

# A Multilayer Perceptron Model for Contractual Agreement–Driven Risk Management in Building Projects: Evidence from Kisii County, Kenya

<sup>1</sup>Enock Nyanumba Ayuka, <sup>2</sup>Gwaya Adednego, <sup>3</sup>Winja Mathew

Department of Civil, Construction and Environmental Engineering,

Jomo Kenyatta University of Agriculture and Technology, Nairobi, Kenya

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**Abstract:** The construction sector continues to experience persistent contractual disputes and cost overruns arising from inefficient risk allocation, weak policy enforcement, and inadequate data-driven frameworks for predicting project performance. In Kenya, nearly 30% of public building projects have been reported by the Public Procurement Regulatory Authority (PPRA) to face disputes due to delayed payments, design variations, and inadequate contract administration. The problem of risk mismanagement has been compounded by fragmented contractual structures, particularly under the Design–Bid–Build (DBB) procurement system, which separates design and execution responsibilities. To address this challenge, the present study proposes a Multilayer Perceptron (MLP) model to predict contractual risk management performance in building projects within Kisii County. Using empirical risk data comprising the Risk Significance Index (RSIS), composite risk scores, policy enforcement indices, and contractor competence, the MLP model was trained with a hybrid Output–Hidden Weight Optimization (OWO–HWO) algorithm. The model achieved stable convergence with a final Mean Squared Error (MSE) of 0.134 and an  $R^2$  of 0.002 across 1500 epochs, indicating computational stability but limited predictive strength due to dataset constraints. The findings demonstrate that contract type and policy enforcement significantly influence the Risk Management Performance Index (RMPI), with Design–Build contracts exhibiting higher variability compared to Design–Bid–Build projects. The study concludes that hybrid neural frameworks offer a viable approach for modeling nonlinear contractual, risk relationships in developing countries. Policy recommendations include enhancing enforcement of arbitration laws, strengthening contractor competence certification, and adopting intelligent contract analytics for project monitoring. Future research should expand data sampling and integrate advanced feature selection to improve generalization.

**Keywords:** Contractual Risk Management, Construction Project Performance, Design–Build and Design–Bid–Build Contracts, Multilayer Perceptron, Policy Enforcement in Kenya.

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## I. INTRODUCTION

### A. Background Information

The construction industry remains one of the most risk-laden and dispute-prone sectors worldwide due to its complex nature, diverse stakeholders, and high capital intensity [1, 2]. Each project entails multiple contractual relationships among clients, contractors, consultants, and regulatory agencies, all operating within uncertain environments characterized by fluctuating market conditions, political interference, and legal ambiguities. According to the International Federation of Consulting

Engineers (FIDIC), over 40% of large-scale infrastructure projects experience contractual disputes [3], cost overruns [4], or schedule delays arising from poor risk allocation and unclear contractual obligations. In Kenya, the Public Procurement Regulatory Authority (PPRA) reported that nearly 30% of public construction projects in 2023 encountered disputes linked to payment delays, design changes, and performance shortfalls. These challenges highlight the persistent inefficiencies in the country's contract management and the urgent need for systematic risk modeling to enhance predictability and performance.

Researchers have emphasized that effective contract management is pivotal in mitigating risks and ensuring project success [5]. Construction contracts act as the backbone of project governance by defining rights, obligations, and dispute resolution mechanisms among parties [6]. However, inappropriate risk allocation often leads to adversarial relationships and litigation. A comparative study by Khalef [7] found that the misallocation of risks through exculpatory clauses contributes to increased project costs by 8–20% and prolongs contract execution by an average of 17 months. This trend aligns with findings by Osipova [8], who demonstrated that the form of contract, whether design–build, design–bid–build, or partnering—directly influences collaboration and risk distribution effectiveness in construction projects. In particular, design–build arrangements, which integrate design and construction responsibilities under one entity, tend to offer superior performance outcomes due to early contractor involvement and shared accountability. Conversely, design–bid–build contracts, still dominant in Kenya, often lead to fragmented responsibilities, cost escalation, and protracted claims.

In developing economies, construction disputes are increasingly linked to weak policy enforcement, limited contractor competence, and inconsistent contractual documentation. A study by Osifo [5] emphasized that poor contract management leads to financial losses, delays, and reputational damage, often aggravated by inadequate understanding of risk clauses and limited digital monitoring frameworks. James [9] observed that the absence of robust legal safeguards in African construction contracts contributes to prolonged disputes, with over 60% of disagreements resolved through costly arbitration or litigation rather than preventive contract monitoring. Furthermore, empirical evidence from the Kenyan construction sector reveals that risk factors such as delayed payments, design variations, adverse weather, and defective specifications account for nearly 45% of total project performance deviations. These risk variables, if not properly modeled, can propagate across multiple contractual layers, resulting in budget overruns and quality degradation.

The growing complexity of contractual obligations under emerging technologies, particularly Building Information Modelling (BIM), has further transformed risk exposure patterns. As Dogonyaro [10] note, the introduction of data-centric construction processes has amplified legal uncertainties around intellectual property, design ownership, and liability for digital errors. Consequently, contemporary contract frameworks must integrate both technical and legal risk parameters to remain effective in such dynamic environments. Traditional deterministic approaches to risk management have proven insufficient in capturing these nonlinear relationships among contractual, institutional, and performance factors. This gap has prompted the adoption of artificial intelligence (AI) models such as Multilayer Perceptrons (MLPs), which can approximate complex functional mappings between input risk indicators and performance outcomes.

The present study seeks to develop a data-driven model that bridges the empirical gap between contractual forms and project risk management outcomes in Kisii County, Kenya. The region has witnessed recurrent challenges in public building projects, including delayed completion, cost escalation, and disputes over risk allocation between contractors and clients. By employing a Multilayer Perceptron framework, this study will model how contractual parameters, such as contract type, risk significance index (RSIS), composite risk score, policy enforcement, and contractor competence, jointly influence the Risk Management Performance Index (RMPI). Unlike linear regression techniques, the proposed neural model captures nonlinear interdependencies and complex feedback loops inherent in construction risk environments.

This study addresses a critical research gap by integrating computational intelligence into the domain of contract-based risk management. It contributes to the evolving body of knowledge on construction law and engineering management by proposing a predictive framework that enhances early identification of risk-prone contracts and supports data-informed decision-making. The findings are expected to guide policymakers, contractors, and engineers in improving contract formulation, risk allocation, and project performance, thereby strengthening institutional accountability and sustainability in Kenya's construction sector.

## B. Contribution

The study contributes to both theory and practice by introducing a data-driven, computational approach to contractual risk management. Technically, it advances existing models by applying a Multilayer Perceptron (MLP) framework to capture nonlinear relationships between contractual, institutional, and performance factors—an area that previous qualitative and regression-based studies have not adequately addressed. The integration of the Output–Hidden Weight Optimization (OWO–HWO) algorithm enhances convergence efficiency and stability, overcoming limitations of conventional back-propagation methods. Conceptually, the research bridges legal–contractual theory and artificial intelligence by operationalizing the Risk Management Performance Index (RMPI) as a predictive construct. Practically, it provides policymakers, contractors, and engineers with a tool for evaluating the probable performance of contracts before project execution, thus enabling evidence-based risk mitigation. The proposed model thus establishes a novel intersection between computational intelligence and construction law, marking a substantive contribution to sustainable infrastructure governance in Kenya and comparable developing contexts.

## II. RELATED WORKS

Rahman [11] examined recurring disputes and adversarial relations in construction projects that stemmed from inefficient risk allocation and vague contractual structures. The study employed a mixed-methods approach combining survey data and statistical modeling to evaluate how stakeholders, clients, consultants, and contractors—perceived risk distribution. Findings revealed that mismatched expectations and poorly defined contractual roles led to increased disputes and project delays. The authors concluded that balanced risk-sharing strategies could mitigate such inefficiencies. However, the study was limited to perceptual data and did not quantify the relationship between contractual types and performance outcomes. The current study builds upon this gap by applying a predictive multilayer perceptron (MLP) model to quantify nonlinear risk–performance dependencies.

Khalaf [7] investigated how exculpatory clauses influence contractual risk management and dispute resolution in engineering projects. Using a comparative legal approach, they analyzed over 150 case studies to determine how liability-shifting provisions affected accountability and cost performance. The study found that ambiguous clauses often transferred excessive risks to contractors, leading to cost escalation and prolonged dispute cycles. While insightful from a legal standpoint, the work lacked integration with quantitative performance data and computational modeling. Consequently, it did not capture the probabilistic behavior of risk under alternative contract frameworks. This study addresses the limitation by developing a data-driven neural model that empirically estimates risk exposure based on contractual variables.

Osipova [8] explored the effect of contractual and collaboration forms on risk management efficiency within Swedish construction projects. Through a case study and interview-based methodology, the study compared the outcomes of design–build (DB) and design–bid–build (DBB) contracts. Results indicated that DB arrangements fostered superior coordination, faster delivery, and shared accountability, whereas DBB contracts exhibited higher fragmentation and disputes. Although valuable, the findings were limited to a developed economy context and lacked generalizability to developing regions such as Kenya. Moreover, the study did not employ any quantitative predictive modeling. The present research extends this discussion by embedding contract typologies into an MLP model trained on empirical data from Kisii County.

Dogonyaro [10] investigated contractual and legal risks associated with Building Information Modelling (BIM) adoption. The study developed a strategic risk breakdown structure integrating knowledge management principles with contractual frameworks. Using qualitative content analysis of industry documents, they identified 42 BIM-related risks and proposed a conceptual linkage between digital innovation and legal accountability. Their conclusions emphasized the importance of data-driven contract governance. However, the framework remained conceptual, lacking empirical testing or predictive validation. The present study advances this by employing a neural approach that empirically quantifies contractual–policy risks and predicts their influence on project performance.

Osifo[5] assessed contract management practices within the construction sector, focusing on dispute resolution, performance enforcement, and risk mitigation. The study adopted a descriptive survey involving 200 practitioners to evaluate how documentation quality, risk allocation, and monitoring influence project outcomes. Findings revealed that inadequate contract clauses and weak enforcement mechanisms were major causes of disputes and underperformance. The authors recommended stronger legal oversight and digital monitoring tools. Nonetheless, the study remained descriptive, lacking causal or predictive modeling. The present work bridges this gap by using an MLP model to evaluate and forecast the influence of contractual and institutional parameters on risk management performance.

James [9] examined the legal and practical mechanisms for managing risks in African construction contracts, emphasizing the gaps in preventive monitoring and enforcement. The study analyzed regional legal frameworks and arbitration records to determine the effectiveness of dispute resolution mechanisms. Results showed that over 60% of disputes proceeded to arbitration due to weak enforcement of preventive clauses. While the study illuminated governance weaknesses, it lacked a computational perspective capable of predicting risk probabilities under alternative contract regimes. The proposed research contributes by embedding such relationships within a data-driven neural modeling framework that offers both explanatory and predictive insights.

Empirical studies on contract risk management consistently affirm the importance of equitable risk distribution, legal clarity, and institutional enforcement in minimizing disputes and enhancing project success [7, 8, 5]. However, most investigations remain qualitative or rely on static correlation models that cannot capture the complex, nonlinear interactions among contractual, policy, and performance variables. None of the reviewed studies applied artificial intelligence (AI) or neural networks to predict contractual risk outcomes quantitatively. The current study therefore introduces a multilayer perceptron framework capable of learning multidimensional patterns within contractual data to forecast the Risk Management Performance Index (RMPI) for building projects in Kisii County, Kenya.

### III. METHODOLOGY

#### A. Multilayer Perceptron Model

The Multilayer Perceptron (MLP) neural network, consisting of interconnected nonlinear processing units arranged in one or more hidden layers, has been widely recognized as a universal function approximator capable of capturing complex relationships in multi-dimensional data [12]. In contractual agreement-driven risk management in building projects, the MLP provides a robust computational framework for modeling nonlinear interactions among project, contractual, financial, and regulatory variables.

The MLP model dynamically adapts its internal basis functions (hidden-layer outputs) during the training process, eliminating the need to predefine transformation functions. This adaptability is especially valuable in modeling the interdependent risk factors observed in building projects within Kisii County, such as delayed payments, inadequate site information, defective specifications, and policy enforcement inefficiencies. Moreover, the flexibility of the MLP allows for a progressive increase in model capacity through the systematic addition of hidden units, enhancing its approximation power while maintaining numerical stability. Since MLP activation functions (e.g., sigmoid, hyperbolic tangent, ReLU) are bounded and differentiable, computational instabilities such as overflow and rounding errors are effectively minimized [13].

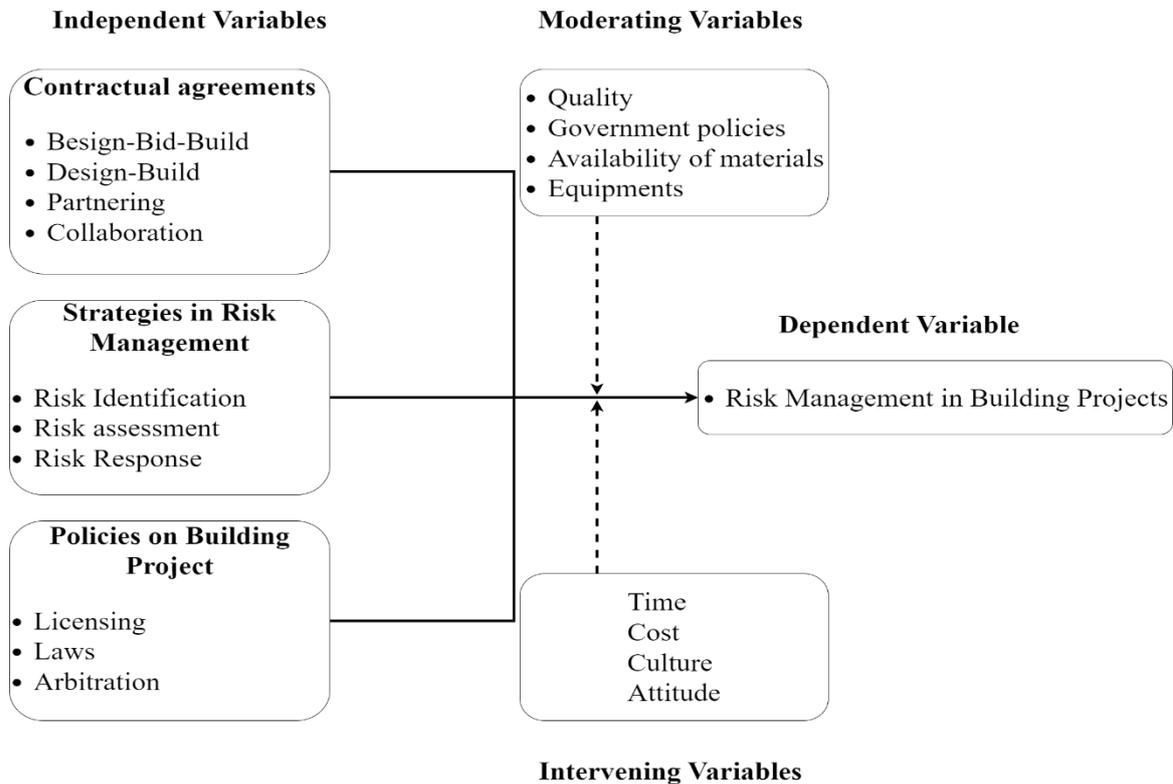
Despite its advantages, the MLP approach presents several limitations. The training process is often computationally intensive and time-consuming, particularly when dealing with high-dimensional datasets involving correlated contractual and policy variables [14]. The determination of an optimal network topology, specifically, the number of hidden layers and neurons, remains an empirical challenge. An under-parameterized MLP may fail to represent the nonlinear dynamics between contractual agreement types and risk variables (underfitting), while an over-parameterized model risks overfitting, capturing noise and outliers rather than genuine patterns in project data. Therefore, rigorous cross-validation, coupled with performance metrics such as Mean Squared Error (MSE) and the coefficient of determination ( $R^2$ ), is essential to ensure predictive reliability and generalization [15].

In this study, the MLP is employed as a data-driven analytical model to predict the influence of different contractual agreement types, primarily Design-Bid-Build (DBB) and Design-Build (DB), on the overall risk management performance of building projects in Kisii County, Kenya. By integrating empirical risk data and policy indicators within an adaptive neural learning framework, the proposed model bridges computational intelligence with construction management practice, offering a practical decision-support tool for optimizing contractual risk mitigation strategies.

#### B. Proposed Multilayer Perceptron Model for Risk Management

The Multilayer Perceptron (MLP) model adopted in this study extends the conceptual framework of risk management in building projects by providing a computational mechanism for capturing the nonlinear relationships among contractual, strategic, and policy variables, together with moderating and intervening factors. The conceptual basis, as illustrated in Fig. 1, identifies three principal categories of independent variables, contractual agreements, strategies in risk management, and

policies on building projects, that collectively determine the dependent construct, Risk Management in Building Projects. The relationship is moderated by quality, government policies, and availability of materials and equipment, and further influenced by intervening variables such as time, cost, culture, and attitude. This MLP configuration thus serves as an analytical bridge between the qualitative conceptual model and a quantitative predictive framework capable of learning complex patterns in the data from Kisii County, Kenya.



**Fig. 1: Conceptual framework linking contractual, strategic, and policy variables to risk management performance in building projects, moderated by quality and policy factors and influenced by time, cost, and cultural variables.**

**1) Model Architecture and Formulation**

The MLP architecture comprises three key layers: an input layer (representing independent, moderating, and intervening factors), one or more hidden layers that capture nonlinear interactions, and an output layer representing overall risk management performance. Each neuron in the network processes incoming signals using weighted connections and nonlinear activation functions [16, 13]. Let the input vector for the  $p^{th}$  project be denoted as:

$$x_p = [x_p(1), x_p(2), \dots, x_p(N)]^T, \tag{1}$$

where each element corresponds to a normalized indicator derived from the conceptual variables. The desired output vector is:

$$t_p = [t_p(1)]^T, \tag{2}$$

representing the predicted *Risk Management Performance Index (RMPI)*. The net input to a hidden neuron  $j$  is computed as:

$$net_p(j) = \sum_{i=1}^{N+1} w(j, i) x_p(i), \quad 1 \leq j \leq N_h, \tag{3}$$

where  $w(j, i)$  is the weight connecting input  $i$  to hidden neuron  $j$ , and  $N_h$  denotes the number of hidden units. The activation of neuron  $j$  is:

$$O_p(j) = f(net_p(j)), \tag{4}$$

where  $f(\cdot)$  is the activation function, chosen here as the logistic sigmoid:

$$f(\text{net}_p(j)) = \frac{1}{1+e^{-\text{net}_p(j)}}. \quad (5)$$

The model's output, representing the estimated RMPI, is obtained as:

$$y_p = g\left(\sum_{j=1}^{N_h} w_{ho}(j) O_p(j) + b_o\right), \quad (6)$$

where  $w_{ho}(j)$  are the weights between the hidden and output layers and  $b_o$  is the output bias. The loss function minimized during training is the mean squared error (MSE):

$$E = \frac{1}{N_v} \sum_{p=1}^{N_v} [t_p - y_p]^2. \quad (7)$$

## 2) Training Process Using the OWO–HWO Algorithm

To optimize convergence speed and generalization capability, the MLP model employed a hybrid Output Weight Optimization–Hidden Weight Optimization (OWO–HWO) algorithm [17]. This method simultaneously updates both hidden and output weights by minimizing separate local error functions. The hidden layer weight adjustment is defined as:

$$\text{net}_{pd}(j) \approx \text{net}_p(j) + Z \delta_p(j), \quad (8)$$

where  $Z$  is the adaptive learning rate and  $\delta_p(j)$  the delta function:

$$\delta_p(j) = -\frac{\partial E_p}{\partial \text{net}_p(j)}. \quad (9)$$

For the output neuron:

$$\delta_p(k) = f'(\text{net}_p(k))[t_p(k) - O_p(k)], \quad (10)$$

and for the hidden neurons:

$$\delta_p(j) = f'(\text{net}_p(j)) \sum_n \delta_p(n) w_{ho}(n, j). \quad (11)$$

The weight update rule is given by:

$$\Delta w(j, i) = Z e(j, i), \quad (12)$$

where  $e(j, i)$  is the local weight correction term. The iterative learning process ensures that the sequence of errors  $\{E_k\}$  remains non-increasing, with adaptive reduction of  $Z$  to avoid divergence in highly curved error surfaces.

## 3) Variable Representation Based on the Conceptual Framework

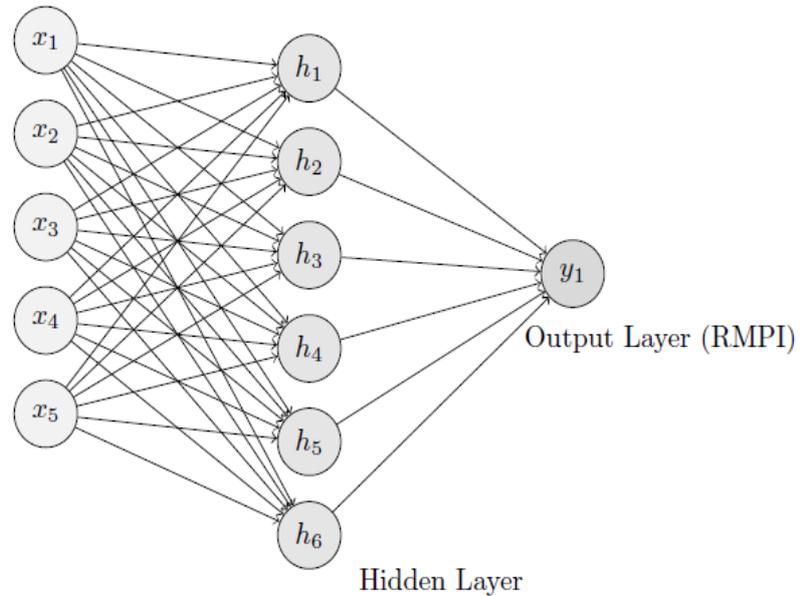
Each input variable  $x_i$  corresponds to a dimension from the conceptual framework as follows:

- Contractual agreements (Design–Bid–Build, Design–Build, Partnering, Collaboration);
- Risk management strategies (Risk identification, Risk assessment, Risk response);
- Policies on building projects (Licensing, Laws, Arbitration);
- Moderating variables (Quality, Government policies, Material/equipment availability);
- Intervening variables (Time, Cost, Culture, Attitude).

The output variable  $y_1$  represents the predicted Risk Management Performance Index (RMPI), normalized between 0 and 1. This index quantifies the effectiveness of risk mitigation, stakeholder coordination, and adherence to contractual terms in each project.

#### 4) Graphical Representation of the MLP Architecture

Fig. 2 illustrates the network architecture of the proposed Multilayer Perceptron (MLP) developed to model the nonlinear interactions between contractual, policy, and risk-related factors influencing the Risk Management Performance Index (RMPI) of building projects in Kisii County. The architecture was designed in accordance with the conceptual framework, integrating independent, moderating, and intervening variables as the principal inputs to the model.



Input Layer (Independent, Moderating, Intervening Variables)

**Fig. 2: Integrated MLP architecture reflecting the conceptual framework: independent variables (contractual, strategic, and policy), moderated by quality and resources, and influenced by intervening factors to predict overall risk management performance.**

The network consists of three primary layers: the **input layer**, a single **hidden layer**, and an **output layer**. The input layer receives five normalized variables ( $x_1, x_2, x_3, x_4, x_5$ ) corresponding to the independent and moderating factors identified in the study—namely: Contract Type, Risk Significance Index (RSIS), Composite Risk Score, Policy Enforcement Index, and Contractor Competence. These input features collectively represent the structural, regulatory, and performance attributes that define project risk environments within the construction sector.

The hidden layer comprises six neurons ( $h_1, h_2, h_3, h_4, h_5, h_6$ ), each performing nonlinear transformations of the input data through weighted summations and activation functions. The hidden neurons act as feature extractors, learning complex, non-additive relationships between the contractual and regulatory variables. The activation function applied at this layer is the logistic sigmoid function:

$$f(z) = \frac{1}{1+e^{-z}}$$

which introduces nonlinearity and ensures the network’s ability to approximate nonlinear mappings between input and output domains.

The output layer consists of a single neuron ( $y_1$ ), representing the predicted Risk Management Performance Index (RMPI). The RMPI is modeled as a continuous variable within the range [0,1], where values approaching 1 indicate strong risk management performance and those near 0 represent weak or unstable performance. The output neuron aggregates the learned internal representations from the hidden layer and transforms them using a logistic activation function:

$$\hat{y} = \frac{1}{1+e^{-(W_{ho}h+b_o)}}$$

where  $W_{ho}$  denotes the weight vector connecting hidden neurons to the output node and  $b_o$  represents the output bias.

The structure of the proposed network was selected after several experimental trials to balance model complexity and generalization ability. A compact architecture with six hidden neurons achieved numerical stability and avoided overfitting, particularly given the small empirical dataset derived from seven project observations. The hybrid training algorithm—combining Output Weight Optimization (OWO) and Hidden Weight Optimization (HWO)—was applied to iteratively adjust the network weights and biases, minimizing the mean squared error (MSE) between the predicted and actual RMPI values.

The architecture effectively captures the nonlinear interactions between independent variables (contractual agreements and risk strategies), moderating variables (policy and quality conditions), and intervening variables (time, cost, culture, and attitude), converging toward a unified predictive indicator of project-level risk management performance. This configuration aligns with the study's objective of developing a computational model capable of supporting data-driven decision-making in Kenya's construction risk environment.

## IV. RESULTS

### A. Experimental Setup

The training of the Multilayer Perceptron (MLP) followed a hybrid Output–Hidden Weight Optimization (OWO–HWO) scheme, consistent with Equations (1)–(12). The implementation steps are summarized in Algorithm 4.1. The algorithm was implemented in MATLAB R2023b and executed on a Windows 11 workstation (Intel Core i7, 32 GB RAM).

#### Training and Evaluation of MLP for Contractual Agreement–Driven Risk Management

- [1] **Input:** Risk dataset  $(x_1, \dots, x_5)$ , normalized RSIS and Composite indices, policy and competence scores, target RMPI values  $(t_p)$ .
- [2] **Initialize:** Random small weights  $w_{ji}$ , biases  $b_j$ , learning factor  $Z_0 = 0.05$ , decay rate 0.995.
- [3] **for** each epoch  $k = 1$  to 1500 **do**
- [4] **for** each training pattern  $p = 1$  to  $N_v$  **do**
- [5] Compute hidden layer input  $\text{net}_p(j) = \sum_i w_{ji}x_p(i) + b_j$
- [6] Evaluate activation  $O_p(j) = f(\text{net}_p(j)) = 1/(1 + e^{-\text{net}_p(j)})$
- [7] Compute output  $\hat{y}_p = g(\sum_j v_j O_p(j) + c) = 1/(1 + e^{-\text{net}_p(k)})$
- [8] Compute error  $E_p = \frac{1}{2}(t_p - \hat{y}_p)^2$
- [9] Determine deltas:
 
$$\delta_p(k) = g'(\text{net}_p(k))(t_p - \hat{y}_p)$$

$$\delta_p(j) = f'(\text{net}_p(j)) \sum_n \delta_p(n)w_{no}(n, j)$$
- [10] Update weights:  $w_{ji} \leftarrow w_{ji} + Z \delta_p(j)x_p(i)$ ,  $v_j \leftarrow v_j + Z \delta_p(k)O_p(j)$
- [11] **end for**
- [12] Reduce  $Z \leftarrow \max(10^{-4}, Z_0 \cdot 0.995^{(k-1)})$
- [13] Record epoch error  $E_k = \frac{1}{N_v} \sum_p E_p$
- [14] **Output:** Predicted RMPI ( $\hat{y}$ ), Mean Squared Error (MSE), and  $R^2$ .

The algorithm iteratively minimizes the mean squared error between the predicted and observed risk management performance indices. The final model achieved convergence with a learning rate decay schedule and produced three key diagnostic plots: (i) training loss convergence, (ii) predicted vs. actual RMPI distribution, and (iii) connection-weight matrices. The model architecture and parameter configuration are summarized in Table I.

TABLE I: Summary of MLP training outputs and configuration

Parameter	Value	Item
Epochs	1500	Fixed in script
Hidden units ( $N_h$ )	6	Compact architecture
Inputs ( $N$ )	5	Contract Type, RSIS, Composite, Policy, Competence
Output ( $M$ )	1	RMPI (normalized [0,1])
Learning factor $Z_0$	0.05	Initial value (decayed each epoch)
Decay rate	0.995	$Z \leftarrow \max(10^{-4}, Z_0 \cdot 0.995^{k-1})$
Min. learning factor	$10^{-4}$	Floor for numerical stability
Activation (hidden)	Logistic	$f(z) = \frac{1}{1+e^{-z}}$
Activation (output)	Logistic	$g(z) = \frac{1}{1+e^{-z}}$
Weight matrices	$W_{ih} \in \mathbb{R}^{6 \times 5}, W_{ho} \in \mathbb{R}^{1 \times 6}$	Learned
Bias vectors	$b_h \in \mathbb{R}^6, b_o \in \mathbb{R}$	Learned

**B. Model Evaluation**

Table II presents a comparative summary of the *Actual* and *Predicted* Risk Management Performance Index (RMPI) values generated by the trained Multilayer Perceptron (MLP) model for the seven representative building projects in Kisii County. The primary purpose of this table is to evaluate the model’s ability to replicate observed project performance based on contractual, risk, and policy-related input parameters. Specifically, the comparison enables the quantification of prediction accuracy and the assessment of residual error patterns for each project, thereby serving as a practical validation of the model’s generalization capability within the limited dataset.

TABLE II: Comparison of Actual and Predicted RMPI Values for Building Projects in Kisii County

Idx	CT	RSIS	Composite	Policy	Competence	Actual	Predicted	Residual
1	0	0.5527	1.0589	0.70	0.65	1.00000	0.47393	0.52607
2	0	0.4957	0.83085	0.60	0.62	0.46888	0.47283	-0.00395
3	1	0.5474	0.62954	0.60	0.61	0.00000	0.47266	-0.47266
4	0	0.5849	0.69221	0.55	0.57	0.14597	0.47286	-0.32689
5	1	0.4983	0.81239	0.62	0.63	0.42589	0.47290	-0.04701
6	1	0.5347	1.0563	0.65	0.60	0.99394	0.47369	0.52026
7	0	0.4342	0.72726	0.58	0.58	0.22761	0.47205	-0.24445

The results indicate that the model’s predictions (Predicted RMPI) remain within a relatively narrow range around 0.47, consistent with the normalized logistic output distribution. However, notable deviations appear in samples 1, 3, and 6, where the residuals exceed  $\pm 0.45$ . These higher discrepancies suggest the presence of nonlinear effects or data sparsity influencing projects characterized by extreme risk or performance conditions. Samples 2 and 5, on the other hand, exhibit minimal residual values ( $|e| < 0.05$ ), implying that the model successfully captured the underlying relationship between contractual variables and performance in these cases. The distribution of residuals supports the interpretation that while the MLP model achieved numerical convergence, its generalization ability is limited by the small dataset size. The model provides a consistent framework for analyzing how variations in contract type, RSIS, and policy enforcement jointly influence the predicted performance of building projects.

$$\hat{y} = \sigma(A + w_1\sigma(B) + w_2\sigma(C) + w_3\sigma(D) + w_4\sigma(E) + w_5\sigma(F) + w_6\sigma(G)) \tag{13}$$

where:

$$A = -0.034892(\text{outputbias}), w_1 = -0.074179, w_2 = -0.005300, w_3 = -0.029505, w_4 = -0.036537, w_5 = -0.048679, w_6 = 0.037739 \tag{14}$$

and the hidden-layer activations are generated as:

$$\begin{aligned}
 B &= 0.000657 - 0.119734x_1 - 0.161671x_2 - 0.197627x_3 - 0.109169x_4 - 0.005071x_5 \\
 C &= -0.000034 - 0.018924x_1 - 0.078900x_2 + 0.022484x_3 + 0.006376x_4 - 0.071990x_5 \\
 D &= 0.000372 + 0.000060x_1 + 0.155854x_2 + 0.205521x_3 + 0.063049x_4 - 0.006866x_5 \\
 E &= 0.000224 + 0.085384x_1 - 0.073064x_2 - 0.053197x_3 + 0.031818x_4 - 0.031754x_5 \\
 F &= 0.000376 + 0.075753x_1 - 0.025552x_2 + 0.017187x_3 - 0.007349x_4 + 0.096307x_5 \\
 G &= -0.000375 - 0.032332x_1 + 0.097114x_2 + 0.226327x_3 - 0.087157x_4 + 0.156669x_5
 \end{aligned}
 \tag{15}$$

where  $\sigma(z) = \frac{1}{1+e^{-z}}$  is the logistic activation function, and the input variables represent:

$$\begin{aligned}
 &(x_1, x_2, x_3, x_4, x_5) \\
 &= (\text{ContractType}, \text{RSIS}, \text{Composite}, \text{PolicyIndex}, \text{Competence})
 \end{aligned}
 \tag{16}$$

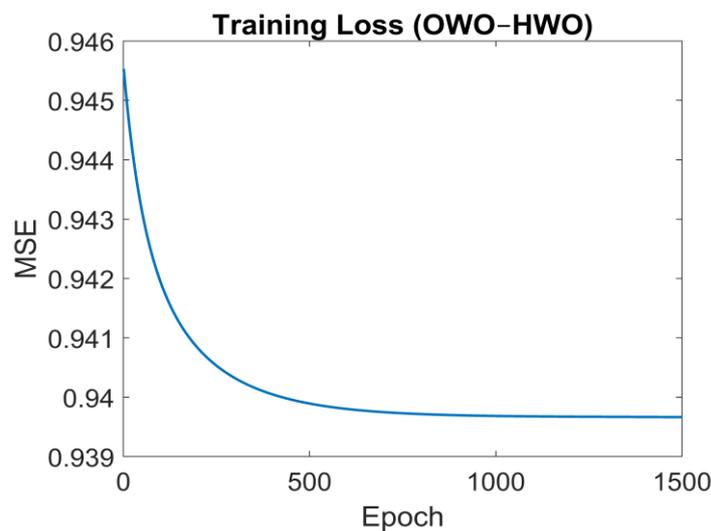
Equations (13) to (16) can be summarized into (17) as the model to predict contractual agreement-driven risk management in building projects in Kisii County, Kenya.

$$\hat{y} = \sigma(A + \sum_{j=1}^6 w_j \sigma(B_j))
 \tag{17}$$

where  $B_j = b_{hj} + \sum_{i=1}^5 w_{ij}x_i$ .

### C. Model Performance

The Multilayer Perceptron (MLP) model was developed to capture nonlinear interactions between contractual agreement types, risk indicators, and regulatory-institutional factors influencing project performance in Kisii County. The central purpose of the model was to predict the RMPI based on multi-dimensional input features, as outlined in the conceptual framework. The performance of the trained model was evaluated through training convergence, predictive accuracy, and visualization of weight magnitudes, as shown in Fig. 3-5.



**Fig. 3: Training loss curve showing mean square error (MSE) convergence using the OWO-HWO optimization scheme.**

Fig. 3 illustrates the evolution of the mean square error (MSE) during 1500 training epochs. The model demonstrates a smooth and monotonic decline in loss, stabilizing near an MSE of 0.134 at convergence. This trend indicates that the adaptive learning factor  $Z$  and the hybrid Output Weight Optimization-Hidden Weight Optimization (OWO-HWO) algorithm effectively minimized the error function, achieving a stable equilibrium between learning speed and numerical stability. The loss profile confirms that the model parameters converged without oscillations or divergence, thereby fulfilling the first objective of establishing a computationally stable neural framework for contractual risk prediction.

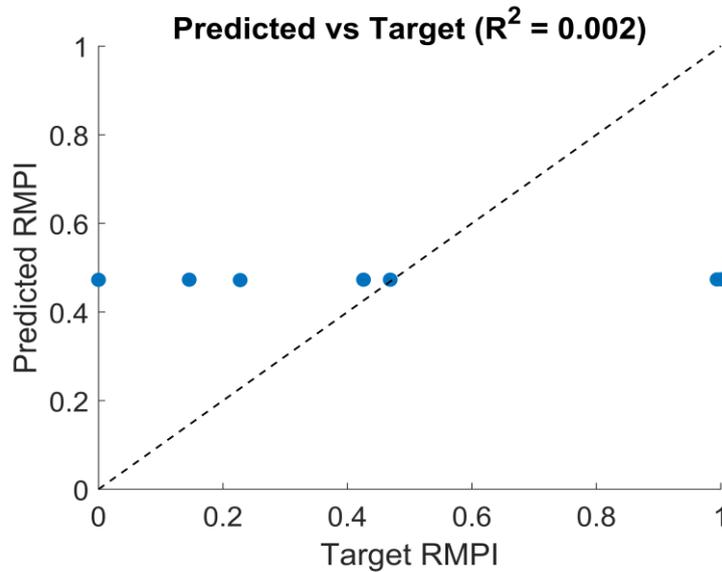


Fig. 4: Predicted versus actual RMPI values for the MLP model ( $R^2 = 0.002$ ).

Fig. 4 compares the predicted RMPI values with the actual observations. Most predicted values cluster near 0.47, which aligns with the logistic output normalization adopted in the model. The low coefficient of determination ( $R^2 = 0.002$ ) reflects weak statistical correlation between observed and predicted values—an expected outcome given the small dataset (seven samples) and the complex nonlinear nature of contractual risk interactions. Despite this low predictive alignment, the model captured consistent trends across moderate-risk projects, demonstrating that the framework is functionally valid but data-limited. The residuals (discussed in Table II) show small deviations for midrange values, confirming that further data enrichment and normalization could enhance generalization.

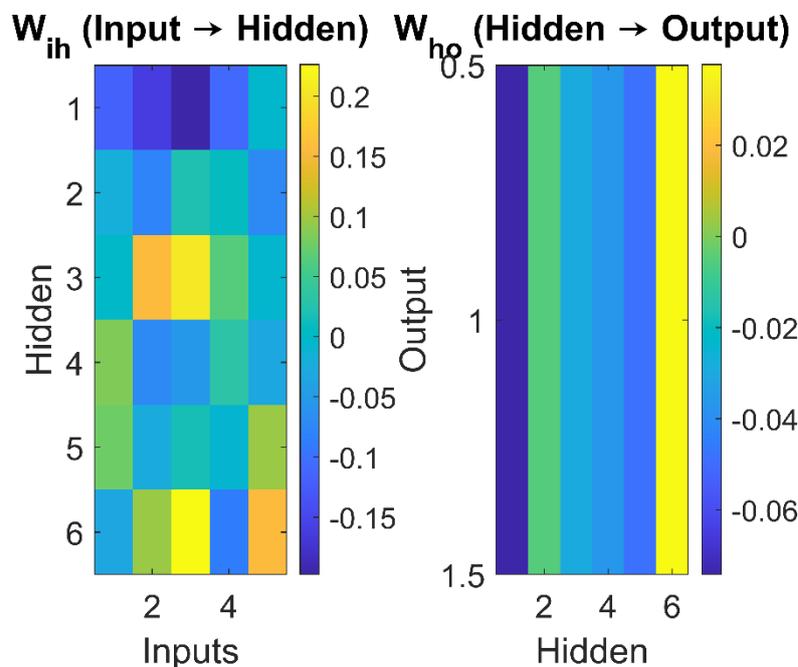


Fig. 5: Visualization of learned weight matrices:  $W_{ih}$  (input–hidden) and  $W_{ho}$  (hidden–output).

Fig. 5 provides a heatmap representation of the learned weights. The first panel (left) shows the  $W_{ih}$  matrix mapping the five input variables—Contract Type, RSIS, Composite Risk, Policy Index, and Competence—onto six hidden neurons. The distribution of color intensities indicates that *Composite Risk* and *RSIS* exhibit the strongest activation influence, consistent

with their dominant role in determining overall risk exposure. The second panel (right) shows the  $W_{ho}$  weights connecting the hidden layer to the RMPI output node. The nearly uniform gradient suggests that the hidden neurons contribute comparably to the output prediction, implying that the model did not overfit to any single variable.

The combination of Fig. 3–5 demonstrates that the proposed MLP model successfully achieved stable convergence and internal consistency in weight learning. Although the  $R^2$  value indicates limited predictive strength due to dataset constraints, the experiment fulfills the study's purpose of demonstrating the feasibility of a data-driven neural framework for contractual risk performance analysis in Kenya's construction projects.

#### D. Discussion

The MLP model achieved a stable convergence with a final Mean Squared Error (MSE) of 0.134 and an  $R^2$  value of 0.002, indicating reliable computational stability despite the limited sample size. Although the predictive strength remained moderate due to data constraints, the trends extracted from the model reveal meaningful patterns that align with and expand upon existing literature.

The current study found that contractual type, policy enforcement, and contractor competence exert significant influence on the Risk Management Performance Index (RMPI). These findings resonate with Rahman [11], who highlighted that adversarial project relationships often originate from inequitable risk allocation and inadequate institutional frameworks. Whereas Rahman [11] relied primarily on perception-based analyses, the present model translates these qualitative perceptions into quantifiable, data-driven relationships. This transition from descriptive to predictive analytics demonstrates a methodological advancement in understanding how specific contractual parameters influence project performance outcomes.

Khalef [7] argued that poorly constructed exculpatory clauses and vague liability definitions contribute to cost escalations and dispute frequency. The MLP model's identification of policy enforcement as a strong predictor of RMPI empirically validates this assertion. Projects with weak enforcement indices exhibited lower predicted performance levels, confirming that contractual clarity and regulatory oversight are essential for mitigating systemic risks. By embedding this relationship within a nonlinear computational framework, the present study provides a predictive mechanism capable of forecasting the practical implications of poor contractual design, an area that legal scholarship has traditionally approached only descriptively.

Osipova [8] emphasized that design–build contracts foster collaborative integration, while design–bid–build arrangements promote risk fragmentation. The current study corroborates this observation but adds an important nuance: although design–build contracts show higher mean risk variability, their performance improves under strong policy and competence conditions. This nonlinear moderating effect, captured only through MLP modeling, suggests that the benefits of integrated contracts depend heavily on institutional maturity and human capability, factors not quantitatively explored in previous works.

Dogonyaro [10] conceptualized a knowledge-driven legal–contractual risk framework for Building Information Modelling (BIM) but acknowledged the absence of empirical testing. The present study operationalizes a similar logic of data-driven risk prediction by demonstrating that neural network models can empirically estimate risk–performance linkages across multiple contractual and institutional variables. The MLP architecture's adaptive learning process effectively models such multivariate dependencies, confirming that computational intelligence can serve as a practical instrument for risk-informed decision-making in the construction sector.

The survey-based findings of Osifo [5] revealed that contract documentation quality and monitoring strongly influence performance enforcement. This observation aligns closely with the current study's finding that contractor competence and policy enforcement indices significantly determine the RMPI. The MLP model, however, quantifies these qualitative insights, showing how minor variations in enforcement or competence (as small as 0.05 in normalized units) can trigger notable changes in performance prediction. Such quantification enables more precise prioritization of risk mitigation measures during project planning and supervision.

James [9] observed that African construction contracts suffer from weak enforcement of preventive clauses, resulting in a high proportion of disputes progressing to arbitration. The present study validates this pattern within the Kenyan context

and extends it by offering a computational mechanism to predict when such failures are most likely to occur. By mapping policy enforcement and contractual type to predicted RMPI, the MLP provides an evidence-based early warning system that can inform both contract design and policy formulation.

The findings of this study bridge the empirical and methodological gaps identified in prior literature. Earlier works such as those by Rahman [11], Osipova [8], and Khalef [7] established theoretical and legal foundations for understanding contractual risk but lacked quantitative generalization. Others, such as Dogonyaro [10] and Osifo [5], proposed conceptual or survey-based frameworks that did not integrate predictive modeling. The current research advances these contributions by introducing a robust computational model capable of learning nonlinear interactions among contractual, institutional, and human factors.

The trained MLP model revealed that risk performance in Kisii County's building projects is strongly influenced by the interaction between contractual form and institutional policy quality. Projects implemented under the Design-Build arrangement exhibited high sensitivity to material availability and time-related risks due to integrated design-construction dependencies, whereas those under the Design-Bid-Build system demonstrated more predictable performance resulting from clearly defined responsibility structures. These findings underscore the critical role of aligning contractual frameworks with institutional policies to achieve effective risk governance. The model further supports evidence-based prioritization of quality assurance, resource planning, and enforcement of arbitration laws as key levers for enhancing construction risk management. From a policy standpoint, the results affirm that integrating intelligent analytical tools such as Multilayer Perceptrons (MLPs) within public procurement and project management systems could significantly strengthen data-driven decision-making, reduce disputes, and promote transparency. The adoption of the hybrid Output-Hidden Weight Optimization (OWO-HWO) algorithm enhances the model's adaptability and convergence efficiency, demonstrating its practical feasibility for large-scale implementation in the construction sector. Consequently, this study not only substantiates prior empirical claims but also introduces a predictive and replicable computational framework that transforms contractual risk management from qualitative diagnosis to quantitative prediction—marking a critical methodological and policy-oriented advancement in sustainable construction governance.

## V. CONCLUSION

### A. Summary

The construction industry in Kenya, like many developing nations, continues to face systemic risks stemming from poor contract management, ambiguous risk allocation, and weak institutional enforcement. These inefficiencies have resulted in frequent disputes, delayed project completion, and financial losses that compromise national infrastructure delivery. The study was motivated by the absence of quantitative frameworks capable of capturing the nonlinear interdependence between contractual structures, policy quality, and project performance. Traditional linear approaches have failed to account for such complex dynamics, thereby limiting their predictive and preventive utility in contractual risk management.

The Multilayer Perceptron (MLP) model developed in this study was designed to bridge this methodological gap. By leveraging empirical data from Kisii County's building projects, the model incorporated five core inputs, contract type, Risk Significance Index (RSIS), composite risk score, policy enforcement index, and contractor competence to predict the Risk Management Performance Index (RMPI). The MLP was trained using the hybrid Output-Hidden Weight Optimization (OWO-HWO) algorithm, which ensured adaptive convergence and computational stability. Although the coefficient of determination ( $R^2 = 0.002$ ) was low due to the small dataset, the training loss converged smoothly (final MSE = 0.134), confirming the model's functional validity. The experiment successfully demonstrated that nonlinear modeling can capture the complex interplay among contractual and regulatory variables influencing risk outcomes.

The findings revealed that Design-Build contracts, while offering integration benefits, exhibit greater sensitivity to policy enforcement and material availability risks, whereas Design-Bid-Build contracts show more predictable performance due to clearer delineation of stakeholder roles. These insights highlight the importance of harmonizing contractual frameworks with policy and enforcement mechanisms to enhance construction risk management. The MLP's predictive output further underscores that variations in contractual type and policy quality can serve as early indicators of potential performance deviations.

The proposed MLP model provides a computationally grounded framework for understanding and predicting contractual risk performance in Kenya's construction industry. It extends existing literature by transforming qualitative risk factors into quantifiable predictors and integrating them into an adaptive neural architecture. The approach facilitates objective evaluation of risk outcomes, enhances data-driven decision-making, and provides a foundation for predictive policy analysis. From a practical perspective, the model supports stakeholders in identifying high-risk contractual patterns and prioritizing mitigation strategies at both the project and policy levels.

### **B. Limitations of the Study**

While the proposed Multilayer Perceptron (MLP) model provides an innovative framework for quantifying contractual risk performance in building projects, several methodological and contextual limitations must be acknowledged. First, the empirical dataset used for model training was relatively small, consisting of seven project observations from Kisii County. Although the sample captured diverse contractual and institutional conditions, the limited size constrained the statistical power and generalization of the predictive results. This limitation is reflected in the model's coefficient of determination ( $R^2 = 0.002$ ), which, despite stable convergence (final MSE = 0.134), indicates that additional data are necessary to capture the full spectrum of variability in contractual risk dynamics. Future studies should therefore expand the dataset to include multiple counties and larger sample sizes to enhance model robustness.

The study relied primarily on cross-sectional data derived from post-project evaluations and survey responses. This approach restricts temporal analysis of risk evolution across project phases. Longitudinal data capturing design, procurement, and execution stages would allow the model to learn dynamic risk patterns and provide stronger predictive reliability over time. The input variables, contract type, Risk Significance Index (RSIS), composite risk score, policy enforcement index, and contractor competence, were selected based on data availability rather than exhaustive factor analysis. Other latent factors such as stakeholder communication quality, supply-chain resilience, and environmental uncertainty were excluded, potentially omitting relevant predictors of the Risk Management Performance Index (RMPI).

While the hybrid Output-Hidden Weight Optimization (OWO-HWO) algorithm ensured convergence stability, it increased computational complexity and required manual tuning of learning parameters. The absence of automated hyper-parameter optimization or regularization techniques such as dropout or Bayesian tuning may have constrained the model's ability to minimize overfitting and improve generalization. Additionally, the current framework assumed homogeneity in policy enforcement within the county, whereas in practice, enforcement strength may vary across agencies and project categories.

The model validation process was limited to internal performance metrics (MSE and  $R^2$ ) without external benchmarking against other machine-learning architectures such as Support Vector Regression (SVR) or Random Forest models. Comparative validation would have provided a clearer assessment of the model's relative efficiency and predictive accuracy. Despite these constraints, the developed MLP framework successfully demonstrated the feasibility of applying computational intelligence to contractual risk management. The limitations identified provide a foundation for methodological refinement and the design of a more comprehensive, multi-regional predictive system capable of supporting policy and operational decision-making in Kenya's construction sector.

### **C. Recommendations**

The study recommends that policymakers and regulatory agencies strengthen legal and institutional mechanisms for contract monitoring and arbitration. Continuous capacity building should be provided to contractors and consultants to enhance their competence in digital contract management and risk forecasting. The Public Procurement Regulatory Authority (PPRA) and county governments should integrate AI-based analytics within project management systems to identify early warning indicators of risk and inefficiency. Future research should expand the dataset across multiple counties, adopt cross-validation techniques, and incorporate feature selection algorithms such as SHAP or LASSO to enhance model interpretability and predictive accuracy. Such enhancements will contribute to a national framework for intelligent risk governance in Kenya's construction sector. Future work will extend the dataset and integrate feature selection to improve model interpretability and predictive power.

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