.277	19.984	0.828	0.489	0.366	20.256	0.893
CP2	0.419	0.341	18.505	0.892	0.526	0.458	32.001	-0.673
DP3	0.923	0.800	52.716	0.063	1.920	1.735	76.367	-2.120
CP3	0.447	0.360	19.704	0.863	0.673	0.456	26.832	0.728
DP8	0.802	0.695	48.118	-0.020	0.678	0.710	53.01	-0.045
CP4	0.428	0.321	17.220	0.840	0.348	0.278	19.648	0.991
EP6	0.455	0.359	20.507	0.767	0.532	0.400	27.370	0.825
CP8	0.406	0.332	18.045	0.881	0.566	0.267	24.902	0.827
DP6	0.797	0.620	40.919	0.036	0.792	0.784	36.903	0.036
IP19	0.829	0.705	47.422	0.106	0.934	0.678	45.347	0.102
EP8	0.346	0.281	15.918	0.865	0.204	0.348	22.936	0.789
EP3	0.456	0.322	19.254	0.639	0.546	0.435	20.000	0.745
IP20	0.739	0.580	38.811	0.059	0.893	0.740	40.000	0.078
IP25	0.824	0.648	42.761	0.011	0.639	0.564	44.003	0.026
IP18	0.809	0.690	47.004	0.072	0.560	0.569	46.456	0.058
EP4	0.491	0.361	23.433	0.793	0.385	0.264	26.945	0.849
DP2	0.788	0.684	47.063	0.001	0.645	0.589	44.091	0.041
EP2	0.366	0.273	19.508	0.867	0.287	0.111	23.902	0.923
IP16	0.796	0.659	44.787	0.099	0.924	0.523	43.123	0.927
EP5	0.399	0.310	19.833	0.867	0.289	0.314	18.345	0.738
DP1	0.728	0.577	40.269	0.241	0.567	0.458	36.902	0.034
IP14	0.916	0.737	48.911	0.134	0.789	0.745	50.043	-0.012
CP7	0.432	0.306	18.410	0.736	0.362	0.349	24.764	0.684
EP7	0.376	0.321	18.803	0.816	0.289	0.300	16.268	0.879
IP15	0.770	0.667	45.461	0.129	0.789	0.736	40.333	0.166

Conclusion: This study developed a value engineering (VE) approach model for gravel road maintenance projects using structural equation modeling (SEM) to predict improvements in cost, time, quality, social and relational aspects, and environmental issues. The model's validity and usefulness were assessed through the PLSpredict tool, with results showing medium predictive power. Specifically, 65.38% and 61.22% of indicators in the training and validation datasets, respectively, demonstrated smaller prediction errors compared to a naïve linear regression model. This suggests the model generalizes well, as most RMSE and MAPE values were lower in PLS-SEM than in the naïve model. The study therefore provides practical and academic insights into VE methods for managing gravel roads maintenance projects, highlighting causal relationships between VE activities and methods. It offers valuable guidance for road management authorities and contractors, emphasizing the need for effective VE approach implementation strategies based on the model's activity flow rankings and predictive power it exhibits. The findings have practical implications for improving roads maintenance practices in Tanzania and similar regions.

Declaration of Conflict of Interest: The authors declare no conflict of interest.

Data Availability Statement: Data are available upon request from the first author or corresponding author.

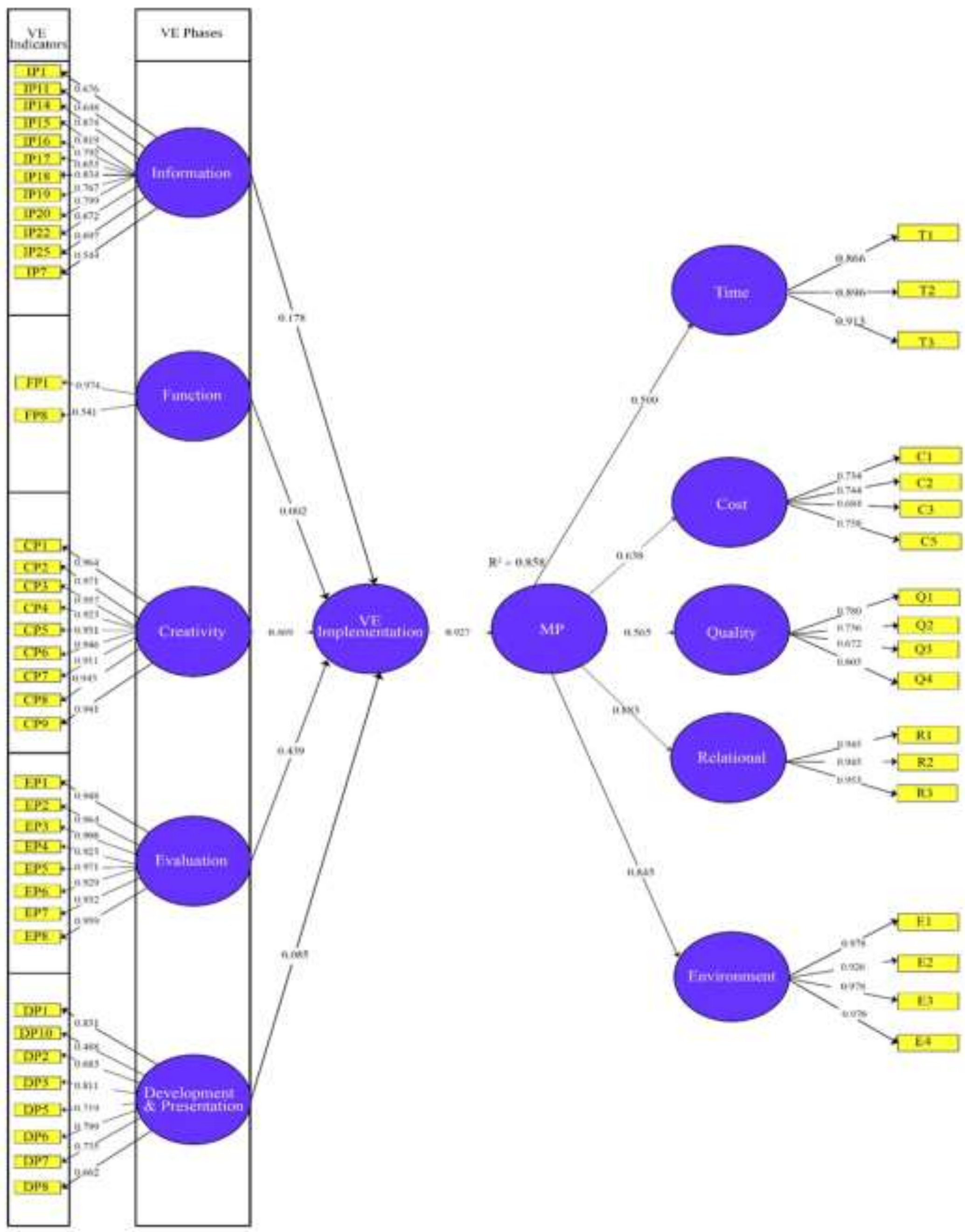

Fig 2: Structural equation model with path coefficients and R^2 for test/validation data

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