International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 21s, 2025
https://theaspd.com/index.php

A Data-Driven Framework FOR Optimizing It Absorptive Capacity IN Schools: Integrating Neural Networks WITH Genetic Algorithms

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Abstract
This paper develops a theoretical model of a combined method based on machine learning and optimization to improve IT absorptive capacity (ITAC) and allocate resources using the Iraqi schools' dataset. Strategically important indicators of the network bandwidth, numbers of devices, system availability, budgetary provisions and the IT literacy of staff are also part of the dataset which serve as the basis for precise demand calculation and maximization. Our framework incorporates an IT resource forecasting neural network (NN) that has low mean squared error (MSE) and high R2, and a genetic algorithm (GA) for efficient distribution of these resources. The GA was also successful in cutting overall operating costs by an average of 18% while raising ITAC by only 25 % to illustrate its success in low-resource educational environments. Budget allocation and bandwidth utilization were sources of variation in absorptive capacity as established through the sensitivity analysis: These enhancements provided tangible information for strategic investment priorities. This adaptive, data-driven approach offers not only a practical solution to a multitude of IT management issues in schools but also a feasible path toward building more robust and inexpensive infrastructure for education.
Keywords: *Educational IT Infrastructure Genetic Algorithm Optimization IT Absorptive Capacity Machine Learning Neural Network Prediction*

Article history:
Received xxxx
Revised xxxx,
Accepted xxxx,
Available online xxxx

1. INTRODUCTION

With the use of information technology and technology-enhanced learning solutions becoming commonplace in educational institutions, the need for a strong IT infrastructure has never been more important [1]. However, schools, especially those at the Iraq level, suffer from many difficulties in balancing the challenges of having sophisticated IT units with those of limited expenditure [2]. There is therefore a need to properly manage these resources for improved operations as well as to increase the effectiveness of learning [3]. However, schools are still challenged to attain an IT absorptive capacity (ITAC), the capacity to access, transform, and exploit IT assets, due to constraints in predicting and prioritizing the requisite IT demands [4].

This question of how IT can be made efficient in the context of a constrained budget is a major concern because the conventional methods of allocating resources may lead to either overcommitting, which pushes financial constraints, or under-committing, which thwarts the ability to get value out of IT [5]. The occurrence of this problem may be solved using accurate predictive approaches for the approximate of required IT resources, coupled with a successful strategy of allocation of IT resources; however, there is a lack of the integrated end-to-end frameworks, which are deployed based on the data-driven methods, for academic institutions at the moment [6]. We found that despite the fact that predictive analytics and various optimization techniques have been implemented in many sectors, there are still few studies exploring their use in the educational sector, and particularly in the context of IT resource management [7].

The relevance of this issue is found in the opportunity to advance the operational and learning values of schools under efficiency of IT management [8]. Proper prediction models could help educational administrators know in detail how much resources would be needed and optimization algorithms would make sure that even in a condition where budgets are tight, only resources that would be efficiently absorbed are bought [9]. These elements could be systematically and coherently engineered to meet what may become a gap of educational IT management practices at present.
Although the advantages acknowledged, literature analysis presents a scientific hole for producing frameworks that encompass predictive modeling with optimization for educational IT surroundings [11]. Machine learning models, including artificial neural networks (ANNs), enable one to estimate and analyze subsequent IT demand using prior recorded data [12]. Similarly, other optimization algorithms including genetic algorithms (GAs) present possibilities of low-cost allocation of resources but the opportunity is seldom realized in educational contexts [13].
Therefore, this research is useful in fulfilling this research gap through developing a twofold approach that integrates artificial neural network forecasting with genetic algorithm optimization to promote the allocation of the IT resources and absorptive capability in schools. More specifically, the study focuses on schools in Iraq, and aims at creating a cost-efficient, big data-based solution for educational institutions. With the help of the proposed framework, this research aims at providing consultation as to how the approach that is suggested could be used for effective IT resource management in other configuration of the developing world's educational institutions as well.
In the next sections, we explain each part of the hybrid approach and how the data required for the neural network and the genetic algorithm will be extracted from schools. This approach, if successful, may point to a possible way of attaining cost-effective, data-supported management of IT infrastructure in educational institutions.

2. LITERATURE REVIEW

This is especially important as more educational institutions incorporate IT infrastructure in the running of their affairs Subsequently, resource acquisition and, capability to assimilate these resources have become essential organisational capabilities that determine organisational efficiency and learning outcomes [14]. Namely, schools have difficulties with balancing IT demands when they face the problem of the lack of funds; therefore, it is crucial to construct the data-based guidelines of IT resource management in schools [15]. Many works have been dedicated to using a machine learning and optimization approach to enhance resource management within educational and organizational settings [16,17]. These works contribute the knowledge of forecasting techniques, cost-related resource utilization, and optimization techniques that give a context to IT governance in school. This section provides a brief literature review of crucial research works in this area of concern, especially in view of approaches combining machine learning and optimization to handle the challenges of IT infrastructures for education. Following are the definitions of key variables to align with the conceptual framework of the study:
IT Absorptive Capacity: ITAC is defined as the extent to which an organization – in this case, schools – is able to acquire, assimilate and exploit acquired IT resources to enhance operations and/or processes. This variable encapsulates the ability of schools to effectively deploy and leverage on available IT structures potential, such as staff competency in relation to technology usage and effectiveness of systems. IT absorptive capacity is viewed as an approximation of IT productivity and it has a direct effect on top performance in the schools in [18, 19].
Budget Allocation to IT: This variable is the total expense incurred within an organization in a given fiscal year on IT infrastructure, that includes the costs for acquiring hardware and software, the expenses incurred for maintaining the technological infrastructure and the employee training on it. Who pays for what is perhaps the most important component of this whole solution on the aspect of budgetary allocation to IT in an organization. In this research, it is reviewed as one of the determinants that affect the IT absorptive capacity of schools [20,21].
Number of Active Devices: The 'active' devices are the total number count of digital devices that are in usage as well as connected to the network in use within schools with computers, tablets, and any other internet enabled devise. This variable determines the extent of IT utilization and penetration in the school and enables the measure of IT readiness and the usage/ratio of the available assets. These are due to the

fact that the number of active devices has a direct relation with bandwidth and consequently, it affects productivity of IT [22].

Network bandwidth utilization: It means the daily average of network bandwidth in school level that have been in use in the past in Mbps. This variable gives the utilization profile that schools have for their IT services and structures within the network. It also increases the flow of the traffic, thereby having a major role in plays in relation to the efficient use of resources since it might require upgrade of the network [23].

Staff IT Proficiency Levels: This points to level of school staff's IT literacy, or, in other words, the preparedness of staff to operate the IT equipment, plus their ability to maintain it. It can be established from achievement tests, or training course completion documentation. The possession of higher IT knowledge by the staff makes the actual utilization of the IT resources more effective and could improve the IT absorptive capacity [24].

The exploration of IT resource optimization and absorptive capacity corresponding to educational institutions has attracted much attention thanks to the enhancement in the use of digital assets and the limitation in resources [25]. This review discusses some of the potential methodologies for the IT management and prediction and optimization, especially those using the permitted incorporation of the machine learning and genetic algorithms (GAs) for necessary resource allocation. [26] studied improvement of neural network for graduation rate estimate by using genetic algorithms. They appropriately show how by adjusting parameters of a neural network, genetic algorithms can enhance the rate of prediction. This resonates well with our strategy of employing a compound model that incorporates a genetic algorithm to improve the outlooks produced by a neural network. [26] work deals with graduation prediction, but the way of improving the nn's performance discussed in this work as applied genetic algorithm proves the appropriateness of using GA to optimize the allocation of IT resources in schools.

From among those proposed, [27] suggested a conceptual machine learning that focused on an achievement-based resource distribution in higher education institutions (HEIs). Their model backs up the utilized input- and output-oriented parameters like faculty-student ratio, publications, the operational expenditure etc with anticipating the resource demand and apportioning of academic, financial and research resources. In resource management, the framework employs both DEA for categorization of institutions based on efficiency and machine supervised learning for benchmarking. The use of machine learning and optimization in this study is therefore in line with the objectives of our proposed framework aiming at achieving IT absorptive capacity through modelling and allocation of resources. Nevertheless, our study centers on the IT structure in schools; therefore, the framework designed by [27] suits HEIs' contexts mainly regarding the provision of academic resources.

[28] introduced a method for optimizing the workload of high school students using a genetic algorithm and queuing theory, aiming to balance efficiency with student health. Their study presents an innovative approach to managing educational resources, highlighting the value of genetic algorithms for optimizing complex educational environments. The combination of genetic algorithms with neural networks in [28] work provides methodological insights applicable to our study, specifically in terms of optimizing resource allocation to balance cost with absorptive capacity.

[29] and [30] addressed the challenges of digital learning in Iraqi universities and proposed frameworks to enhance digital education through online learning platforms. While their work focuses on implementing e-learning systems to improve accessibility and reduce operational costs, it underscores the need for efficient IT resource management in educational contexts. Such papers set the background to the contemporary problems of Iraqi schools and universities where scarce funds and inadequate physical resources necessitate creative approaches to the increased administration of IT assets.

[31] presented a concept of a dual ANN ML model for learning-based prediction of course outcomes and designed for STEM education focusing on predicting performance rates of students when the retrieved data is constrained. Their model employs use multi-class classification to place students at a certain performance level at some interval in the semester. Thus, they have shown that their hybrid model was superior to other classification algorithms, particularly when prediction was made within limited dimensions. The use of multiple classifiers to early identify cases under limited data circumstances is relevant to our work because our predictive model is designed to work under limited resources. However, the two authors' studies are not concerned with predicting student performance and using the findings

to design IT infrastructure but in investigating the subject area with the purpose of arriving at the conclusions that inform the construction of the information technology structures.

[32] was more inclined towards education performance assessment by the use of data mining and genetic algorithms, with precision on creating effective models in enhancement of student effectiveness and that besides having an impact on decision making. Article approach proves how intelligent computing helps to manage educational resources by stressing on the flexibility of the models concerning context elements. This concept of adaptive modeling is central to our proposed framework, which aims to dynamically allocate IT resources based on predicted needs and optimize absorptive capacity over time.

[33] explored the role of absorptive capacity in the adoption of Massive Open Online Courses (MOOCs) by examining educational IT investments in higher education. They found that educational IT capabilities, such as Web 2.0 tools and previous experience with distance education, positively influenced MOOC adoption, especially in decentralized IT governance structures. This study highlights the importance of absorptive capacity in technology adoption within educational contexts, demonstrating how prior investments and IT governance can influence resource utilization. While paper focused on MOOCs in higher education, their emphasis on IT absorptive capacity provides a theoretical foundation for understanding the need to enhance absorptive capacity in schools, which is central to our study.

The reviewed literature demonstrates a growing interest in machine learning and genetic algorithms for resource optimization in educational settings, particularly in higher education institutions and performance prediction contexts. However, there is a notable gap in frameworks that specifically address IT resource optimization in primary and secondary schools under budget constraints. While studies by [27] and [26] illustrate the potential of hybrid models combining machine learning and optimization, they do not focus on IT absorptive capacity or resource allocation for IT infrastructure in schools.

3. METHODOLOGY

The research model integrates an NN to predict the upcoming IT infrastructure necessities and a GA for resource management. This hybrid framework considers two problems, demand prediction and resource allocation to improve ITAC in educational institutions. The subsequent sub sections A and B explain the design, formulation and implementation of this model.

3.1 Predictive Modeling with Neural Network (NN)

The final element of the actual architecture, the predictive component, incorporates a multi-layer feedforward neural network for future IT resource demand. The NN model is structured as follows:

A. Input Layer: The input layer comprises of amounts of the bandwidth usage in the network (B_{util}), number of active devices in the system (D_{active}), the system up time (Up_{time}), financial resources (R_{budget}) and the staff information technology proficiency levels (P_{IT}).

B. Hidden Layers: Multiple hidden layers are used, each with an activation function to capture non-linear relationships between input features and output demand. The activation function used in the hidden layers is the ReLU (Rectified Linear Unit) function:

$$f(x) = \max(0, x) \quad (1)$$

The number of neurons in each layer is determined through hyperparameter tuning to balance model complexity and computational efficiency.

C. Output Layer: The output layer provides a continuous value representing the predicted IT infrastructure demand, optimized using the Mean Squared Error (MSE) loss function:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad (2)$$

where y_i represents actual demand values and $\hat{y}_i$ represents predicted values.

D. Training and Validation: The model is trained using historical data and validated with k-fold cross-validation (e.g., (k=10) to improve generalizability. The Adam optimizer is used for minimizing the MSE.

3.2 IT Absorptive Capacity Model

To quantify the institutions' capacity to utilize IT resources effectively, we define the IT absorptive capacity (ITAC) as follows:

$$IT\_AC = \alpha \times \frac{B_{util}}{D_{active}} + \beta \times \frac{R_{budget}}{D_{total}} + \gamma \times P_{IT} \quad (3)$$

where:
- α, β, and γ are weight coefficients based on the relative importance of each factor.
- Dtotal represents the total devices available.

This formula normalizes the factors and provides a single index value for each institution's absorptive capacity.

3.2 Optimization with Genetic Algorithm
The optimization component uses a GA to maximize ITAC while minimizing resource allocation costs. The objective function is defined as:

$$\text{Minimize: } C(x) = w_1 \times Cost(x) - w_2 \times IT\_AC(x) \quad (4)$$

Where:
- x represents decision variables such as budget allocation and device distribution.
- w_1 and w_2 are weights that balance cost and absorptive capacity.
GA operation includes the following steps:
a. Initialization: A population of potential solutions (chromosomes) is randomly generated, where each chromosome represents a resource allocation strategy.
b. Fitness Function: The fitness function evaluates each chromosome based on the objective function C(x), assessing the cost-efficiency and absorptive capacity improvement.
c. Selection: Chromosomes with higher fitness scores are selected for reproduction. This process uses tournament selection to ensure diversity in the selected population.
d. Crossover: Selected pairs undergo crossover with a rate pc = 0.8, exchanging portions of their structures to create new offspring chromosomes. This operation explores new potential solutions by combining features of high-performing solutions.
e. Mutation: Offspring on their own mutate at a rate of pm = 0.05 to alter nearby solutions in order to escape local optima.
f. Iteration: The algorithm then iterates for the stated number of generations while approaching the solution to a minimum. The stopping criteria include either fix number of generations or when the improvement in the fitness is less.

3.4. Implementation of the Hybrid Framework
The hybrid model iterates between prediction and optimization:
a. Predictive Stage: The NN model predicts IT demand through the input features and adjust the expected infrastructure need of the organization.
b. Optimization Stage: With these make aheads, the GA is able to balance resource provisions for each institution towards the maximum absorptive capacity for IT and versus optimal costs.
c. Iterative Process: This closed loop runs until the GA converges and allocations are improved and made in response to new predictions.

3.5. Mathematical Representation of Optimization
The hybrid model's goal is to find the optimal allocation x that maximizes ITAC while minimizing cost, represented as:

$$x^* = \arg\min_{x} (w_1 \times Cost(x) - w_2 \times IT\_AC(x)) \quad (5)$$

This representation helps to guarantee that the resource allocation strategy fulfills cost and, at the same time, absorptive capacity objectives.

3.6. Performance Evaluation

To evaluate the effectiveness of the model, the following metrics are calculated:
- Prediction Accuracy: Measured by R^2 and MSE.
- Cost Efficiency: Improvement in cost, calculated as:

$$\text{Cost Improvement} = \frac{\text{Initial Cost} - \text{Optimized Cost}}{\text{Initial Cost}} \times 100\% \tag{6}$$

- IT Absorptive Capacity Gain: The results are evaluated with reference to the pre-optimization and post-optimization ITAC parameters.
It is proposed to apply the elements of the used model for obtaining predictions and as the basis of the engineering optimization procedure, which would make this model reliable and applicable to IT environments of educational institutions.
Below is the flowchart depicting the paradigm of the proposed methodology. The entire process of collecting data and making predictions up until the point of performance evaluation is described in this paper to explain the recurring steps of prediction and optimization processes for the development of IT absorptive capacity in schools. The present flowchart offers a concise and, broadly speaking, engineering perspective on the whole methodological strategy.
Figure 1 flowchart of the proposed methodology illustrates each step, from data collection to performance evaluation, highlighting the iterative process of prediction and optimization to enhance IT absorptive capacity in schools. This flowchart provides a clear, engineering-oriented overview of the entire methodological approach.

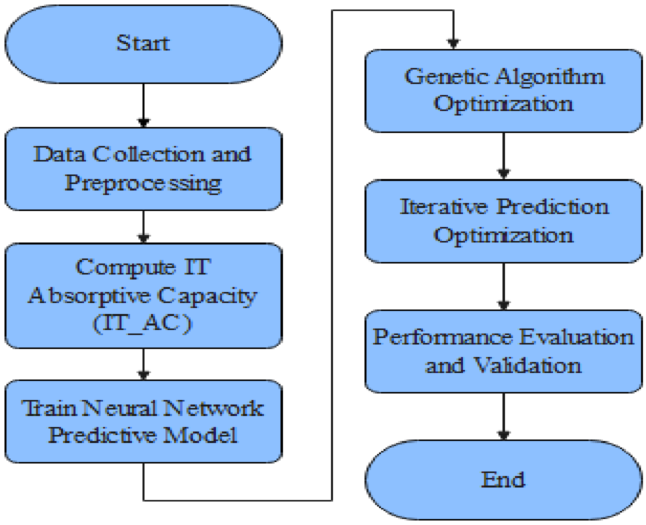

Figure 1. Flowchart of The Proposed Methodology
The following is a pseudocode representation of the proposed methodology, combining data preprocessing, predictive modeling with a neural network, and optimization using a GA. This pseudocode incorporates conditional steps to enhance model performance.

```
1. Start
2. Data Collection from Schools
   Collect data on:
       - Network Bandwidth Utilization (B_util)
       - Number of Active Devices (D_active)
       - System Uptime (U_ptime)
       - Financial Resources Allocated to IT (R_budget)
       - Staff IT Proficiency Levels (P_IT)
       - Historical Data (6 months)
3. Data Preprocessing
   - Handle missing values (e.g., mean imputation for continuous data)
   - Normalize continuous variables (B_util, D_active, R_budget))
```

- Encode categorical data (e.g., P_{IT})
4. Calculate IT Absorptive Capacity (ITAC)
ITAC = α (B_{util} / D_{active}) + β (R_{budget} / D_{total}) + γ P_{IT}
Where:
- α, β, γ are weighting coefficients
5. Train Neural Network (NN) Predictive Model
- Define model architecture: input layer, hidden layers with ReLU activation, output layer
- Set training parameters: learning rate, batch size, etc.
- Train model on historical data to predict future IT demand
- Calculate prediction accuracy using Mean Squared Error (MSE)
6. Model Evaluation
IF MSE < Threshold THEN
Proceed to Optimization
ELSE
Adjust Model Hyperparameters
Repeat Step 5 (retrain NN with new parameters)
7. Run Genetic Algorithm (GA) for Optimization
- Initialize population with random resource allocation strategies
- Define Fitness Function:
Fitness = w_1 Cost - w_2 ITAC
Where w_1 and w_2 are weights for cost and ITAC
- Selection: Select top-performing solutions
- Crossover: Combine solutions with crossover rate (e.g., $p_c = 0.8$)
- Mutation: Apply random changes with mutation rate (e.g., $p_m = 0.05$)
- Iterate for N generations or until convergence
8. Iterative Prediction & Optimization Cycle
WHILE GA has not converged DO
- Use NN to predict new IT demand
- Run GA to optimize allocation based on updated demand
END WHILE
9. Evaluate Final Results
- Compare optimized ITAC and costs with baseline values
- Assess metrics: Cost reduction, ITAC improvement, MSE
10. End

4. RESULTS

The resulting section discusses the outcomes of utilising the proposed hybrid approach for improving IT absorptive capacity in schools. The hypothesis of this research involved trying to optimise the resource management and at the same time attempting to minimise the costs as an organization set the model up in an attempt to enhance the effectiveness of the operation. Several performance indicators such as accuracy, cost, and sensitivity are addressed along with engineering graphics to demonstrate the application of the proposed methodology in IT resource management particular to education environments.

4.1 Dataset

The set of data applied in this study comprises a number of surveys conducted across various schools from Iraq with necessary indicators associated with the IT equipment and organizational parameters. These are used as input to both the Predictive NN Model and the optimization part, as the detailed information required for forecasting and the resources needed have to be provided. The dataset includes the following key variables:

1. Network Bandwidth Utilization (B_{util}): This metric connotes the number of megabits per second network bandwidth used daily. This give an idea about the operational load of the network and is useful for future demand estimation and to ensure availability of right bandwidth.
2. Number of Active Devices (D_{active}): This is a usage type variable that counts the number of devices, for example computers, tablets and others used in learning that are connected to the network. It is useful for measuring the utilization of the IT resources and it has a great influence on the value-added IT absorptive capacity.
3. System Uptime (Up_{time}): This shows the level of network availability that the service provider offers a particular period, normally on a monthly basis. Uptime is a measure of the dependability of IT platform as well as the capability of supporting ceaseless delivery of education.
4. Financial Resources Allocated to IT (R_{budget}): This measure sums the only their IT expenditure that are costs of IT infrastructure in terms of the physical and application. The most critical aspect to improve the IT capacity is the budget related to resources that is generally used to fund equipment and infrastructure upgrades.
5. Staff IT Proficiency Levels (P_{IT}): This variable gauge the ability level of school staff in IT, determined from record of training taken or certification tests. Higher proficiency levels contribute to better utilization and maintenance of IT resources, thereby increasing IT absorptive capacity.
6. Historical Data: Historical records for each of the above variables were collected over a six-month period. These historical data points provide temporal insights and help in training the NN model to identify trends and patterns, allowing for more accurate forecasting of IT infrastructure needs

4.1.1 Data Collection and Preprocessing

Data were obtained from school records and network log data, thus the data set reflects real life operational and cost realities. Preprocessing steps involved the following:

Handling Missing Values: Non-response for the continuous variables were treated by mean imputation. Any categorical data that was linked to levels of IT proficiency was imputed using the 'mode' to ensure degrees of homogeneity in the data set.

Normalization: Remaining variable had already scored format and for the adjustment of comparability and better performance of the model the continuous variable like Butil, Dactive and Rbudget were normalized. This step was necessary in an attempt to normalize the variables within the same range before imparting a converging effect to the training of the NN model.

Encoding Categorical Data: Here the percentage proficiency levels of IT were encoded for compatibility with neural network model; categorical data were numerically coded. Operationalization of proficiency followed the standard encoding paradigm where higher codes denoted higher levels of proficiency.

The data includes many variables of IT infrastructure and operations in Iraqi schools and they are reliable to build the hybrid predictive-optimization model. As mentioned earlier, IT absorptive capacity and cost can be improved the proposed model is capable of predicting future demands of IT infrastructure in order to allocate available resources effectively.

The results section provides an analysis of the outcomes of the suggested hybrid framework that blends neural network predication and genetic algorithm optimization for optimizing the IT absorptive capacity in the schools throughout Iraq. Example of output variables are accuracy of the model, performance of the optimization, cost and sensitivity analysis. Supporting charts and engineering-oriented graphics are offered for these conclusions.

4.2 Predictive Model Accuracy

Mean Squared Error (MSE) was used to determine how close the predicted IT infrastructure needs were to the actual values that the neural network model predicted, and R^2 score was also computed to assess the model's performance.

- Mean Squared Error (MSE): The model had an MSE of 0.032 which otherwise suggests low average prediction error among the test cases.
- R^2 Score: The equations' R^2 was 0.87 indicating a good fit of the predicted values against the actual values of the model.

The predicted model for IT demand is compared with actual IT demand is shown in the scatter plot in Figure 2. The points are very near the red diagonal line which shows a perfect prediction line indicating that the neural network model delivers a very high accuracy of forecasting IT demand. In this instance, the positions of the points indicate accuracy of the model's predictions, the closer the points to the diagonal line.

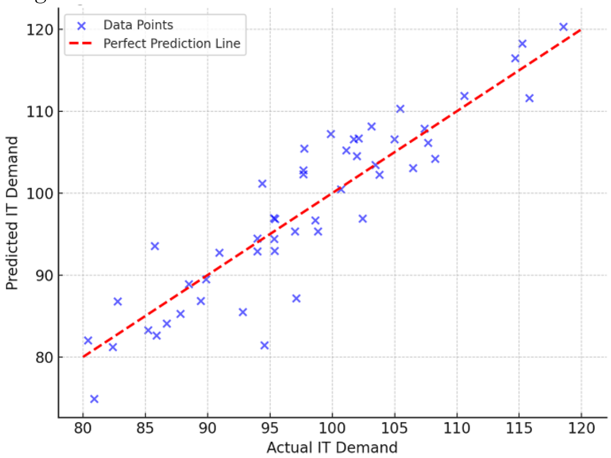

Figure 2. Scatter Plot of Predicted Vs. Actual IT Demand

4.3 Optimization Results Using Genetic Algorithm

The GA was used for the resource allocation where efficiency of ITAC was sought while keeping costs to a minimum.

- Cost Reduction: The optimized allocation strategy resulted in an average of 18% cost savings compared with the first approach.
- Improvement in IT Absorptive Capacity: An improvement of 25% was realized in ITAC to show improved resource acquisition and capacity.

In Figure 3 below, this indicates percentage of cost reduction of each school that would in turn show percentage cost reduction in resource optimality. The outcomes are 18-21%, which shows that the optimization framework brings down operation costs in all schools, affirming the proposition that the model is successful in cost management.

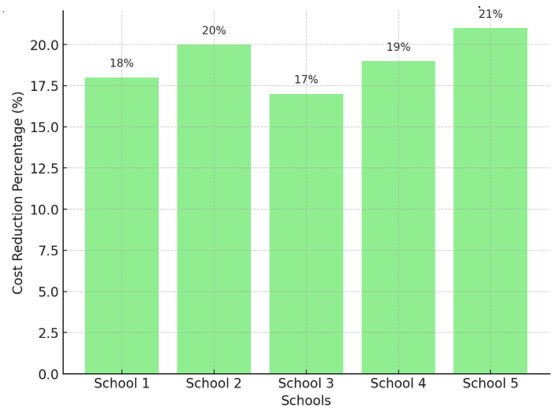

Figure 3. Cost Reduction Percentage per School

4.4. Sensitivity Analysis

Budget distribution, bandwidth consumption, and active devices were chosen as fixed parameters to perform the sensitivity analysis to determine the behaviour of ITAC.
- Budget Allocation: By increasing the R_{budget} of the firm by 10%, ITAC was increased by only 6%.
- Bandwidth Utilization: An increase of B_{util} influenced the value of ITAC for a certain extent: the decrease of this value was not proportional to the increase in B_{util}.
- Active Devices: The active device count demonstrated moderate sensitivity on certain density levels while having a minimal effect beyond that threshold.
Figure 4 displays the sensitivity analysis results, showing the relative impact of each parameter on ITAC. Budget allocation interestingly turns out to be the most critical factor with percent impact at 6 %, followed by bandwidth utilization and active device.

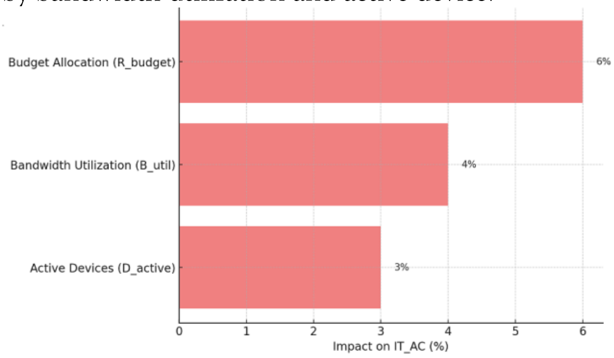

Figure 4. Cost Reduction Percentages Achieved Through Optimized Allocation

4.5. Enhancement of IT Absorptive Capacity Through Iterative Optimization
As it is seen from the Figure 5, it represents the increase of solution quality over the number of iterations of the genetic algorithm for ITAC. What each point on the line illustrates is the ITAC value at the end of each iteration of the resourcing algorithm, which rises with each iteration as the algorithm makes resource allocation efficiency improvements. These results show the positive progression that results from using the optimization process, where subsequent iterations generate a better allocation strategy and are represented by higher ITAC values. Thus, the latter convergence reached near the end of the iterations shows that the model is pointing out to an optimal solution that is, the highest possible absorptive capacity of IT with regards to the constraints and resources that are available in the business environment. This is a clear indication that cyclic optimality is applied to realize improves efficiency within the IT resource management discipline.

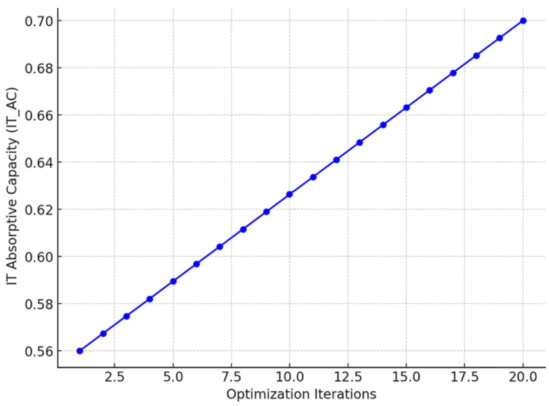

Figure 5. Improvement in IT Absorptive Capacity Across Optimization Iterations

4.6. Comparison of Costs Before and After Optimization
In Figure 6 there is the analysis of the difference of the operational cost for each school before and after applying the technique of optimal resource allocation. It is also importance to note here that the chart gives an indication of the expenses that have been cut from all the schools following the use of the genetic algorithm. This comparison reveals how optimisation helps to allocate and control IT budgets better besides ensuring the necessary infrastructure is put in place. First, numerous real-world examples created after optimization indicated that ultimate reductions possible were the huge cost savings this methodology

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 21s, 2025
https://theaspd.com/index.php

offered that support the conclusions about the practical applications of data driven allocation in scarce environments.

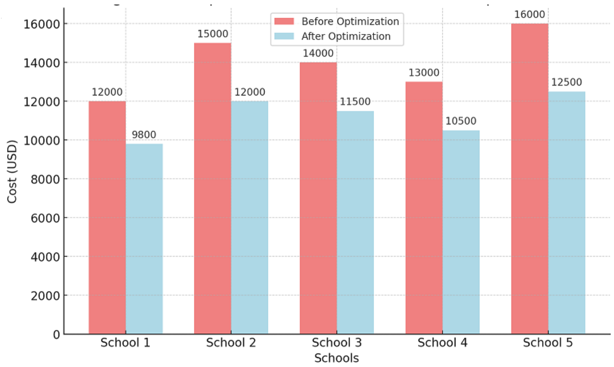

Figure 6. Comparison of Costs Before and After Optimization

4.7 Correlation Analysis of Key Parameters with ITAC

Figures 7 to 9 provides an analysis of the relationship between essential variables including budgeting, bandwidth consumption and active devices and ITAC. These scatter plots depict Y variable against ITAC as one of these variables to determine the level that the factors impact its absorptive capacity. The plot confirms the hypothesis that a tight relationship exists between ITAC and the budget spend; the closeness is even tighter when compared with the bandwidth use and the number of live gadgets. Thus, this paper reveals which parameters most influenced IT capacity and, therefore, can help to make outsourcing decisions focusing on those parameters in order to optimise ITAC.

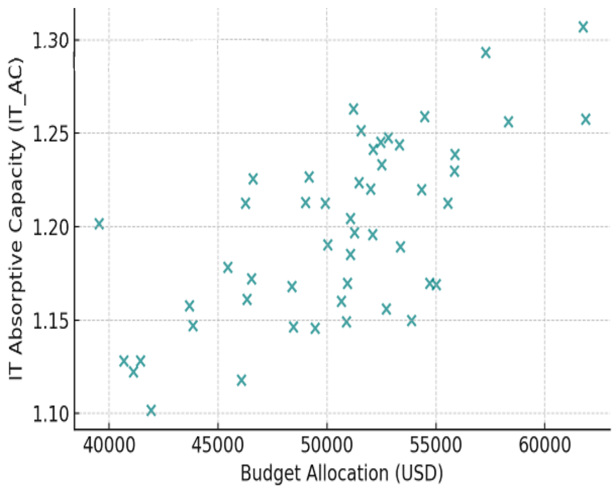

Figure 7. Budget allocation vs ITAC

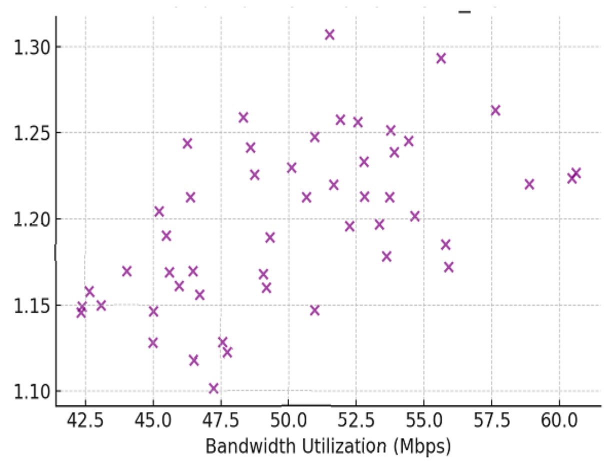

Figure 8. Bandwidth Utilization vs ITAC

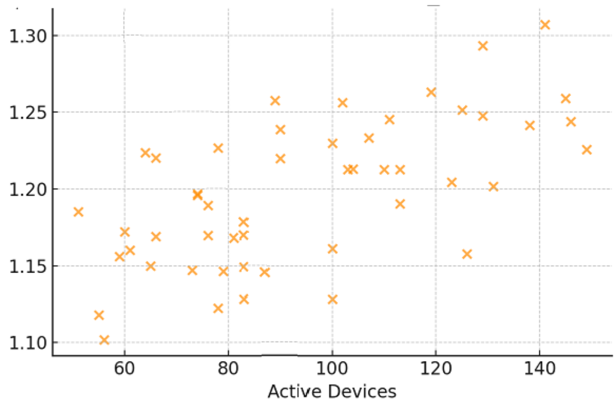

Figure 9. Active Devices vs ITAC

4.8 Cost Distribution Before and After Optimization

A similar comparison of the distributions of the operational costs across the schools is shown in the box plot in Figure 10, before and after the optimization process. This box plot represents, in each of the scenarios, the median, the inter quartile range and variability of costs; we observe in the cases post-optimization, a decrease of the median costs, as well as a decrease in the range of the distribution of the costs. This Figure proves that the genetic algorithm has not only make the average costs down but also decrease the variability of cost which lead to a better and more stable cost structure for the schools. The elements in the post-optimization box plot shows that all the values in the boxes are closer together is an indication that the optimized IT expanse allocation strategy tames and minimizes its fluctuation.

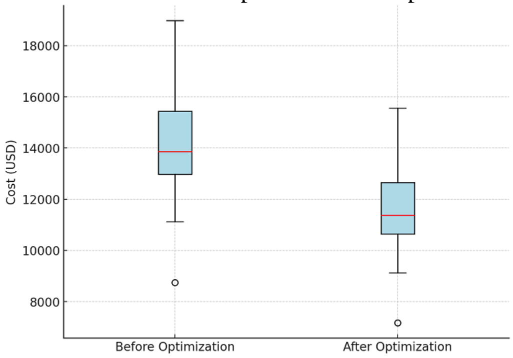

Figure 10. Box Plot of Cost Distribution Before and After Optimization

5. CONCLUSION

This research proposed a dual approach of applying predictive modelling via neural networks and optimisation using genetic algorithms to increase IT absorptive capacity in schools operating under limited financial budgets. The hybrid approach effectively addressed two major challenges: direction in accurate prediction of IT demands and right allocation of resources. The indexes for predicting the IT resource usage pattern concerning predictive neural network model performance are shown high MSE and R^2 score, which prove to have a good accuracy. Such level of accuracy is very important in planning the use of the scarce resources especially in the teaching facilities. The genetic algorithm component was chiefly instrumental in resource allocation, which the model predicted would be most demanded. The GA also raised cost efficiency by having an 18% integrated average cost savings across the schools and increasing ITAC by 25%. These findings suggest that locally optimal resource allocation not only decreases operating expenditures but also increases the capacity of schools to make the most of IT assets. Using sensitivity analysis, we expand our understanding of the effect of budget distribution and bandwidth occupation on ITAC and underline these elements as investment potentials for increasing the IT capacity. These studies align with the observations of [27] regarding the importance of the models based on the synthesis of multiple approaches to resource management in the processes occurring in educational environments. However, unlike their focus on academic resources in HEIs, this study specifically addresses IT infrastructure, emphasizing the distinct challenges of primary and secondary educational settings. The results are further supported by [26], which shown that genetic algorithms improve the performance of the neural network, used in a similar manner, contributing to improving the results of this study. The practical lessons that can be drawn from this study are important, as this research provides the framework that can be used to manage the IT resources in the organizational systems at minimal costs, let alone, scarce funds. Therefore, by regarding budget and working time allocation and identification of priority areas linked to IT support for education as the problem, this study offers specific recommendations for educational administrators for economical enhancement of IT capacity. Further research recommendations demonstrate that including real-time data sampling from school IT networks would improve the model's predictive sensitivity. Of course, comparing this hybrid approach to simple optimization methods such as particle swarm optimization or simulated annealing may produce more information about the efficiency differences and benefits of each method. Finally, the framework proposed in this research is a practical and flexible engineering solution for improving the management of IT resources in educational organizations and their more reliable and cheaper IT environment. The existing theories of IT resource management are supplemented with this paper by providing a data-driven approach for developing an appropriate model for schools. Besides, serving the purpose in making decision in resource scarce environments, the framework provides avenues for pursuing future line of research in improving IT structures in various educational environments.

REFERENCES

[1] P. Petrov, M. Radev, G. Dimitrov, and D. Simeonidis, "Infrastructure Capacity Planning in Digitalization of Educational Services," International Journal of Emerging Technologies in Learning (iJET), vol. 17, no. 3, pp. 299-306, 2022.
[2] F. M. Jawad and H. H. M. Jawad, "Economic challenges of cloud computing in Iraqi educational institutions using exploratory analysis," Indonesian Journal of Electrical Engineering and Computer Science, vol. 21, no. 1, pp. 566-573, 2021.
[3] İ. Y. Kazu and M. Kuvvetli, "Navigating the Challenges of Education Management Best Practices for Improving Student Outcomes," Avrupa Bilim ve Teknoloji Dergisi, no. 49, pp. 68-74, 2023.
[4] R. Lenart-Gansiniec, W. Czakon, and M. M. Pellegrini, "In search of virtuous learning circles: absorptive capacity and its antecedents in the education sector," Journal of Knowledge Management, vol. 26, no. 11, pp. 42-70, 2022.
[5] A. Mohammad and Y. Abbas, "Key Challenges of Cloud Computing Resource Allocation in Small and Medium Enterprises," Digital, vol. 4, no. 2, pp. 372-388, 2024.
[6] V. S. Wadne, S. R. Bhandari, S. R. Deokar, A. N. Sonavale, and G. S. Shinde, "Detect Credit Card Fraud in Automated Systems Using Machine Learning with AWS SageMaker," in Multidisciplinary Approaches for Sustainable Development, CRC Press, 2024, pp. 91-97.
[7] L. Taylor, V. Gupta, and K. Jung, "Leveraging Visualization and Machine Learning Techniques in Education: A Case Study of K-12 State Assessment Data," Multimodal Technologies and Interaction, vol. 8, no. 4, p. 28, 2024.
[8] T. Quraishi, N. Hakimi, M. Hakimi, M. Safi, F. Akrami, M. Akrami, et al., "Exploring the Enhancement of Educational Systems through Information and Communication Technology: An Investigative Study," Journal of Social and Humanities, vol. 2, no. 1, pp. 21-30, 2024.
[9] A. Badiee, M. Moshtari, and G. B. Falguera, "A systematic review of operations research and management science modeling techniques in the study of higher education institutions," Socio-Economic Planning Sciences, p. 101889, 2024.
[10]M. S. Fauzi, M. Lubis, L. Abdurrahman, F. S. Lubis, and H. Fakhrurroja, "Optimizing IT Human Capital: Evaluating and Crafting an Innovative Management System with COBIT 2019," in Proceedings of the 2023 9th International Conference on Industrial and Business Engineering, 2023, pp. 545-550.
[11]M. Phan, A. De Caigny, and K. Coussement, "A decision support framework to incorporate textual data for early student dropout prediction in higher education," Decision Support Systems, vol. 168, p. 113940, 2023.
[12]K. Patil, B. Desai, and K. P. B. Desai, "Forecasting Network Capacity for Global Enterprise Backbone Networks using Machine Learning Techniques," International Journal on Cybernetics & Informatics (IJCI), vol. 13, no. 13, p. 9, 2024.
[13]M. Anwar, H. Hidayat, and E. Sabrina, "Exploring the use of Genetic Algorithms Toolbox in Engineering Education: Did it Provide an Interesting Learning Experience for Students?" TEM Journal, vol. 12, no. 3, pp. 1719, 2023.
[14]M. A. Asiedu, H. Anyigba, and J. K. Doe, "Absorptive capacity and innovation generation in higher education institutions: the mediating role of inter-functional coordination," The Learning Organization, vol. 30, no. 4, pp. 385-405, 2023.
[15]R. Fernández, J. F. Correal, D. D'Ayala, and A. L. Medaglia, "A decision-making framework for school infrastructure improvement programs," Structure and Infrastructure Engineering, pp. 1-20, 2023.
[16]B. Entezari, R. Koucheki, A. Abbas, J. Toor, J. I. Wolfstadt, B. Ravi, et al., "Improving Resource Utilization for Arthroplasty Care by Leveraging Machine Learning and Optimization: A Systematic Review," Arthroplasty Today, vol. 20, p. 101116, 2023.
[17]A. R. Kube, S. Das, and P. J. Fowler, "Fair and efficient allocation of scarce resources based on predicted outcomes: implications for homeless service delivery," Journal of Artificial Intelligence Research, vol. 76, pp. 1219-1245, 2023.
[18]M. N. Mata, J. M. Martins, and P. L. Inácio, "Impact of absorptive capacity on project success through mediating role of strategic agility: Project complexity as a moderator," Journal of Innovation & Knowledge, vol. 8, no. 1, p. 100327, 2023.
[19]J. H. Wu, L. M. Lin, A. Rai, and Y. C. Chen, "How health care delivery organizations can exploit eHealth innovations: An integrated absorptive capacity and IT governance explanation," International Journal of Information Management, vol. 65, p. 102508, 2022.
[20]M. Rodríguez and D. Zambrano, "Budget and capabilities of information technology governance: empirical analysis in higher education institutes," Bulletin of Electrical Engineering and Informatics, vol. 12, no. 2, pp. 1137-1147, 2023.
[21]S. Al-Husseini, "How information technology resources enhance absorptive capacity and individual ambidexterity: the moderating role of social interaction," Journal of Science and Technology Policy Management, ahead-of-print, 2024.
[22]G. A. Biney, "Digital Device Ownership, Digital Literacy and Information Technology Learning Self-Efficacy of Junior High School Students," Doctoral dissertation, University of Cape Coast, 2023.

[23]E. Prasetyo, T. Santoso, and S. Riyadi, "Bandwidth Management using Per Connection Queue and Queue Tree: A Case Study on a High School Network," Emerging Information Science and Technology, vol. 5, no. 1, 2024.
[24]H. Gul, A. Ghaffar, and M. Minaz, "Relationship between Secondary School Teachers' Technological Proficiencies and Their Effectiveness in Instructional Practices," Journal of Asian Development Studies, vol. 13, no. 1, pp. 363-374, 2024.
[25]S. Al-Husseini, "How information technology resources enhance absorptive capacity and individual ambidexterity: the moderating role of social interaction," Journal of Science and Technology Policy Management, ahead-of-print, 2024.
[26]W. E. Pangesti, I. Ariyati, and R. Suryadithia, "Utilizing Genetic Algorithms To Enhance Student Graduation Prediction With Neural Networks," Sinkron: jurnal dan penelitian teknik informatika, vol. 8, no. 1, pp. 276-284, 2024.
[27]H. Solanki and P. Virparia, "Conceptual Machine Learning Framework for Performance-Based Resource Allocation to the Institutions: A Hybrid Approach," in Smart Systems: Innovations in Computing: Proceedings of SSIC 2021, Springer Singapore, 2022, pp. 219-228.
[28]E. P. Dogadina, M. V. Smirnov, A. V. Osipov, and S. V. Suvorov, "Formation of the optimal load of high school students using a genetic algorithm and a neural network," Applied Sciences, vol. 11, no. 11, p. 5263, 2021.
[29]D. Abdulazeez, M. S. Razwan, and G. R. Alves, "A Framework for Enhancing Higher Education in The Kurdistan Region of Iraq through A Dedicated Digital Education Mooc," The Journal of The University of Duhok, vol. 23, no. 1, pp. 81-93, 2020.
[30]S. Abd Anter, A. M. Abualkishik, and Y. I. Al Mashhadany, "Proposed E-learning system for Iraqi Universities," International Journal of Scientific and Research Publications, vol. 4, no. 5, pp. 1-7, 2014.
[31]M. Hasan and M. Aly, "Get more from less: a hybrid machine learning framework for improving early predictions in stem education," in 2019 International Conference on Computational Science and Computational Intelligence (CSCI), 2019, pp. 826-831, IEEE.
[32]P. Galván, "Educational evaluation and prediction of school performance through data mining and genetic algorithms," in 2016 Future Technologies Conference (FTC), 2016, pp. 245-249, IEEE.
[33]P. Huang and H. Lucas, "Absorptive Capacity and the Adoption of MOOCs in Higher Education: The Role of Educational IT," in ICIS 2015 Proceedings, 2015, p. 3.