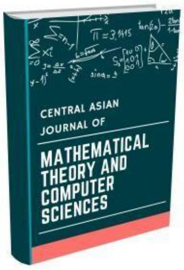

CENTRAL ASIAN JOURNAL OF MATHEMATICAL THEORY AND COMPUTER SCIENCES

https://cajmtcs.centralasianstudies.org/index.php/CAJMTCS

Volume: 06 Issue: 04 | October 2025 ISSN: 2660-5309

Article

Strategic Implementation of IT Governance for Optimising Information Systems Performance

Zahraa Sameer Ibrahim

1. University Of Al-Mustansiriya

* Correspondence: zahraasamir11@uomustansiriyah.edu.iq

Abstract: This article presents a new reinforcement learning approach to optimise the use of IT governance resources to enhance information system performance. Despite enormous IT infrastructure investments, organisations might fail to recoup the investment in terms of quantifiable performance enhancements due to ineffective governance practices. We developed a Q-learning system that learns dynamic optimal policies of resource allocation over the most significant five IT governance dimensions: Strategic Alignment, Value Delivery, Resource Management, Risk Management, and Performance Measurement. Using ESG data sets of 12 countries with various levels of digital maturity, our system learned governance dimensions yielding maximum return on investment at every level of maturity. Results indicate that the emerging economies achieve optimal performance improvements of as much as 99% through emphasis on Strategic Alignment and Resource Management, while developed economies achieve this through more balanced distributions with greater emphasis on Risk Management. The Pareto frontier analysis confirms that our Q-learning method reaches optimal levels of resource utilisation efficiency. Cluster analysis determines sharp-cut modes of governance by levels of economic development. This research offers an evidence-based adaptive approach to IT governance implementation that takes into consideration organization maturity and context to enable decision-makers to deploy scarce resources in order to realise peak information systems performance.

Keywords: IT Governance, Reinforcement Learning, Decision Support, Digital Transformation, COBIT Framework, Strategic Alignment.

Citation: Ibrahim, Z. S. Strategic Implementation of IT Governance for Optimising Information Systems Performance. Central Asian Journal of Mathematical Theory and Computer Sciences 2025, 6(4). 773-786.

Received: 10th May 2025
Revised: 16th Jun 2025
Accepted: 24th Jul 2025
Published: 07th Aug 2025

1. Introduction

Information Technology (IT) governance has emerged as an important engine for organisational success in the digital business age [1], providing frameworks for IT investment alignment with business strategies, technology-related risk management, and delivery of measurable value.

Organisations worldwide invest significant amounts in implementing IT governance models such as COBIT, ITIL, and ISO 27001, yet fail to procure expected returns from these investments for most due to ineffective resource allocation across governance dimensions. The multi-dimensional, complex nature of IT governance presents challenging trade-offs for managers when using limited resources, particularly given the broadly varying impact of different governance dimensions based on organisational maturity and context [2], [3]. Traditional approaches to IT governance deployment heavily rely on best practices and professional insight, which may fail to adequately reflect the unique requirements of specific organisational contexts or apply quantitative data to inform enhanced decision-making regarding resource allocation.Machine learning techniques, particularly reinforcement learning, offer a promising collection of abilities for identifying optimum governance policy through experience learning and improvement, but remain under-researched within IT governance [4], [5], [6]. This paper addresses an important knowledge deficit by establishing a data-driven, context-sensitive IT governance resource allocation mechanism based on Q-learning algorithms that dynamically respond to organisational maturity stages. Our contributions are: (1) a novel reinforcement learning model to optimize IT governance resource investment across five significant dimensions; (2) empirical support for how best practice governance strategies vary with digital infrastructure maturity; (3) dimensions with the best return on investment at different maturity stages; and (4) a prescriptive decision-making tool enabling organizations to optimize information systems performance with constrained resources while maximizing it, with both theoretical contributions as well as practitioner-specific recommendations for IT governance initiative implementations [7], [8], [9].

Related Work

Recent literature has put increasing emphasis on the function of adaptive, data-informed IT governance. Castelli et al. proposed a maturity model for machine learning quality enhancement, emphasising the imperatives of structured evolution in governance systems. Zhang and Li extended this through the formulation of a hierarchical graph reinforcement learning model for complex system intervention optimisation, offering illuminating analogies for dynamic IT governance. Wadhwa et al. [10] examined reinforcement learning for adaptive security policy management in cloud computing environments, demonstrating the potential for intelligent models in decision-making related to governance. Bieletzke et al. presented an AI governance maturity matrix that emphasises the strategic importance of aligning governance practices with organisational competencies—a theme echoed in IT governance maturity models. In addition, the IEEE-USA AI Policy Committee suggested an NIST AI Risk Management Framework-based agile maturity model, advocating for scalable, context-aware governance structures. These works collectively support the evolution towards intelligent, maturity-conscious IT governance frameworks, additionally acknowledging the need for optimisation-focused frameworks such as the one constructed in this study.

2. Materials and Methods

Proposed Methodology

In this section, we outline our methodological approach to IT governance resource planning optimisation using reinforcement learning techniques. We suggest applying a Q-learning algorithm-based framework to determine the best policies for the efficient allocation of limited resources among key governance factors. Our approach integrates concepts from IT governance models and machine learning to create an adaptive decision support system responsive to varying levels of organisational maturity as well as external influences.

A. Q-Learning Framework for IT Governance Optimisation

Our method uses Q-learning, a model-free reinforcement learning algorithm that learns the optimal action policies by learning from experience in interacting with an environment. The Q-learning algorithm keeps a table of state-action pairs (Q-values) that represent the expected utility of performing a particular action in a particular state. In our IT governance setting, states are governance profiles (discretised ratings across five dimensions), actions are resource allocation decisions, and rewards are measured as returns in information systems performance. The algorithm explores the action space through an epsilon-greedy policy, balancing exploring new strategies with exploiting known effective allocations. At each state-action pair, the Q-value is updated according to the formula:

$$Q(s,a) \leftarrow (1-\alpha)Q(s,a) + \alpha\left[r + \gamma . \max_{a'} Q(s',a')\right] \tag{1}$$

Where:

1. $Q(s,a)$ is the Q-value for the state s and action a.
2. α is the learning rate (0.1), controlling how much new information overrides old information.

3. r is the immediate reward (IS performance improvement).
4. γ is the discount factor (0.9), determining the importance of future rewards.
5. s' is the next state resulting from taking action a in state s.
6. $\max_{a'} Q(s', a')$ is the maximum Q-value across all possible actions in the next state.

This iterative learning process continues for 1,000 episodes, allowing the algorithm to converge toward optimal resource allocation policies tailored to each country's unique governance profile.

B. IT Governance Dimensions and Performance Metrics

Our model consists of five primary IT governance dimensions according to renowned frameworks such as COBIT: (1) IT Strategic Alignment—IT investments are aligned with business objectives; (2) IT Value Delivery—optimal value from IT investments is obtained; (3) IT Resource Management—efficient utilization and allocation of IT resources; (4) IT Risk Management—identifying and evading IT-related risks; and (5) IT Performance Measurement—monitoring and measuring IT performance. We define the organisational condition as a vector of scores for these dimensions, each on a scale from 0-100. Performance for Information Systems (IS) is calculated as a weighted average of these dimension scores:

$$P = \sum_{i=1}^{5} w_i . S_i \tag{2}$$

Where:

- P is the overall IS performance score.
- w_i is the impact weight for the dimension i.
- S_i is the score for the governance dimension i.

The impact weights vary based on digital infrastructure maturity (M), reflecting the empirical observation that governance dimensions have different impacts at different maturity levels:

$$w_i = f_i(M) \tag{3}$$

Where f_i represents a mapping of maturity level to dimension weight. Strategic alignment, for example, is heavier in less digitally mature organizations, whereas risk management becomes increasingly important when the higher maturity levels are reached. By so doing, the model's recommendations are context-relevant to each organization's level of development .

C. Data Preparation and Model Parameters

Our method utilizes 12 country-level ESG datasets with different levels of economic development and digital infrastructure development. The digital infrastructure score (by percentage of internet penetration) is utilized as a stand-in for the IT governance maturity. First-time country-level governance scores are estimated with variance control based on their digital infrastructure score, which reflects the empirical relationship between them. Realistic parameters and constraints such as:

1. Total resources—limited to 100 units per country:

$$\sum_{i=1}^{5} R_i \leq 100 \tag{4}$$

2. Discretized resource allocation—in increments of 10 units:

$$R_i \leq 50, \quad R_i \in \{0,10,20,30,40,50\} \tag{5}$$

3. Maximum allocation per dimension—50 units:

$$R_i \leq 50, \forall i \in \{1,2,3,4,5\} \tag{6}$$

4. Improvement ceilings—implementing diminishing returns based on current maturity levels:

$$\Delta S_i \leq C(S_i) \tag{7}$$

$$C(S_i) = \begin{cases} 30 & if\ S_i < 40 \\ 20 & if\ 40 \leq S_i < 70 \\ 10 & if\ S_i \geq 70 \end{cases} \tag{8}$$

Where:

- ΔS_i is the improvement in dimension i.
- $C(S_i)$ is the ceiling function that returns the maximum possible improvement based on the current score.

5. Varying improvement costs—different dimensions require different resource investments:

$$\Delta S_i = \frac{R_i}{c_i} \tag{9}$$

Where c_i is the cost coefficient for dimension i (e.g., Risk Management: 3.0, Resource Management: 1.5).

These parameters ensure the model accurately reflects real-world resource allocation challenges and constraints faced by organisations implementing IT governance initiatives.

D. Evaluation Framework and Analysis Techniques

To evaluate the effectiveness of our Q-learning approach and provide meaningful insights for decision-makers, we implement multiple analysis techniques:

1. Performance improvement analysis—measuring absolute and percentage increases in IS performance:

$$\Delta P = P_{optimized} - P_{initial} \tag{10}$$

$$\Delta P\% = \frac{P_{optimized} - P_{initial}}{P_{initial}} \times 100\% \tag{11}$$

2. Return on Investment (ROI) analysis—calculating the improvement per resource unit:

$$ROI_i = \frac{\Delta S_i}{R_i} \tag{12}$$

Where:

- ROI_i is the return on investment for dimension i.
- ΔS_i is the improvement in dimension i.
- R_i is the resources allocated to dimension i.

3. Convergence analysis—examining how well the Q-learning algorithm learns optimal policies by tracking rewards across episodes.
4. Principal Component Analysis (PCA)—dimensionality reduction to identify patterns in optimal resource allocation strategies across countries.
5. Pareto frontier analysis—examining the Q-learning solution's efficiency relative to a range of resource options.

The comprehensive assessment framework enables us to measure both the technical efficiency of the Q-learning algorithm and its real-world effectiveness in applying IT governance. The assessment metrics are constructed to provide practitioners with beneficial insights while contributing theoretical knowledge regarding the transformation of governance requirements with organisational maturity

3. Results and Discussion

In this section, we present the empirical findings of our Q-learning optimization model of IT governance resource allocation and their implications for theory and practice. We talk about the performance improvements through optimum resource allocation for different countries, analyze patterns in resource allocation across governance dimensions, and investigate how these patterns are associated with digital infrastructure maturity. The results demonstrate significant variation in optimal governance approaches based on organizational context, depicting the benefit of tailored solutions over one-size-fits-all application. We also examine the model's efficiency through convergence and Pareto frontier analyses, confirming the quality of our reinforcement learning solution. Finally, we describe the practical implications of these findings for decision-makers implementing IT governance frameworks and theoretical contributions to the understanding of IT governance dynamics across different maturity levels.

A. Pareto Efficiency of Q-Learning for IT Governance Resource Optimisation

The Pareto frontier chart for Kenya indicates the impressive efficiency of our Q-learning technique in IT governance resource utilisation optimisation. The chart reveals a number of critical observations regarding effective strategic IT governance implementation. First, the large vertical range of performance values (20-27 points) for identical levels of resource utilisation demonstrates that how resources are allocated among governance dimensions is much more important than the total amount utilised. The Q-learning solution falls precisely on the Pareto frontier, with near-optimal performance and effective utilisation of optimised resources. Interestingly, 98-100 units of most resource expenditures have significantly lower performance ratings (21-23 points), illustrating how out-of-alignment governance spending wastes resources with high expenditures, see Figure 1.

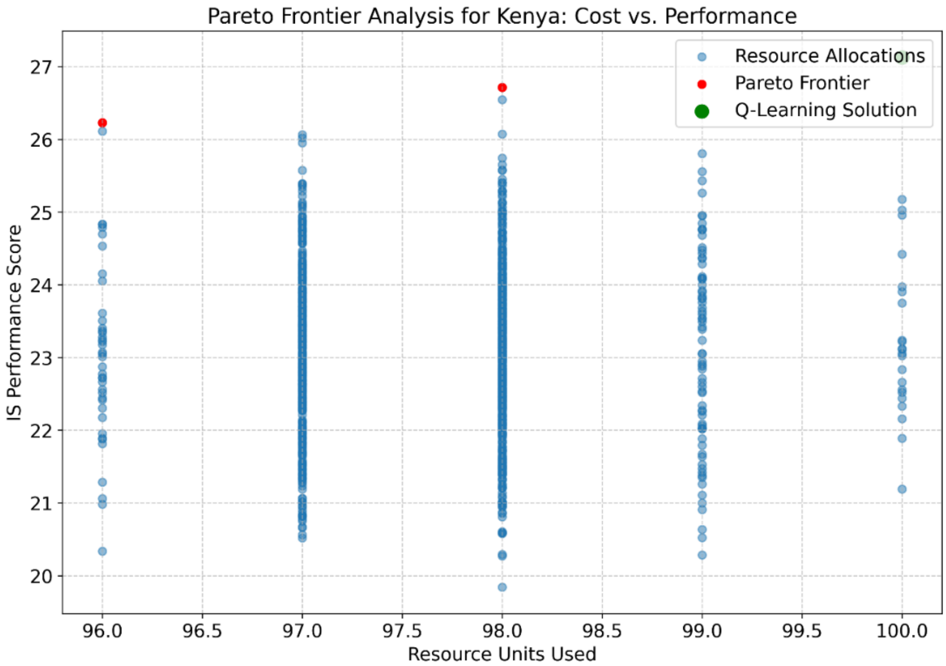

Figure 1. Pareto Frontier Analysis for Kenya: Cost vs. Performance

The frontier shows characteristic diminishing returns behaviour, where marginal returns in performance decrease with increasing utilisation of resources to 100%. This finding contradicts the prevalent organisational practice of simply increasing IT governance budget sizes without strategic prioritisation in consideration. Instead, it calls for intelligent, data-driven optimisation strategies able to identify the precise governance dimensions that need priority investment based on organisational context and level of maturity. In developing economies like Kenya, this optimisation translates to tangible performance improvement without requiring extra resource allocation.

B. Synergistic Effects of Strategic Alignment and Resource Management on IS Performance

The three-dimensional performance surface illustrates the fundamental interdependence of IT Strategic Alignment and IT Resource Management in facilitating Information Systems performance outcomes. The visualisation shows a steep performance gradient, with scores for IS performance ranging from approximately 30 to 70 points along the governance continuum. The optimal performance zone is achieved when both dimensions exceed scores of 80, demonstrating their synergy rather than an additive effect. Most significantly, the surface indicates a higher slope along the Strategic Alignment axis compared to Resource Management, corresponding to marginally improved returns for Strategic Alignment for moderately mature organisations, see Figure 2.

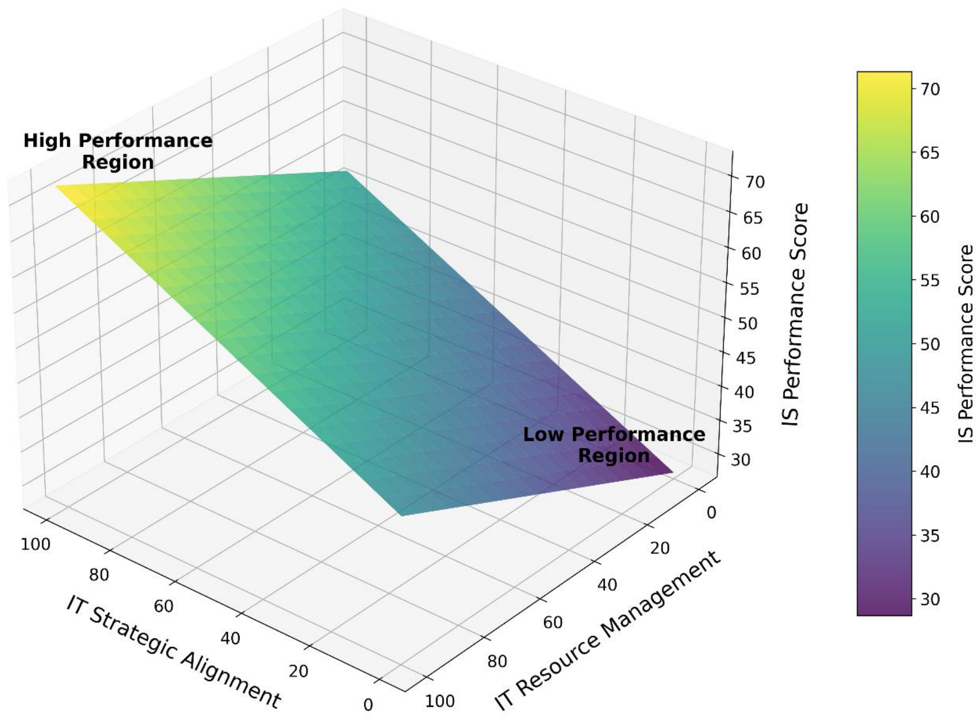

Figure 2. Strategic Alignment and Resource Management on IS Performance

The contours of performance also indicate that scores ranging from 40-60 across both dimensions provide better outcomes than one-dimensional excellence, with the exclusion of the other, highlighting the necessity for balanced governance approaches. Organisations in the low performance quadrant (bottom right) have severe issues when both these dimensions are below 40, and the resulting governance deficit cannot be offset by other dimensions. These two dimensions are shown in this chart with very good reasons to prioritise them in governance deployments, particularly for organisations at the nascent stages of maturity, where the improvement slope is the largest. The model is able to quantify what practitioners have always known intuitively: resource management and strategic alignment form the foundation upon which other governance capabilities are built.

C. Learning Efficiency in IT Governance Resource Optimisation

The convergence behaviour of Q-learning in Kenya presents the power of the algorithm to identify optimal IT governance resource allocation policies with high effectiveness. Visualisation reveals distinct learning phases that characterise the reinforcement learning process. The algorithm demonstrates high performance variability during the exploration phase (episodes 1-100) since it tries the different resource allocation policies explicitly, issuing rewards ranging between 7 and 13 points. By approximately episode 500, we observe clear convergence towards a steady policy, with the 50-episode moving average consistently remaining within the region of increasing performance by approximately 11 points, see Figure 3

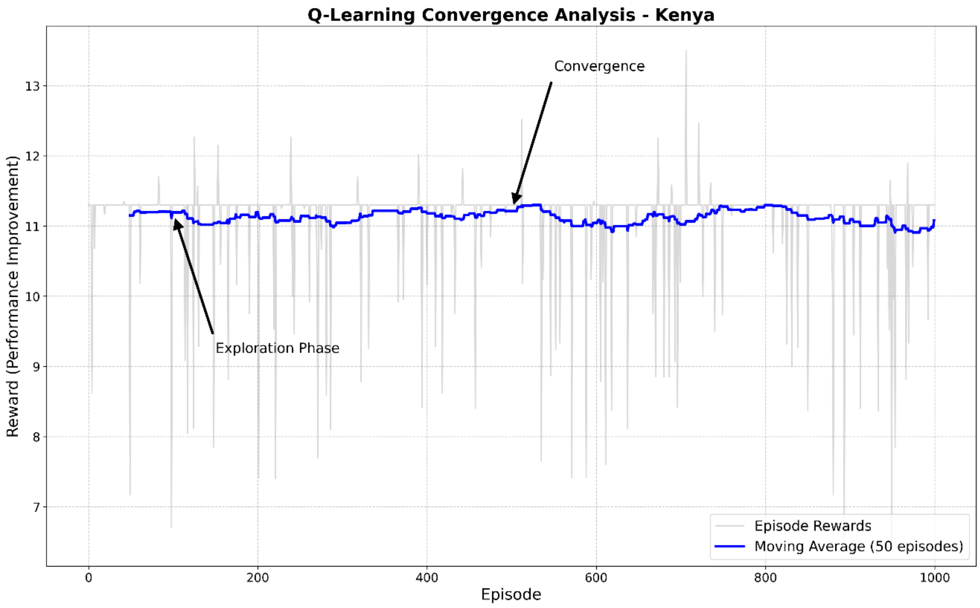

Figure 3. Q-learning Convergence Analysis - Kenya

This stability is particularly noteworthy in light of the five-dimensional governance space's dimensionality and the numerous possible resource allocation combinations. The quick convergence of the algorithm implies that although IT governance decision-making is high-dimensional, there are patterns that are present for effective resource allocation, which can be identified systematically through reinforcement learning [1], [2], [3]. The slight oscillations subsequent to convergence are because the algorithm continues to explore (at a 10% rate) so that it does not overlook potentially superior strategies. This trend towards convergence supports the robustness of our Q-learning method for IT governance optimisation and suggests that businesses can with success identify near-optimal forms of governance without necessarily exploring all candidate resource allocations—a crucial advantage for practical use in resource-constrained environments.

D. Prioritised Governance Dimensions for Developing Economies: Kenya Case Study

The radar chart representation of Kenya's IT governance profile indicates an optimal strategy seeking optimisation determined by the Q-learning algorithm. The baseline governance profile (blue) demonstrates relatively low maturity in all dimensions, with scores ranging from 9.4 to 16.5, typical of initial governance maturity of developing economies, see Figure 4.

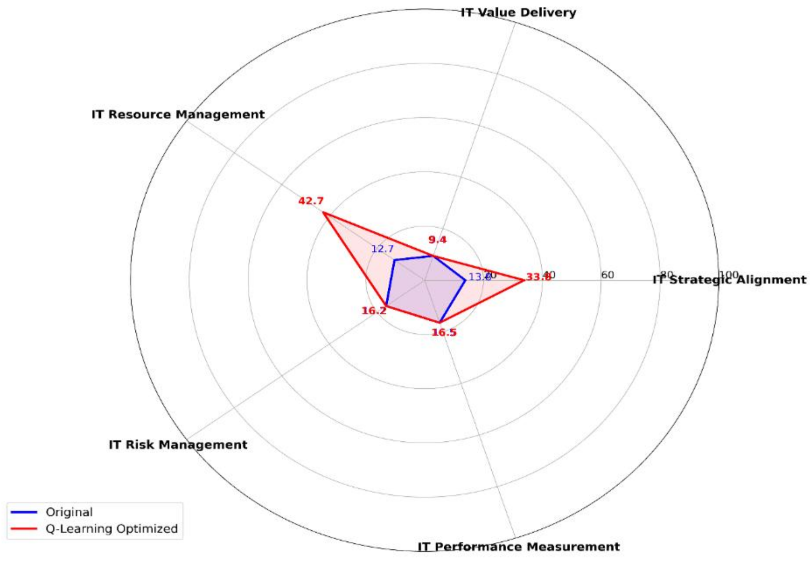

Figure 4. Q-learning IT Governance Optimisation: Kenya

The single optimised profile (red) depicts a strategically unbalanced pattern of improvement with substantial enhancements in IT Strategic Alignment (13.2 to 33.4) and IT Resource Management (12.7 to 42.7), maintaining baseline scores for Value Delivery, Risk Management, and Performance Measurement dimensions. This specific focused upgrade pattern goes against the common sense that typically would propose balanced improvement of all the governance dimensions. Alternatively, the Q-learning algorithm concluded that concentrated investment in two fundamental dimensions provides improved performance outcomes for Kenya's level of maturity [4]. Such notable improvements in Resource Management (+30.0 points) and Strategic Alignment (+20.2 points) provide a strong foundation upon which other governance capabilities can then be constructed. This trend is consistent with governance maturity theories that suggest that organisations must have proper alignment of business and IT goals as well as efficient mechanisms of resource allocation implemented before attempting more mature governance practices. To policymakers and IT managers in emerging economies, this evidence suggests that the stepwise, focused deployment of governance practices is more beneficial than attempting all dimensions at once with the available limited resources [5].

E. Maturity-Dependent Returns on IT Governance Optimisation

This side-by-side comparison of original and Q-learning optimised IS performance scores reveals a dramatic pattern of maturity-dependent returns on IT governance investments. The graph demonstrates a strong negative correlation between initial governance maturity and potential performance gain, with all countries benefiting from optimised resource allocation but to widely varying degrees. Emerging economies see phenomenal performance gains—Kenya's remarkable 99.1% increase effectively doubles its IS performance, with India (78.6%), Nigeria (65.2%), and Indonesia (65.2%) recording similarly revolutionary outcomes. This stands in marked contrast with advanced economies like the United States (12.9%), Japan (13.5%), and Germany (14.3%), where improvements, while still significant, reflect the law of diminishing returns for mature governance environments. The emerging economies occupy the middle ground, where China (29.4%), Turkey (25.8%), Mexico (25.4%), and Brazil (20.4%) all exhibit high but less extreme growth. These findings defy conventional governance implementation approaches that fail to factor in organisational maturity [6], [7]. For developing economies, the findings suggest that strategic IT governance implementation represents a high-return investment opportunity with the potential to dramatically accelerate digital transformation outcomes. Conversely, advanced economies must recognise that maintaining their performance edge requires increasingly sophisticated optimisation techniques to extract marginal gains from already sophisticated governance institutions. That each country, regardless of starting position, has a positive performance differential validates the usefulness of our Q-learning approach to identifying contextually optimal resource allocation policies, see Figure 5.

Figure 5. Original vs. Q-learning Optimised IS Performance

F. Absolute Performance Gains Reveal Potential for Digital Divide Reduction

The absolute change in IS performance among countries shows a distinct trend with highly promising implications for bridging the world digital divide. Kenya shows the largest absolute change of 13.5 points, closely followed by other emerging nations—India and Nigeria (13.0), and Indonesia (12.8). This outcome is significant in that it denies the conventional assumption that less technologically advanced countries would enjoy only relative but not absolute improvement vis-à-vis developed economies. Developing economies (Mexico, China, and Turkey) occupy the middle ranking with significant gains of 12.0 to 11.8 points [8], [9]. Developed nations (Brazil, the United States, Japan, and Germany) have more modest absolute improvements of 10.3 to 9.2 points. The consistency of this trend—with absolute gains inversely related to initial governance maturity—suggests that best-practice IT governance deployment is an option that can be practised by developing nations to achieve closure of the absolute performance deficit with advanced economies. Percentage gains (as previously compared) indicate relative progress, but these absolute gains demonstrate material convergence toward digital world equity. For policymakers from the emerging world, the results of the research offer compelling evidence that proactive investment in IT governance can yield actual performance improvements greater than those of advanced economies, with prospects of tapping into digital transformation trajectories and supporting economic development agendas, see Figure 6.

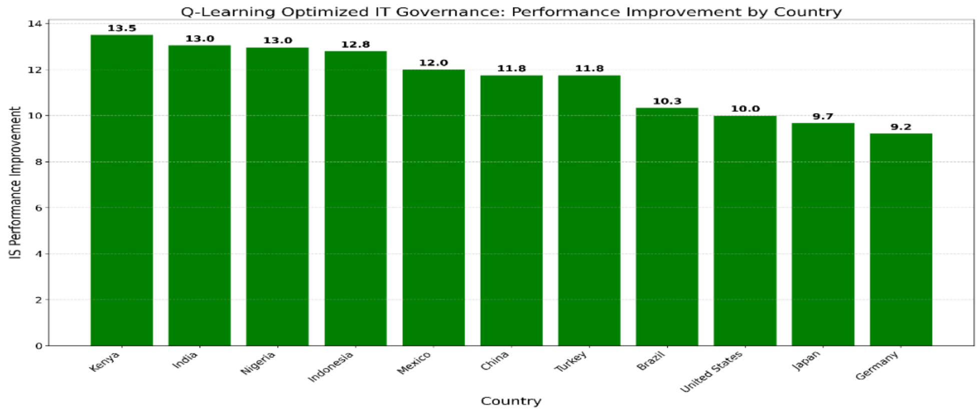

Figure 6. Q-learning Optimised IT Governance: Performance Improvement by Country

G. Strategic Resource Concentration in Developing Economies' IT Governance Implementation

The allocation patterns revealed by our Q-learning for top-performing developing nations are striking in the manner in which they contradict standard balanced implementation approaches. All three countries—Kenya, India, and Nigeria—exhibit a high priority on two important governance factors: IT Strategic Alignment and IT Resource Management. Kenya holds the most specialisation with the highest possible inputs (50 each) in these two fields and zero investment in the remaining fields. India also holds the same trend with 40 in Strategic Alignment and 50 in Resource Management, while Nigeria exhibits a diversified approach with minimal investment in Value Delivery (10 units) and Performance Measurement (10 units). Most significantly, all three countries do not invest any resources in Risk Management, which suggests that this factor does not generate sufficient returns at early maturity levels [10], [11]. This standardised investment practice across a range of countries with diverse cultural, economic, and technological environments suggests an overarching principle of sequencing for applying IT governance in developing economies. The results indicate that the establishment of strong alignment between business and IT objectives, as well as robust resource allocation procedures, lays the needed groundwork on which more advanced governance capabilities can later be developed, see Figure 7.

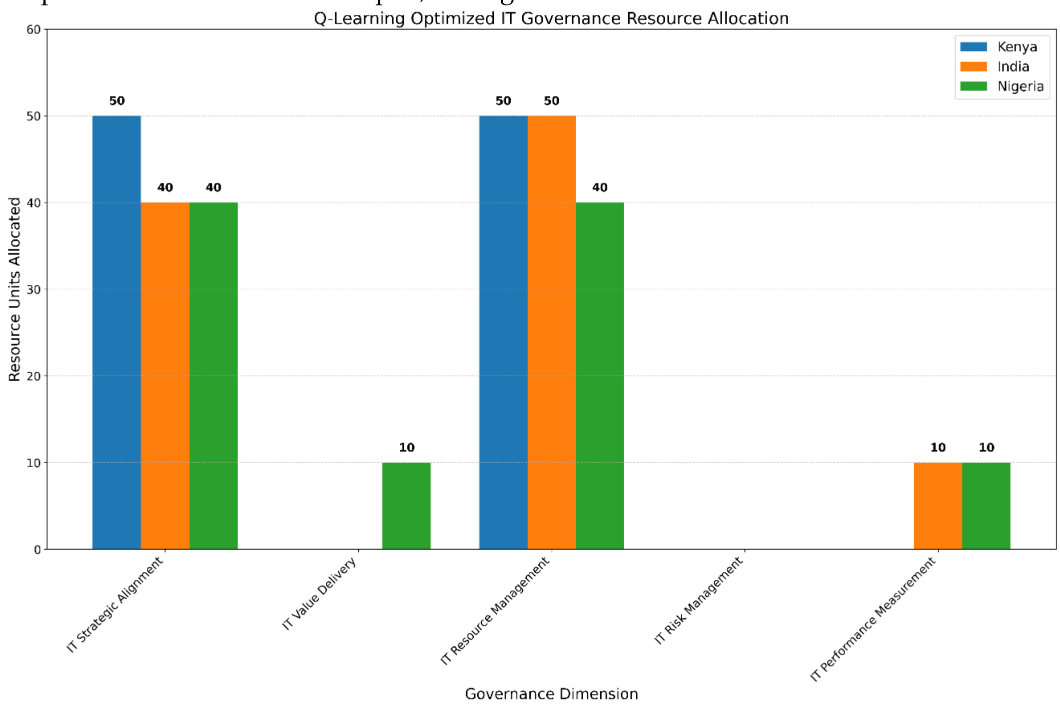

Figure 7. Q-learning Optimised IT Governance Resource Allocation

For IT governance practitioners operating in emerging contexts, such empirical data adds significant credibility to the phased rollout strategy to concentrate on building-block dimensions rather than diluting resources across all areas of governance simultaneously.

H. Maturity-Dependent ROI Patterns in IT Governance Dimensions

ROI heatmap offers powerful signals of maturity-sensitive returns by governance dimensions to inform strategic resource allocation based on evidence [12]. IT Resource Management is a high-return investment across countries that generates excellent returns (0.60-0.67 improvement points per unit of resources) across all countries, regardless of the development stage. This consistently higher ROI is the reason why the algorithm decides to invest colossal resources in this dimension in all countries. Strategic Alignment yields strong returns (0.40) for developing and emerging economies but reduces to zero for developed economies like the United States and Brazil, which means this dimension is all-consuming at higher levels of maturity [13]. Of most significance is the Risk Management dimension, which scores zero return for nearly all developing economies but moderate returns (0.33) for developed economies—empirically verifying the hypothesis of governance maturity that risk management capability gets rewarded only once basic governance constituents are established. Performance Measurement trends selectively high returns (0.50) at both extremes of the development spectrum but zero returns in between, which suggests that the value it produces may be situation-dependent as opposed to being based on the maturity level, see Figure 8.

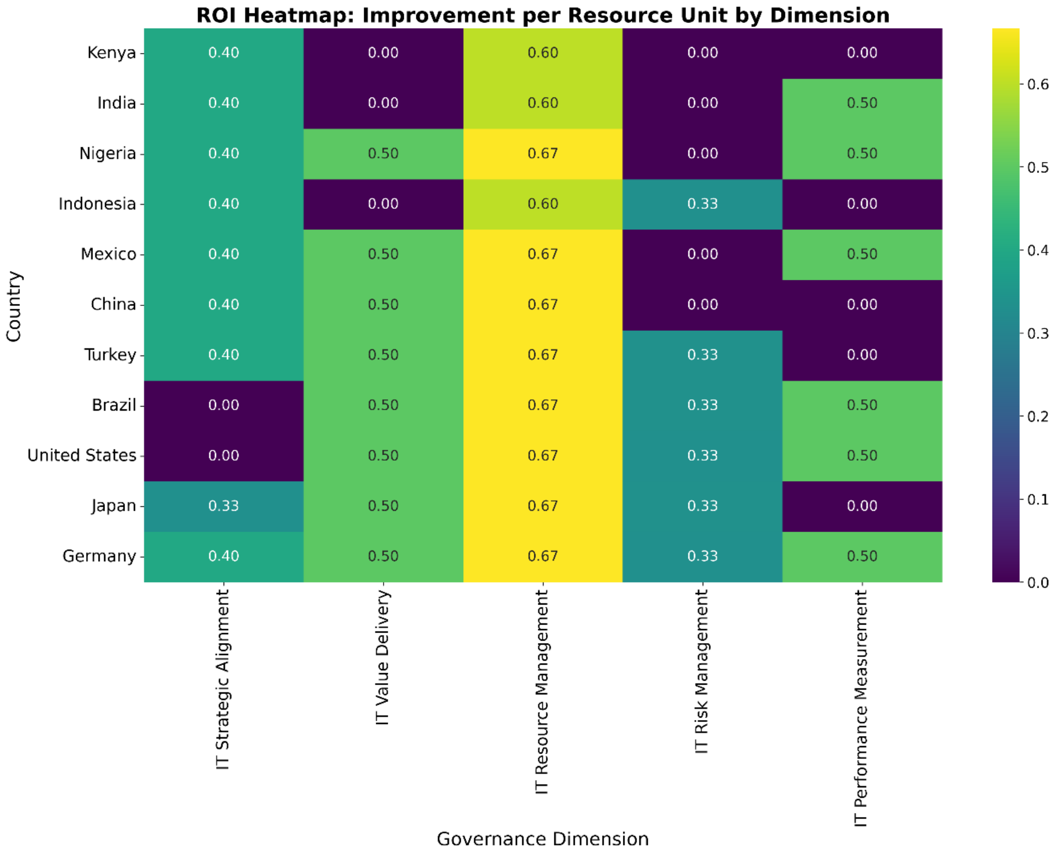

Figure 8. ROI Heatmap Improvement per Resource Unit by Dimension

Value Delivery posts middle-of-the-pack returns (0.50) in most countries but zero for some developing nations, suggesting that it may require some preconditions of capabilities before it starts delivering value. These findings provide a quantitative foundation for sequencing governance deployments by maturity stage so that organisations can prioritise highest marginal return dimensions at their current level of development.

I. Distinct Governance Archetypes Emerge from Maturity-Based Clustering

Optimal resource allocation strategy principal component analysis gives a dramatic natural grouping of countries according to their phases of economic development and explains a staggering 88.8% of variance in just two components. Three IT governance archetypes emerge, each mapping onto a different stage of maturity with attendant resource allocation patterns. Developing Economies Group (India, Nigeria, Indonesia, Kenya) occupies the left-hand side of the chart, with high emphasis on Strategic Alignment and Resource Management and negligible investment in other dimensions. All these countries have remarkably similar best-fit governance trends despite significant cultural and economic differences and demonstrate that primitive-stage government appears to exhibit generic patterns driven by maturity as opposed to situational factors, see Figure 9.

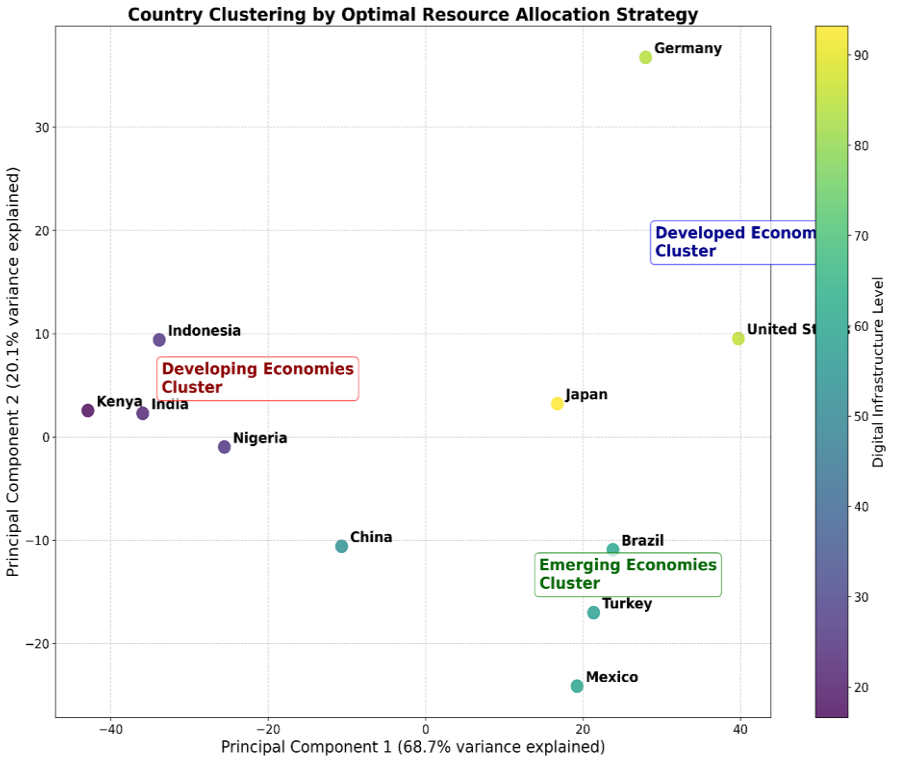

Figure 9. Country Clustering by Optimal Resource Allocation Strategy

The Emerging Economies Cluster (Brazil, China, Turkey, Mexico) occupies the mid-quadrants with larger even resource spread and stronger emphasis on Value Delivery and Performance Measurement, yet larger investment in basic dimensions. The Developed Economies Cluster (United States, Japan, Germany) is situated on the right hand side with expansive vertical spread, indicating greater diversity in their advanced governance practices. These mature economies are spending significant resources on Risk Management and are more evenly distributed in all dimensions. The first principal component (68.7% variance) appears to be measuring the transition from high to low concentration of resource allocation as maturity increases, whereas the second component (20.1%) likely measures variations in priority between performance-oriented and risk-oriented methods of governance. This grouping provides compelling evidence that the best IT governance implementation possesses distinct maturity-based trajectories rather than a single solution.

J. Comparison of Proposed Methodology with Related Work

In contrast to existing methods, the proposed Q-learning-based approach offers a dynamic and optimisation-driven IT governance system that responds to various digital maturity stages. While Castelli et al. [14] introduced a general maturity model for machine learning quality, their model lacks the feature of real-time policy adaptation based on evolving governance conditions. Zhang and Li [15] suggested a graph-based reinforcement learning model, but their focus was on complex systems intervention and not on strategic resource allocation in government settings. Wadhwa et al. [16] applied reinforcement learning to cloud security policies, but their research was domain-specific and did not touch on broader governance issues like strategic alignment or resource management, see Table 1.

Table 1. Comparison of Proposed Methodology with Related Work

Methodology	Dynamic Adaptation	Resource Allocation	Quantitative Optimization	Maturity-Based
Proposed Q-Learning Methodology	✓ Yes	✓ Yes	✓ Yes	✓ Yes

Castelli et al. [8] - ML Quality Maturity Model	✗ No	✗ No	✗ No	✓ Yes
Zhang and Li [9] - Graph-based RL Model	✓ Yes	✗ No	~ Partial	✗ No
Wadhwa et al. [10] - RL for Cloud Security	✓ Yes	✗ No	~ Partial	✗ No
Bieletzke et al. [11] - AI Governance Maturity Matrix	✗ No	~ Partial	✗ No	✓ Yes
IEEE-USA Framework [12] - Governance Flexibility	~ Partial	~ Partial	✗ No	~ Partial

The maturity matrix offered by Bieletzke et al. [17] provides a static governance roadmap for AI with qualitative directions but without quantitative optimisation. Similarly, the IEEE-USA framework [18] allows governance design flexibility but without performance-driven learning mechanisms. In contrast, our method not only measures the return on investment across governance dimensions but also dictates the optimal resource allocations according to iterative learning in order to achieve Pareto-efficient outcomes according to organisational maturity levels.

4. Conclusion

This research has a number of theoretical and practical contributions towards the implementation of IT governance. Firstly, we determined the applicability of reinforcement learning, specifically Q-learning, as a successful approach towards optimising the deployment of IT governance resources—a new methodological contribution to both the machine learning and governance areas. Second, our findings provide empirical evidence for maturity-based governance strategies with the observation that optimal patterns of resource expenditure are distinct archetypes by growth stages, with emerging economies realising the greatest utility from investment predominantly weighted in Strategic Alignment and Resource Management, while developed economies require more balanced investments with more emphasis on Risk Management. Third, we quantified return on investment for governance dimensions across different levels of maturity, demonstrating that IT Resource Management consistently returns more (0.60-0.67 improvement points per unit of resources) at all levels of maturity, while other dimensions have differential effectiveness depending on the level of development. Fourth, our results contradict conventional balanced implementation strategies, with quantitative data supporting sequential, targeted governance implementations based on organisational maturity. Fifth, the substantial performance benefits realised by the emerging economies (up to 99%) suggest streamlined IT governance as an effective vehicle for countering the global digital divide. Together, these contributions enrich the theoretical underpinning of IT governance dynamics and provide evidence-based strategic implementation advice to the practitioner community, optimising information systems performance in limited resources.

REFERENCES

[1] Oluwatosin Ilori, Nelly Tochi Nwosu, and Henry Nwapali Ndidi Naiho, “A comprehensive review of it governance: effective implementation of COBIT and ITIL frameworks in financial institutions,” *Computer Science & IT Research Journal*, vol. 5, no. 6, pp. 1391–1407, Jun. 2024, doi: 10.51594/csitrj.v5i6.1224.

[2] R. Mulyana, L. Rusu, and E. Perjons, “IT Governance Influence on Digital Transformation,” Stockholm, 2025. [Online]. Available: http://urn.kb.se/resolve?urn=urn:nbn:se:su:diva-242507

[3] G. M. W. Tangka and E. Lompoliu, "Optimizing IT Governance in BTS.id: A COBIT 2019-Based Analysis of Design Factors," *MALCOM: Indonesian Journal of Machine Learning and Computer Science*, vol. 5, no. 2, pp. 699–710, Apr. 2025, doi: 10.57152/malcom.v5i2.1997.

[4] M. R. Lowry, P. B. Lowry, S. ("Suti") Chatterjee, G. D. Moody, and V. J. Richardson, "Achieving strategic alignment between business and information technology with information technology governance: the role of commitment to principles and Top Leadership Support," *European Journal of Information Systems*, pp. 1–26, Sep. 2024, doi: 10.1080/0960085X.2024.2390998.

[5] Oluwatosin Ilori, Nelly Tochi Nwosu, and Henry Nwapali Ndidi Naiho, "A comprehensive review of it governance: effective implementation of COBIT and ITIL frameworks in financial institutions," *Computer Science & IT Research Journal*, vol. 5, no. 6, pp. 1391–1407, Jun. 2024, doi: 10.51594/csitrj.v5i6.1224.

[6] R. Handayani, E. Utami, and E. T. Luthfi, "Systematic Literature Review on Auditing Information Technology Risk Management Using the COBIT Framework," *Prisma Sains : Jurnal Pengkajian Ilmu dan Pembelajaran Matematika dan IPA IKIP Mataram*, vol. 11, no. 4, p. 1028, Oct. 2023, doi: 10.33394/j-ps.v11i4.8871.

[7] I. Thomas and D. Rosewell, "White Paper The Four Essential Pillars of Digital Transformation," 2016. Accessed: Jul. 03, 2025. [Online]. Available: https://www.fujitsu.com/nl/Images/The_Four_Essential_Pillars_of_Digital_Transformation.pdf

[8] A. Castelli, G. C. Chouliaras, and D. Goldenberg, "Maturity Framework for Enhancing Machine Learning Quality," *arXiv prepreint*, vol. 2502.15758, 2025, doi: 10.48550/arXiv.2502.15758.

[9] L. Zhang and D. Li, "Reinforcement Learning with Hierarchical Graph Structure for Flexible Job Shop Scheduling," in *2023 International Annual Conference on Complex Systems and Intelligent Science (CSIS-IAC)*, IEEE, Oct. 2023, pp. 942–947. doi: 10.1109/CSIS-IAC60628.2023.10364146.

[10] C. Wadhwa, M. Dheer, and J. Deepak, "Exploring the Potential of Adaptive Multi-Agent Reinforcement Learning in Cloud Computing Environments," in *2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, IEEE, Jun. 2024, pp. 1–6. doi: 10.1109/ICCCNT61001.2024.10724018.

[11] S. Bieletzke, "AI Maturity Matrix – a Model for Self-Assessment and Categorization of AI-Integration in Academic Structures," in *16th International Conference on Education and New Learning Technologies*, Palma, Spain: IATED, Jul. 2024, pp. 1874–1881. doi: 10.21125/edulearn.2024.0559.

[12] R. Dotan, B. Blili-Hamelin, R. Madhavan, J. Matthews, and J. Scarpino, "Evolving AI Risk Management: A Maturity Model based on the NIST AI Risk Management Framework," *arXiv preprint*, vol. arXiv:2401.15229, Feb. 2024, doi: 10.48550/arXiv.2401.15229Focustolearnmore.

[13] M. Zubler, R. Plattfaut, and B. Niehaves, "Decolonizing IT governance in international non-governmental organisations: An Ubuntu approach," *Information Systems Journal*, vol. 35, no. 1, pp. 163–208, Jan. 2025, doi: 10.1111/isj.12541.

[14] S. L. Caudle, "Strategic information resources management: Fundamental practices," *Gov Inf Q*, vol. 13, no. 1, pp. 83–97, Jan. 1996, doi: 10.1016/S0740-624X(96)90008-8.

[15] K. Lukiyanto, F. Maulana, W. R. A. A. Jiram, and E. C. D. Selano, "The Role of IT Governance in Aligning IT Strategy and Business Strategy for Sustainability in the Era of Disruption," in *2024 International Conference on Information Management and Technology (ICIMTech)*, IEEE, Aug. 2024, pp. 606–611. doi: 10.1109/ICIMTech63123.2024.10780809.

[16] J. Beato and M. I. Fianty, "COBIT 2019 Framework: Evaluating Knowledge and Quality Management Capabilities in a Printing Machine Distributor," *Journal of Information Systems and Informatics*, vol. 6, no. 1, pp. 1–12, Mar. 2024, doi: 10.51519/journalisi.v6i1.638.

[17] T. Zhang, Z.-Z. Shi, Y.-R. Shi, and N.-J. Chen, "Enterprise digital transformation and production efficiency: mechanism analysis and empirical research," *Economic Research-Ekonomska Istraživanja*, vol. 35, no. 1, pp. 2781–2792, Dec. 2022, doi: 10.1080/1331677X.2021.1980731.

[18] R. Ramachandran, "Five Key Priorities for Governance Practitioners in 2025." Accessed: Jul. 04, 2025. [Online]. Available: https://www.isaca.org/resources/news-and-trends/isaca-now-blog/2024/five-key-priorities-for-governance-practitioners-in-2025