Structural Equation Modeling for Successful Water Management in the Northeastern Mekong River Basin under the Royal Irrigation Department

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Received July 17, 2025, Revised August 31, 2025, Accepted September 10, 2025, Published July 1, 2026

Abstract. *This study aims to: (1) examine the influence of causal factors that affect the success of water management, and (2) verify the consistency of the developed model with empirical data. This is a quantitative research study that employed questionnaires distributed to 375 staff members responsible for water management under the Royal Irrigation Department in the Northeastern Mekong River Basin. The participants were from 15 agencies and had at least one year of work experience. The data were analyzed using Structural Equation Modeling (SEM) techniques. The findings from the quantitative research were also analyzed qualitatively using the documentary analysis method. The results revealed that: (1) Continuous quality improvement, becoming a learning organization, leadership, farmer participation, and environmental conditions all had a statistically significant influence (at the 0.05 level) on the success of water management by the Royal Irrigation Department, with influence values of 0.93, 0.90, 0.80, and 0.71, respectively. Therefore, a key strategy for the Royal Irrigation Department to achieve successful water management involves the proper and timely management of a learning organization in response to changing circumstances. Furthermore, there is an urgent need to enhance the efficiency and effectiveness of leadership, farmer participation, and environmental management to ensure sustainable water management development in the future.*

Keywords: Leadership, Learning Organization, Farmer Participation, Environmental Conditions, Water Management to Success

1 Introduction

Water is an essential resource for life on earth and a finite natural asset. Water scarcity for household consumption, agriculture, and industry has become an increasingly serious issue across various regions of the country [1]. Many nations have recognized the severity of water shortages and have implemented long-term plans to mitigate or prevent such problems in the future [1, 2]. The development of water sources and the effective and sustainable management of water resources require the cooperation of all stakeholders, including government agencies at both the central and local levels [3], the private sector, water users, and those who may be affected [1, 4]. In Thailand, over the past decade, there has been a growing risk of water shortages in many areas [5]. This is due to inefficient water management and increasing demand for water [6]. The Northeastern region in particular, which mostly lies outside the irrigated zones, has faced severe water scarcity. This has led to consequences, such as insufficient water for agriculture and reduced income for farmers [7]. It is, therefore, imperative to develop irrigation systems in the region to ensure adequate water storage for farming, domestic consumption, and year-round usage across all three seasons. To achieve this, operations must be carried out while considering the key factors that influence the success of the Royal Irrigation Department's organizational water management efforts, as indicated below [1, 8].

The environmental context plays a vital role in the dimension of sustainable organizational development. This includes efforts to encourage water user groups to adapt their operations and practices in alignment with the "New Normal" lifestyle [9, 10]. It also involves strengthening these groups to help achieve operational goals by leveraging technology to enhance work processes. Key strategies include the development of data systems to promote transparency and open government data, fostering data integration and sharing, improving workflows, and adopting digital technologies as core mechanisms in operations [1, 11]. These approaches aim to drive innovation in process improvement and encourage inclusive participation, especially from the public sector, in collaborative planning and problem-solving. Ultimately, this will lead to sustainable success, reduce conflicts, and improve overall operational efficiency [1, 12, 13].

Public Participation is a critical process in environmental impact assessment. Previous studies by DEPA Thailand [11] and earlier research by DEPA, which applied National Statistical Office Ministry of Information and Communication Technology [13] Theory of Planned Behavior, suggest that it is essential to study behavioral intention as a precursor to participation [14]. These studies highlight that public participation is a nuanced issue that can be implemented in various ways and at different levels. Some methods are simple and straightforward, while others are time-consuming, depending on both the public's willingness to participate and the institutions' desire for such participation [15]. Therefore, agencies must develop a sound understanding of how to provide accurate and accessible information to the public, create opportunities for public engagement in policy implementation, and simultaneously strengthen the skills and capacity of public officials at all levels [16]. National Statistical Office Ministry

of Information and Communication Technology [13] theory has been widely cited and is considered one of the most influential models for predicting human social behavior [17]. It has been adopted as a foundational framework in participatory research. Quesada and Weikard [17] supported this theoretical approach, and Busscher [18] further demonstrated that the Planned Behavior Model can effectively predict public participation, particularly when expanded to include socioeconomic characteristics. These additions help explain the driving factors behind public engagement in both governmental and private sector activities more comprehensively [1].

Leadership plays a crucial role in organizational development and driving progress. One significant form is transformational leadership, which is characterized by the leader's ability to create meaningful change. Research has shown that the traits and behaviors of transformational leaders greatly influence the behavior of individuals within an organization. When an organization seeks to undergo change, transformational leadership becomes a key determinant of success, helping guide the organization toward improved outcomes. Kotter's [19] Change Management Model emphasizes transformational leadership as a vital component for facilitating effective organizational change. This type of leadership supports the organization in navigating transitions and implementing change initiatives successfully. Moreover, the application of the Sufficiency Economy Philosophy as a guiding principle in organizational practice highlights the leader's responsibility in developing and implementing strategic directions. It calls for a balance between growth and sustainability, underlining the leader's role in ensuring long-term, resilient development for the organization [1, 3, 5].

Therefore, effective organizational management is essential, particularly in the context of water resource management in the Northeastern Mekong River Basin under the responsibility of the Royal Irrigation Department. This management must be guided by the principles of equity, continuity, and efficiency. In the past, research related to water management in this region has been limited, fragmented, and lacking in-depth or continuous efforts. There has been a notable absence of studies focusing on the causal relationships and the direct and indirect influence of various factors affecting water management in this area. For this research, Structural Equation Modeling (SEM) was selected because it is a model capable of analyzing the influence of causal factors, a matter that cannot be identified through conventional models. Moreover, this research applies a modeling approach that yields the most accurate and reliable results, consistent with the study of Sutthichaimethee [5]. This study aims to address those research gaps by exploring these influential pathways and contributing to a more comprehensive understanding of the factors leading to successful water management in the Northeastern Mekong River Basin. Ultimately, the goal is to generate insights that maximize national benefit and support sustainable development across the region.

For the conceptual framework of this research, it is illustrated in the following figure:

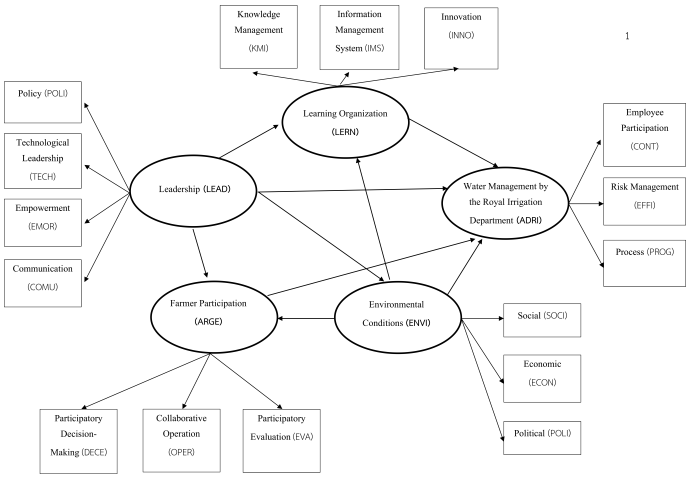


Figure 1: Conceptual Framework.

The conceptual framework of this research is illustrated in Figure 1 and comprises both latent and observed variables.

1) There are five latent variables: Water Management by the Royal Irrigation Department (ADRI), Learning Organization (LERN), Leadership (LEAD), Farmer Participation (ARGE), and Environmental Conditions (ENVI).

2) There are sixteen observed variables: Knowledge Management (KMI), Information Management System (IMS), Innovation (INNO), Policy (POLI), Technological Leadership (TECH), Empowerment (EMOR), Communication (COMU), Participatory Decision-Making (DECE), Collaborative Operation (OPER), Participatory Evaluation (EVA), Social (SOCI), Economic (ECON), Political (POLI), Employee Participation (CONT), Risk Management (EFFI), and Process (PROG).

For this research, the researcher constructed a model using Structural Equation Modeling (SEM) to estimate the influence of relationships derived from three latent variables. However, since latent variables cannot be measured directly, they must be calculated based on 14 observed variables [5]. The research methodology involves two types of data analysis.

1. Quantitative data analysis: It involves examining the water management of the Royal Irrigation Department (ADRI), learning organization (LERN), leadership (LEAD), farmer participation (ARGE), and environmental conditions (ENVI). The analysis

employs structural equation modeling (SEM) to test the model's consistency with the hypotheses, using statistical software to determine the influence of causal factors based on the conceptual framework of the research.

2. Qualitative data analysis: The data was collected through secondary analysis (2000-2024) and systematically categorized into key issues. Documentary analysis and inductive reasoning (analytic conclusion) were then used to interpret the meanings, explore relationships, and derive conclusions from the gathered data. This process was conducted alongside the ongoing collection of additional data on various topics. The analysis involved verifying and interpreting the consistency and interconnections among the data, presented in a descriptive format based on the conceptual framework. The quality of this type of research was validated through careful examination of credibility, confirmability, dependability, and transferability, to ensure the accuracy and performance of the findings and discussion.

2 The Material and Method

Structural Equation Modeling (SEM): Defining variables and their relationships clearly, where external variables are considered the starting points of the model. Internal variables can be both predictor variables and criterion variables that are predicted by external variables and other internal variables. All variables must be based on theory to be linked together and to create a causal equation model. This model, in the form of a matrix, is defined by three types of equations [19, 20]:

1) Structural Equation Model: This describes the causal relationships between variables, explaining the influence in terms of cause and effect [21].

$$\eta = B\eta + \Gamma\xi + \zeta \begin{cases} \eta_1 = \beta_{12}\eta_2 + \gamma_{11}\xi_1 + \gamma_{12}\xi_2 + \zeta_1 \\ \eta_2 = \beta_{21}\eta_1 + \gamma_{21}\xi_1 + \gamma_{22}\xi_2 + \zeta_2 \end{cases} \tag{1}$$

2) Measurement Model: This involves latent variables or hypothetical constructs that depend on or are indicated by observed variables. The latent variables explain the reliability characteristics of the observed variables [22].

$$y = \Lambda_y\eta + \varepsilon \begin{cases} Y_1 = \lambda_{\gamma 11}\eta_1 + \varepsilon_1 \\ Y_2 = \lambda_{\gamma 22}\eta_2 + \varepsilon_2 \end{cases} \tag{2}$$

From the structural equation model and the measurement model mentioned above, matrices are created for use in model estimation. These matrices are divided into three groups of types

Group 1 represents parameters, consisting of 8 parameters (the full model), which are classified into two subgroups. The first subgroup includes parameters along the influence paths between variables in the model, namely B,Γ and Λ, or represented by the matrix symbols $[BE]$, $[GA]$, $[LX]$ and $[LY]$, respectively. The second subgroup includes two parameters of variance-covariance between external latent variables and between error variables, consisting of the variance-covariance matrix among internal latent variables, denoted as PH, and the variance-covariance matrix among error variables (all error variables are uncorrelated and equal to zero), denoted as PS for $[\zeta]$, TD for $[\delta]$, and TE for $[\varepsilon]$ [23].

Group 2 represents variable vectors, including 4 vectors: η, ξ, X, and Y, which are represented by the matrix symbols $[E]$, $[K]$, $[X]$, and $[Y]$, respectively.

Group 3 represents error vectors, including 3 vectors: ζ, δ and ε or symbolized by the matrix symbols $[Z]$, $[d]$ and $[e]$, respectively [24].

In research, there may not be all types of variables present as in the full model; some may be only parts of the full model, called sub-models, and the parameter matrices may not include all 8 matrices. The sub-models are divided into three groups.

Subgroup 1 is the measurement model and confirmatory factor analysis models, which include only external variables (both latent and observed) and do not include any internal variables (latent or observed) [25].

The model is expressed in the form of matrix equations of error variables and parameters as follows:

$$[X] = [LX][K] + [d] \tag{3}$$

Subgroup 2 is the causal structural models, which include both models with and without measurement errors.

1. Models without measurement error include only observed variables and no latent variables. The model is written in the form of matrix equations of error variables and parameters as follows [22, 23]:

$$[Y] = [LY][E] + [e] \tag{4}$$

2. Models with measurement error include all types of variables, involving both the structural model equations and measurement model equations, and include matrices GA, BE, PS, PH, LY, and TE [24].

Subgroup 3 includes models without observed external variables but with latent external variables, latent internal variables, and observed internal variables only. In some cases, there may be no latent external variables. These models are expressed in matrix equations of error variables and parameters as [20]:

$$[Y] = [LY][E] + [e] \tag{5}$$

$$[E] = [BE][E] + [GA][K] + [Z] \tag{6}$$

Only the matrices GA, BE, PS, PH, LY, and TE are present. In the case where there are no latent external variables, only the matrices BE, PS, LY, and TE are present. The matrix forms are as follows [21]:

1. Structural equation model:

$$\eta = B\eta + \Gamma\xi + \zeta \tag{7}$$

$$\begin{bmatrix}\eta_1\\ \eta_2\end{bmatrix} = \begin{bmatrix}\beta_1\\ \beta_2\end{bmatrix} + \begin{bmatrix}\gamma_{11} & \gamma_{12}\\ \gamma_{21} & \gamma_{22}\end{bmatrix}\begin{bmatrix}\xi_1\\ \xi_2\end{bmatrix} + \begin{bmatrix}\zeta_1\\ \zeta_2\end{bmatrix} \tag{8}$$

$$\begin{bmatrix}E_1\\ E_2\end{bmatrix} = \begin{bmatrix}0 & BE_{12}\\ BE_{21} & 0\end{bmatrix}\begin{bmatrix}E_1\\ E_2\end{bmatrix} + \begin{bmatrix}GA_{11} & GA_{12}\\ GA_{21} & GA_{21}\end{bmatrix}\begin{bmatrix}K_1\\ K_2\end{bmatrix}\begin{bmatrix}Z_1\\ Z_2\end{bmatrix} \tag{9}$$

2. Measurement model for external variables.

$$X = \Lambda_x\xi + \delta \tag{10}$$

$$\begin{bmatrix}X_1\\ X_2\end{bmatrix} = \begin{bmatrix}\lambda_{x11} & 0\\ 0 & \lambda_{x22}\end{bmatrix}\begin{bmatrix}\xi_1\\ \xi_2\end{bmatrix} + \begin{bmatrix}\delta_1\\ \delta_2\end{bmatrix} \tag{11}$$

$$\begin{bmatrix}X_1\\ X_2\end{bmatrix} = \begin{bmatrix}L_{x11} & 0\\ 0 & L_{x22}\end{bmatrix}\begin{bmatrix}K_1\\ K_2\end{bmatrix} + \begin{bmatrix}d_1\\ d_2\end{bmatrix} \tag{12}$$

3. Measurement model for internal variables.

$$Y = \Lambda_y\eta + \varepsilon \tag{13}$$

$$\begin{bmatrix}Y_1\\ Y_2\end{bmatrix} = \begin{bmatrix}\lambda_{y11} & 0\\ 0 & \lambda_{y22}\end{bmatrix}\begin{bmatrix}\eta_1\\ \eta_2\end{bmatrix} + \begin{bmatrix}\varepsilon_1\\ \varepsilon_2\end{bmatrix} \tag{14}$$

$$\begin{bmatrix}Y_1\\ Y_2\end{bmatrix} = \begin{bmatrix}L_{y11} & 0\\ 0 & L_{y22}\end{bmatrix}\begin{bmatrix}E_1\\ E_2\end{bmatrix} + \begin{bmatrix}e_1\\ e_2\end{bmatrix} \tag{15}$$

There are two types of input data: correlation matrices and covariance matrices, including variance and covariance matrices [22, 23].

Model fit evaluation tools are divided into three groups for assessment: Examination of the solution, which includes [24, 25]:

1. Parameter values in the relevant matrices of the model (checking if all parameters are present).

2. Standard errors (smaller values indicate better decision-making) and t-values (values greater than 2.00 indicate the parameter is significantly different from zero), both shown during parameter estimation.

3. Correlation matrix of parameter estimates (if two or more parameters are highly correlated, the model and parameters may not fit the data well).

4. Squared multiple correlations (provided for each observed variable) and coefficients of determination (provided for groups of variables in each component).

A. Measures of Overall Fit

Measures of overall fit are presented in the book A Beginner's Guide to Structural Equation Modeling as follows:

1. The chi-square statistic (χ) is used to test the null hypothesis that the model fits the data well. A large and statistically significant χ value indicates that the model does not fit the data adequately. Conversely, a small and non-significant χ value suggests that the model fits the data well.

2. Comparative Fit Index (CFI) is an index used to compare the baseline model, called the "Null" or "Independence" model, which assumes no relationships among variables (no paths between variables), to the theoretical or hypothesized model, called the "Model," which has degrees of freedom (df or d).

3. Root Mean Squared Residual (RMR) is used only when comparing models using the same dataset. This index indicates the size of the residual differences between the fit of two models to the empirical data. It works best when external and observed variables are standardized. The closer the value is to zero, the better the model fits the empirical data.

4. Goodness-of-Fit Index (GFI) is an index based on the chi-square value that compares the fit between two models and the empirical data. The data may come from the same or different datasets. It is calculated as the ratio of the difference between the fit function before adjustment (with a high chi-square) and after adjustment (with a reduced chi-square) to the fit function before adjustment. This value is not affected by sample size. The closer it is to 1.00, the better the model fits the empirical data. GFI is also suitable for detailed cross-validation, where the model is tested on randomly selected subsamples when no separate sample is available, and in very large sample studies.

5. Adjusted Goodness-of-Fit Index (AGFI) adjusts the GFI by considering degrees of freedom, including the number of variables and sample size, when comparing two models. The data may come from the same or different datasets.

6. Root Mean Square Error of Approximation (RMSEA) addresses the problem that the chi-square test often rejects good models in large samples because it depends on degrees of freedom. RMSEA is suitable for detailed cross-validation using randomly selected subsamples without separate datasets and large sample studies. This measure is popular for evaluating model fit.

7. Normed Fit Index (NFI) compares the fit of the research model against an independence model (where all observed variables are uncorrelated) and indicates the percentage of fit. It is useful when comparing to an independence model with a very large chi-square.

8. Relative Fit Index (RFI) is similar to NFI but does not express results as a percentage. It indicates how much better the research model fits compared to the independence model.

9. Incremental Fit Index (IFI) is similar to RFI but also accounts for differences in degrees of freedom between the two models.

For the research procedure in this study, the steps can be summarized as follows:

1. Define five latent variables and sixteen observed variables.
2. Examine the properties of the observed variables by testing for stationarity.
3. Assess the system's ability to adjust toward equilibrium.
4. Analyze the magnitude of the causal relationships.
5. Evaluate the validity and reliability of the model.

3 Empirical Analysis

The findings of this research can be summarized as follows:

From Figure 2, it is evident that The Learning Organization (LERN), Leadership (LEAD), Farmer Participation (ARGE), and Environmental Conditions (ENVI) each exert a unidirectional influence on the transformation of water management by the Royal Irrigation Department (ADRI), with effect sizes of 0.93, 0.90, 0.80, and 0.71, respectively, at a statistical significance level of $\alpha = 0.05$. In addition, Leadership (LEAD) was found to influence the Learning Organization (LERN), Farmer Participation (ARGE), and Environmental Conditions (ENVI), with effect sizes of 0.69, 0.60, and 0.68, respectively, all at a significance level of $\alpha = 0.05$. Furthermore, Environmental Conditions (ENVI) were found to affect both the Learning Organization (LERN) and Farmer Participation (ARGE), with effect sizes of 0.54 and 0.57, respectively, also significant at $\alpha = 0.05$.

Moreover, based on the above-mentioned causal relationships, it is evident that certain causal factors act both as causes and as effects. This demonstrates the influence of both direct effects and indirect effects, which can be measured by the following statistical indicators. In cases where the model did not align with empirical data, the researcher performed model modification based on modification indices and theoretical rationale. Adjustments were made parameter by parameter to reduce correlated errors. The initial Structural Equation Model (SEM) analysis showed that several fit indices did not meet the acceptable criteria: Relative Chi-square of 1397.68 / 125 is equal to 11.18, RMSEA is equal to 0.17, SRMR is equal to 0.12, GFI is equal to 0.71, AGFI is equal to 0.60, and CN (Critical N) is equal to 53.04. These results indicate that the initial model had issues with goodness-of-fit to the empirical data.

Therefore, the researcher modified the model using modification indices as recommended by the SEM software used in the analysis. The adjustments aimed to improve the model for better alignment with the data. During the model refinement process,

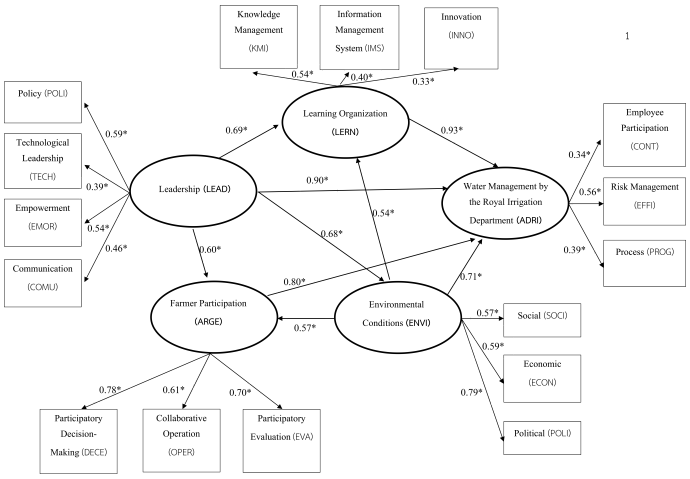


Figure 2: Analysis of the Influence and Relationships of Causal Factors.

the SEM software provided guidance and suggested specific changes based on the modification indices derived from the analysis results, as shown in Table 1.

Table 1: The Goodness-of-fit Indices after Model Adjustment

Indicator	Goodness-of-Fit Criteria	Before Model Adjustment	After Model Adjustment
Chi-square/df	Less than 3.00	11.18	2.15
RMSEA	Less than or equal to 0.05	0.17	0.05
SRMR	Less than 0.05	0.12	0.050
GFI	Value of 0.90 or higher	0.71	0.95
AGFI	Value of 0.90 or higher	0.60	0.90
CFI	Value of 0.90 or higher	0.89	0.99
PNFI	Value of 0.50 or higher	0.71	0.52
CN	No less than 200	53.04	242.15

From Table 1, the results after model modification show the overall improvement in the model. After the modification, the goodness-of-fit indicators were found to meet the acceptable criteria, and can be explained as follows:

1. Relative Chi-square (Chi-square/df) was 2.15, indicating that the model is consistent and in harmony with the empirical data, as the value is less than 3.00.

2. The Root Mean Square Error of Approximation (RMSEA) was 0.05, indicating that the model fits the empirical data well, as the RMSEA is less than or equal to 0.05.

3. The Standardized Root Mean Square Residual (SRMR), also referred to as the goodness-of-fit index in the form of residual error, was 0.050. This indicates a good fit with the empirical data, as it falls below the acceptable threshold of 0.05.

4. The Absolute Fit Indices were assessed using two indicators. The Goodness of Fit Index (GFI) was 0.95, which indicates good model fit, as GFI values range from 0 to 1, and acceptable values are greater than 0.90. The Adjusted Goodness of Fit Index (AGFI) was 0.90, also indicating a good fit, as AGFI values range from 0 to 1, and acceptable values are 0.90 or higher.

5. The Comparative Fit Index (CFI) was 0.99, which indicates a strong comparative fit, as CFI values of 0.90 or higher are considered acceptable.

6. The Parsimony Normed Fit Index (PNFI), also referred to as the measure of model compatibility, was 0.52. This indicates that the model demonstrates an acceptable level of parsimony, as PNFI values of 0.50 or higher are considered adequate.

7. The Critical N (CN), which serves as an index for assessing sample size adequacy, was 242.15. This demonstrates that the sample size was sufficient for the model, as CN values above 200 indicate an acceptable model fit.

Based on these analytical results, the researcher was able to identify the appropriate level of influence for each factor within the model.

From Table 2, it was found that the Learning Organization (LERN) has the highest direct influence on the water management of the Royal Irrigation Department (ADRI), with a standardized effect size of 0.93, statistically significant at $\alpha = 0.05$. Following this, Leadership (LEAD) has a direct influence on ADRI's water management with an effect size of 0.90, also statistically significant at $\alpha = 0.05$. Farmer Participation (ARGE) has a direct influence with an effect size of 0.80, and Environmental

Table 2: Results of the Analysis on the Influence of Factors Affecting the Success of Water Management in the Northeastern Mekong River Basin by the Royal Irrigation Department

Dependent Variable / Independent Variable	ADRI		
	Direct effect	**Indirect effect**	**Total effect**
LERN	0.93*	–	0.93*
LEAD	0.90*	0.05*	0.95*
ARGE	0.80*	–	0.80*
ENVI	0.71*	0.10*	0.81*

Conditions (ENVI) has a direct influence with an effect size of 0.71, both statistically significant at $\alpha = 0.05$, in that order.

4 Discussion of Research Findings

The results of this study, analyzed in line with the research objectives, show consistency with those objectives. It was found that the Learning Organization (LERN) has the highest direct influence on water management by the Royal Irrigation Department (ADRI), with an effect size of 0.93, statistically significant at $\alpha = 0.05$. Next, Leadership (LEAD) directly influences ADRI's water management with an effect size of 0.90, also significant at $\alpha = 0.05$. Farmer Participation (ARGE) has a direct influence with an effect size of 0.80, and Environmental Conditions (ENVI) has a direct influence with an effect size of 0.71, both statistically significant at $\alpha = 0.05$, respectively. The fact that the Learning Organization (LERN) is the most significant factor and causal influence indicates that organizational structure sets the framework for staff performance and budgeting. Meanwhile, leadership, which involves decision-making in management, is a key causal factor that drives policy formulation in water management and public service delivery. Other factors also influence water management at the Royal Irrigation Department but to a lesser extent. These findings are consistent with, Dooley and Gupta [26]. Sandler [27], van. Norren [28], Sénit [29], Faran [30], Bardi et al. [32], Mykhnenko, and Wolff [32], Bocse1 [33] , Shen1, and Faure [34], Switzer et al. [35], Handrlica and V. Sancin [36], Gupta et al. [37], Sutthichaimethee [38], Sutthichaimethee [39], Sutthichaimethee, and Dockthaisong [40], Sutthichaimethee, and Ariyasajjakorn [41], Sutthichaimethee and Ariyasajjakorn [42], Sutthichaimethee and Kubaha [43], Sutthichaimethee, and Ariyasajjakorn [44], Sutthichaimethee and Ariyasajjakorn [45], and Sutthichaimethee et al. [46], who identified that key indicators of organizational readiness or capacity include leadership, organizational structure, and personnel management systems in municipalities (MAN). The study found that the municipality's capacity (POT) had the greatest direct influence on municipal public health service management (MAN), with an effect size of 0.93, followed by government policy (PUB) with a negative influence of -0.39, and public participation (PAR) with an effect size of 0.17. Environmental conditions (ENV) did not have a direct influence but exerted an indirect effect on public health service management with a total effect size of 0.04, differing from the original hypothesis. However, Leadership (LEAD) and Environmental Conditions (ENVI) have a direct influence on Farmer Participation (ARGE). It was found that farmer participation is directly influenced by leadership and environmental conditions, with effect sizes of 0.60 and 0.57, respectively. Additionally, environmental conditions (ENVI) are directly influenced by leadership (LEAD), with an effect size of 0.68. This indicates that policies set by leadership directly impact environmental conditions, leading to changes in economic, social, and political aspects. Furthermore, leadership (LEAD) and environmental conditions (ENVI) also have direct influences on the learning organization (LERN), with effect sizes of 0.69 and 0.54, respectively. This suggests that changes in leadership or environmental conditions will directly affect the learning organization, which in turn strengthens its influence on the transformation of water management by the Royal Irrigation Department (ADRI). Moreover, changes in leadership or environmental conditions also indirectly affect the transformation of water management at ADRI. This demonstrates that these two factors are significant drivers that can greatly influence changes in water management within the Royal Irrigation Department.

The limitation of this study is that the analysis of causal influence was confined to quantitative relationships, without incorporating qualitative dimensions into the in-depth analysis. Such qualitative insights could be obtained through methods such as in-depth interviews or focus group discussions, which would help formulate more comprehensive strategic directions. Nevertheless, the quantitative findings of this research can be integrated with future qualitative analyses to generate deeper and more sustainable insights.

Academic Recommendations and Suggestions for Future Research

1. It is recommended to study water management processes and policies of the Royal Irrigation Department in other countries, in order to consider adopting best practices as guidelines for future water management improvements.
2. It is advisable to study and gather public opinions regarding the water management by the Royal Irrigation Department to inform decision-making in designing management approaches that enhance efficiency and effectiveness in the long term.

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