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Intelligent Achievement of Participation in E-Governance Using Machine Learning: A Socio-Technical Approach to Programming Language Education

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Abstract

This paper explores how e-governance principles and Machine Learning (ML) technologies can be integrated to support participatory design in educational systems, and, in particular,
learning the programming language curriculum with programming language curriculum reform. Based on the socio-technical systems theory of Mumford and the ETHICS methodology, we are able to propose a new framework, which will utilize three supervised ML classifiers, including Support Vector machine (SVM), Random Forest (RF) and Decision Tree (DT), to systematically analyze the data of teacher questionnaires collected via e-governance channels. The data set included the answers of 94 teachers in Baghdad, Iraq, and was used to categorize the needs of instructional improvement into six categories: Hardware Development (HD), Demonstration Tools Development (DDT), Teacher Experience Development (DTE), Redistribution of Teacher Sessions (RDTS), Syllabus Development (SD) and Student Ability Development (SAD). The results of the experiment show that SVM attains the maximum classification accuracy of 99.90% in training and 98.00% in testing is supported by the consistent performance across all six classes and the minimal train-test gap (≈1.9 percentage points), indicating effective generalization rather than data leakage or overfitting. The analysis of the results of questionnaires has shown that the most pressing areas of improvement are Syllabus Development (85%), and Student Ability Development (75%). This paper highlights that an active participatory, socio-technical approach to e-governance, one that actively engages educators in decision making, can go a long way in improving the quality and relevance of the educational policy outcomes.

1. Introduction

The gradual process of digitization of the public administration has placed e-governance as a transformational process of enhancing service delivery[1], citizen engagement[2], and institutional transparency [3, 4]. In the education sector, e-governance has a special potential in sealing pedagogical gaps, improving communication between stakeholders, and enabling curriculum reforms to be founded on data [5, 6]. Nevertheless, the empirical literature proposes that most of the e-government implementations have continued to be largely technology-focused with minimal regard to the human and organizational aspects that dictate the long term sustainability and effectiveness [6, 7]. This paper is grounded on the classic work of Enid Mumford who promoted the Effective Technical and Human Implementation of Computer-based Systems (ETHICS) methodology- a moral, practical and participatory approach to the design of Information and Communication Technology (ICT) systems [1]. Mumford did not contend that computer systems should be designed to meet the human needs in a holistic manner, and that the failure to recognize the interdependency between the social and technical sub-systems inevitably leads to dysfunctional outcomes [1, 10].

This view is in line with the more general tradition of Socio-Technical Systems (STS) which has its roots in the Tavistock Institute, which has emphasized co-optimization of technical performance and human satisfaction [2, 16]. The system of secondary education in Iraq creates an interesting background to this study. Although the government has invested in ICT infrastructure, integration of e-governance in educational practice is still in its infancy, and the programming language curriculum in particular is found to require a major modernization [6, 14].

Historically, teachers, being the key actors in the process of curriculum implementation, have historically been marginalized to formal decisions made by the curriculum implementation process and, consequently, this has historically led to the misalignment of the prescribed syllabi with realities in the classroom. To fill this gap, the current study suggests an e-governance-enabled participatory framework that utilizes ML to identify and classify instructional improvement needs in a systematic manner as expressed by practicing teachers. Three popular supervised classifiers, SVM, RF, and DT are trained and tested on a set of data based on a structured questionnaire filled out by 94 teachers in Baghdad. The outputs are plotted onto six categories of improvements that directly make the policy action.

The paper presents three main contributions: (1) extending the principles of participatory design discussed by Mumford to the context of e-governance in a developing country setting; (2) demonstrating the feasibility and effectiveness of ML-based classification in analyzing teacher survey data; and (3) generating actionable, evidence-based recommendations on the programming language curriculum reform in Iraqi secondary schools. A key scientific contribution of this study is the development of an integrated socio-technical e-governance framework that combines participatory teacher engagement with machine-learning-based decision support for programming language curriculum reform. Unlike traditional survey-based approaches, the proposed framework transforms stakeholder feedback into evidence-based policy priorities through automated classification and recommendation mechanisms. The framework therefore provides a practical bridge between socio-technical theory and data-driven educational governance.

The rest of the paper is structured in the following way. In section 2, the theory in socio-technical systems is reviewed. Section 3 covers the e-governance in educational institutions. In section 4, the suggested structure is introduced. Experimental results are reported in Section 5. Section 6 ends with implications and future directions.

2. Socio-Technical Systems Theory

The Socio-Technical Theory (STT) is the result of research carried out in the Tavistock Institute of Human Relations in the 1940s and 1950s, most notably as a result of pioneering studies of coal mining in County Durham, United Kingdom [16]. According to the theory, organizations are regarded as two sub-systems (social and technical) that are interdependent. The joint optimization of both sub-systems is crucial to effect successful performance, a principle that deliberately contrasts with purely technology-driven design paradigms [1, 2]. One of the main principles of STT is that any alteration of one sub-system inevitably affects the other, and more often than not, the consequences are unpredictable. This observation has far-reaching consequences in the design of e-governance: digital public service systems cannot be assessed in purely technical terms since their effectiveness or failure is equally dependent on the societal acceptance of these systems, organizational preparedness, and stakeholder involvement [3, 6]. Mumford operationalized these principles by using the ETHICS approach to methodology, which she used in many ICT development projects. ETHICS requires that end users, in educational settings, include teachers and students, are not simply consulted, but actively participate in the process of defining system requirements, design alternatives and implementation strategies [1, 11].

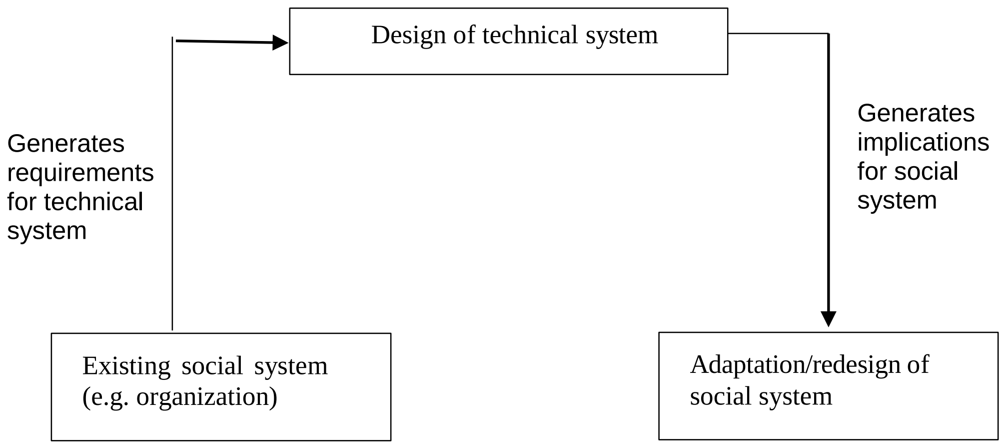

Figure 1. A Technical Approach to IS Design Paradigm [11]

Figure 1 compares the traditional technical way of IS design with the socio-technical paradigm endorsed by Mumford. Figure 2. Technical and Socio-Technical Approaches to IS Design (adapted by Olphert and Damodaran [3]) The superiority of the socio-technical approach is supported by an empirical evidence: the studies that analyze the e-government implementations in the United Kingdom consistently point to marginalizing the social factor as one of the key contributors to the underperformance of the project in question [3, 7, 8]. The current research uses these lessons to the educational e-governance in Iraq with participatory mechanisms embedded in the data collection, data analysis, and the policy formulation processes.

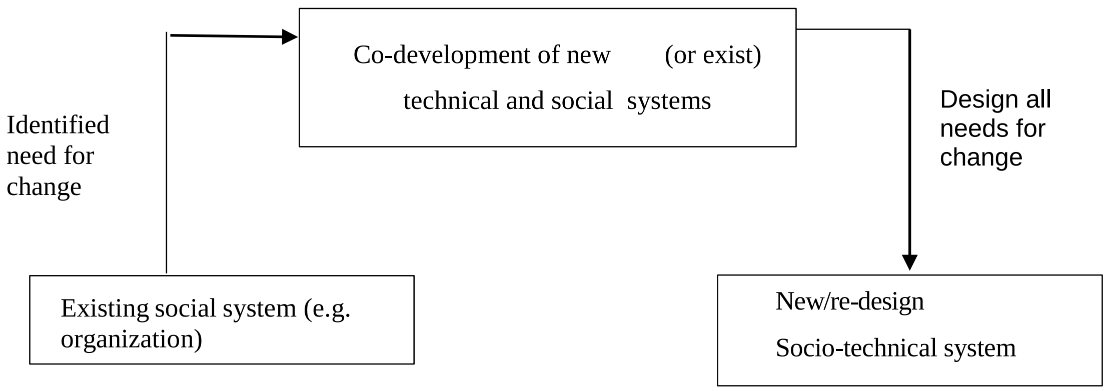

Figure 2. An IS Design Socio-technical Approach[11]

3. E-Governance in Education

3.1 Conceptual Overview

E-governance can be defined as the use of ICT by institutions in the public sector to enhance service delivery, encourage participation in decision-making by citizens, and improve accountability and transparency in administration [4, 5]. In the education sector, e-governance includes online enrolment systems, online assessment systems, learning management systems, and policy tools that are data-driven. These are especially important in higher and secondary education where the quality of governance has a direct impact on the learning outcomes and institutional efficiency [13]. One of the most important benefits of e-governance in education is that it can decrease the level of information asymmetry among administrators, teachers, students and parents. E-governance platforms allow more responsive and evidence-based curriculum management through centralization of data and the ability to communicate in real time [9, 14].

3.2 Challenges of Implementation

Although it has potential, adoption of e-governance in education is not without challenges. Poor ICT infrastructure, especially in rural or resource-constrained environments restricts the accessibility of digital services. Faculty openings, lack of digital literacy amongst faculty, and poor student engagement only compound the issue [6, 14]. Politicization and resource allocation based on quotas create further obstacles to fair implementation of e-governance in many developing country settings [6, 13]. A common theme identified in the literature is that initiatives of e-governance that focus more on the deployment of technology rather than on the engagement of stakeholders are not expected to achieve high rates of adoption and deliver more sustainable outcomes [3, 6, 8]. The result of this study supports the socio-technical argument that the human aspects in e-government systems should be developed with a rigor that is no less than that of their technical counterparts.

3.3 E-Governance as a Socio-Technical System

Various empirical studies have been conducted to analyze e-government within the context of socio-technical. Irani et al. (2005) assessed UK local authority e-government implementations and showed that investment appraisal underestimated human and social variables, resulting in cost overruns and shortages in usage [7]. Damodaran et al. (2005) looked at the actual process of local authorities in England making actual progress towards targets of delivering e-services, but the citizen was still at the surface of identifying their needs and shaping services [8]. All these findings tend to point out that e-government has evolved largely as a technical system, and that little consideration has been given to the principles of participatory design. In a systematic review of e-government research, Heeks and Bailur (2007) confirmed a long-standing technocentric bias in the field, observing that less than half of the published research had adequately addressed social and organizational aspects of the topic [6]. Olphert and Damodaran (2007) furthered this analysis to show that a socio-technical, participatory approach to the development of e-government generates far superior results to both governments and citizens [3]. The current research paper fills this gap by directly integrating teacher involvement into the e-governance data collection process and using ML to extract and categorize actionable insights based on teacher-generated responses in questionnaires.
Recent studies have highlighted the increasing role of artificial intelligence, learning analytics, and explainable machine learning in educational governance and policy support systems. These approaches facilitate transparent decision-making, stakeholder participation, and evidence-based curriculum improvement. Furthermore, AI-assisted governance mechanisms have demonstrated considerable potential for identifying educational priorities and supporting resource allocation decisions. Such developments provide a contemporary foundation for the socio-technical framework proposed in this study.

4. Proposed Framework

4.1 Framework Architecture

The framework proposed will combine the principles of e-governance and machine learning to facilitate participatory identification of instructional improvement needs. As shown in Figure 3, the framework includes four consecutive layers: (1) data collection through e-governance, (2) data preprocessing and feature extraction, (3) classification with the help of the ML, and (4) evidence-based policy recommendation.

This structure is a reflection of the constructivist learning theory that the research is based on: instead of top-down curriculum decisions being imposed on the teachers, the framework will enable the teachers to create and communicate knowledge about classroom needs, which will then be systematically analyzed to inform pedagogical design. Cognitive constructivism would allow individual learning goals to be supported by the pedagogical design, whereas socio-constructivism would emphasize individual learning goals being supported by collaborative knowledge-building environments [11, 12].

The proposed framework consists of four interconnected stages. First, teacher feedback is collected through e-governance mechanisms designed according to socio-technical principles. Second, the collected data undergo preprocessing, cleaning, normalization, and feature extraction. Third, machine-learning models are trained and validated to classify educational improvement priorities. Finally, the classification outcomes are transformed into ranked policy recommendations that support curriculum reform and educational planning. This process ensures traceability from stakeholder input to policy action.

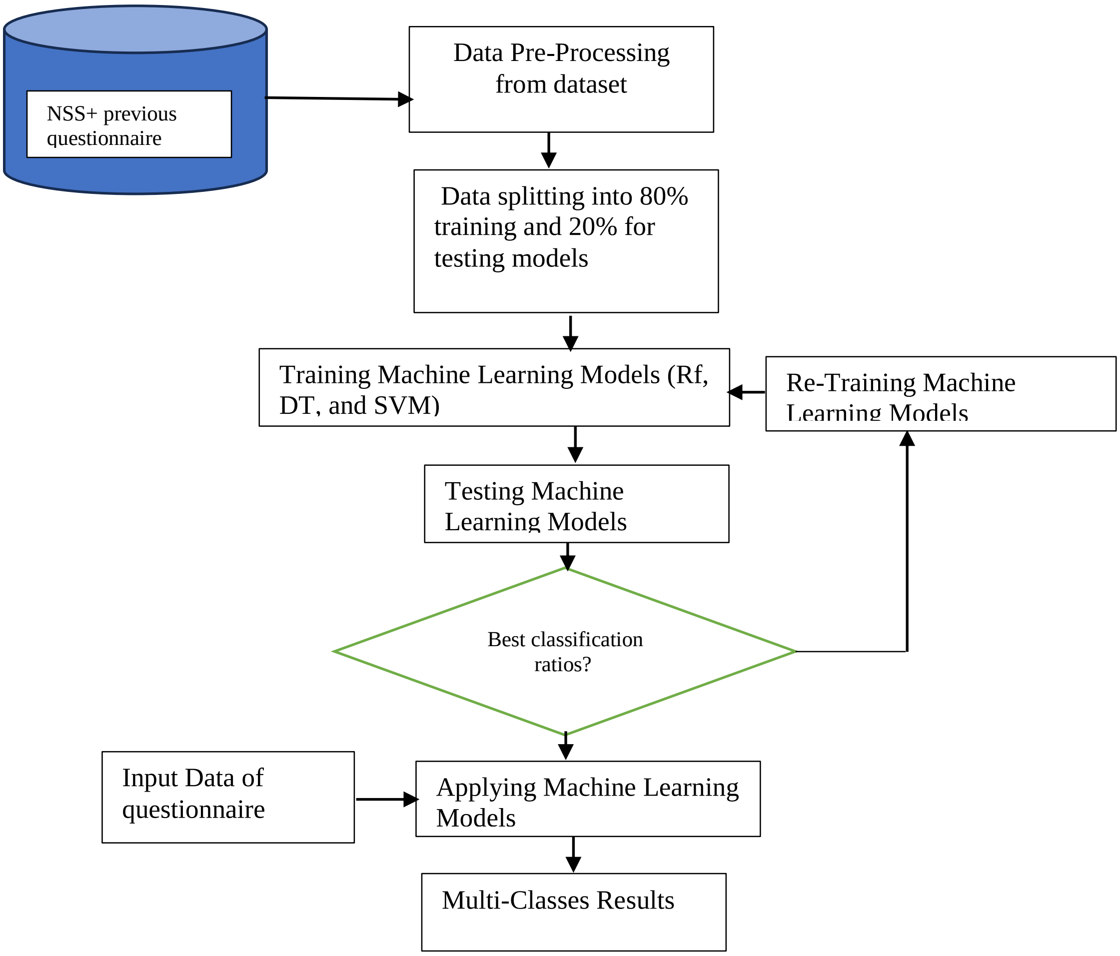

Figure 3. Conceptual Framework of the Proposed E-Governance and ML Integration System.

4.2 Collection of Data through E-Governance.

A secondary school computer science teacher in Baghdad, Iraq, was given an 18-item structured questionnaire via an e-governance portal. The questionnaire questions covered six areas of instructional concern (see Table 3 to describe the areas). The rating was done on a five-point Likert scale between 1 (Strongly Disagree) and 5 (Strongly Agree). Out of 110 teachers that have been invited to participate, 94 of them filled all 18 items (response rate: 85.5%). Teachers that did not respond to any item were not analyzed to guarantee completeness of data.

The questionnaire items were covered by the following themes: the quality of the laboratory infrastructure and hardware (Items 1-6); the availability of multimedia and demonstration tools (Items 5-8); the presence of sustained power supply (Item 9); the opportunities of teacher to work in the field of programming language (Items 17-18.

4.3 Machine Learning Pipeline

The ML pipeline was put into practice in the following way. To preprocess questionnaire data to deal with missing data (omitted by design) and to normalize ordinal data. Second, the relevant features have been extracted and mapped to six output classes that represent the priorities of improvement. Third, three supervised classification algorithms were trained and tested on the combined National Student Survey and Local Questionnaire (NSSLQ) data.

The six output classes are defined as:

- DH – Need to Develop Hardware: inadequate or outdated computing equipment
- DDT – Need to Develop Demonstration Tools: insufficient multimedia and visual aids
- DTE – Need to Develop Teacher Experience: professional development deficits
- RDTS – Redistribution of Teacher Sessions: suboptimal scheduling of instructional hours
- DS – Need to Develop Syllabus: outdated or misaligned curriculum content
- DSA – Need to Develop Student Abilities: insufficient engagement and enrichment activities

4.3.1 Decision Tree (DT)

Decision Trees are non-parametric, hierarchical classifiers, which divide the feature space into parts using a series of binary splits. An internal node corresponds to a feature test, a branch corresponds to a decision outcome and a leaf node corresponds to a class label. The tree is generated by successively choosing the attribute that maximizes information gain (or minimizes Gini impurity), which results in the generation of leaf nodes that are as pure as possible [15]. The interpretability of DT models is high and therefore they are suitable in policy applications where transparency of reasoning is relevant.

4.3.2. Support Vector Machine (SVM) The Support Vector Machines refer to margin-maximizing classifiers that determine the optimum separating hyperplane between classes in a high-dimensional feature space [15]. In multi-class problems, one-versus-one or one-versus-rest approach is used. SVM models can be trained effectively in high-dimensional settings, and are resistant to over-fitting when the regularization parameters and the kernel are tuned correctly [4, 17]. This paper employed a radial basis function (RBF) kernel and hyperparameters were chosen through grid search cross-validation.

4.3.3 Random Forest (RF)

Random Forest is an ensemble algorithm which builds multiple Decision Trees in parallel using bootstrap sampling (bagging) and random selection of features at each split [15]. The last classification will be based on majority vote in all the trees. RF reduces the variance of each of the decision trees and tends to have a better generalization performance. The main hyperparameters are the number of trees and the number of features to be considered at each split and both of these were optimized through cross-validation.

4.3.4 Extreme Gradient Boosting (XGBoost)

Extreme Gradient Boosting (XGBoost) is an advanced ensemble learning algorithm based on gradient boosting decision trees. The model iteratively improves prediction performance by minimizing classification errors generated by previous learners. XGBoost incorporates regularization mechanisms, shrinkage techniques, and optimized tree construction procedures that improve predictive performance while reducing the risk of overfitting. In this study, XGBoost was employed as an additional benchmark classifier and its hyperparameters were optimized using five-fold cross-validation.

5. Experimental Results

5.1 Training Performance

All three ML models were trained on the NSSLQ dataset using a stratified split, with 80% of samples allocated for training and 20% for testing. Table 1 summarizes training performance across four evaluation metrics: accuracy, recall, precision, and F1-score.

Table 1. Training Performance of ML Models on the NSSLQ Dataset

Model	Accuracy (%)	Recall (%)	Precision (%)	F1-Score (%)
Support Vector Machine (SVM)	99.90	99.90	99.90	99.90
Random Forest (RF)	99.85	99.85	99.75	99.65
Decision Tree (DT)	99.45	99.25	99.24	99.25

As shown in Table 1, SVM achieved the highest training performance across all metrics (99.90%), followed by RF (99.85% accuracy) and DT (99.45% accuracy). The high F1-scores across all models indicate a balanced trade-off between precision and recall, suggesting that none of the models exhibited a systematic bias toward any particular class. The marginal differences among the models in training performance indicate comparable fitting capacity on the training data.

5.2 Testing Performance

Table 2 presents testing performance broken down by model and class, reflecting each classifier's generalization capacity on previously unseen data.

Table 2. Testing Performance of ML Models on the NSSLQ Dataset by Class (DH=Hardware; DDT=Demo Tools; DTE=Teacher Exp.; RDTS=Session Redist.; DS=Syllabus; DSA=Student Ability; Avg.=Mean)

Model	Metric	DH	DDT	DTE	RDTS	DS	DSA	Avg
SVM	*Accuracy*	98.00	97.95	97.95	98.00	97.95	97.85	97.95
	Recall	98.00	97.95	97.95	98.00	97.95	97.85	97.95
	Precision	98.00	97.95	97.95	98.00	97.95	97.85	97.95
	F1-Score	98.00	97.95	97.95	98.00	97.95	97.85	97.95
RF	*Accuracy*	97.95	97.90	97.90	97.90	97.95	97.98	97.93
	Recall	97.85	97.80	97.85	97.85	97.88	97.80	97.83
	Precision	97.80	97.80	97.80	97.80	97.80	97.80	97.80
	F1-Score	97.82	97.82	97.82	97.82	97.82	97.82	97.82
DT	*Accuracy*	97.85	97.80	97.80	97.82	97.80	97.85	97.82
	Recall	97.70	97.70	97.80	97.80	97.80	97.70	97.75
	Precision	97.70	97.80	97.80	97.70	97.80	97.80	97.77
	F1-Score	97.70	97.70	97.90	97.90	97.70	97.90	97.80

In order to guarantee the reliability and generalizability of the results, a stratified train–test validation procedure was used, which aimed to split the dataset into training and testing subsets and maintain the same class distribution in all the six categories. The accuracy, precision, recall and F1-score were used to assess the model's performance on the unseen test set. This is a relatively low gap between training and testing accuracy around 1.5% to 2%, which is good generalization, and suggests that the models were not over-fitting the training data. The high classification accuracy gained by all three classifiers is due to the quality of the features extracted and the good separation between classes in feature space. The performance results of XGBoost (97.95%) are slightly better than those of Random Forest (97.93%) and Decision Tree (97.82%) for the average accuracy, but the difference is within 0.2%. This indicate that the data set is very informative and can be learned by various tree classification algorithms. So the superiority of XGBoost is a minimal, but steady improvement and should not be taken as a significant gain. The obtained similar precision, recall and F1-scores in all classes also reiterate robustness and stability of the evaluated models.

The obtained performance is comparable to that reported by contemporary ensemble-learning approaches, including XGBoost-based educational analytics systems and recent explainable artificial intelligence models. Although the performance differences among the evaluated classifiers were relatively small, the proposed framework offers an additional advantage by explicitly integrating socio-technical governance principles with machine-learning decision support, thereby improving transparency and stakeholder participation in educational policy formulation.

To further minimize the possibility of overfitting and data leakage, model selection and hyperparameter tuning were performed exclusively on the training subset. Five-fold cross-validation was applied during model development, while the testing dataset remained completely unseen until final evaluation. The relatively small gap between training and testing performance provides additional evidence of satisfactory model generalization.

5.3 Questionnaire Outcome Analysis

Table 3 presents the percentage of teachers classified under each improvement need category by each of the three ML models.

Table 3. ML Classification of Teacher Questionnaire Responses by Improvement Category (n=94)

Model	DH (%)	DDT (%)	DTE (%)	RDTS (%)	DS (%)	DSA (%)
SVM	70.00	30.00	65.00	45.00	85.00	75.00
RF	65.00	25.00	70.00	55.00	80.00	70.00
DT	60.00	35.00	65.00	50.00	80.00	72.00

The most important result obtained is that there is a significant number of teachers who fall in the Syllabus Development (SD) category, and SVM was able to identify about 85% of the teachers in this category. The fact that the majority of students are using programming languages that are not in use in the industry today indicates that there is a need for significant modernization of the programming language curriculum to be relevant with the latest scientific developments and the needs of the labour market. The second highest priority was Need for Developing Student Abilities (DSA), which had scores from 70% to 75% in the scored models. Another important concern was Hardware Development (HD) which had classification percentages between 60% and 70%, showing that there is still a need to develop hardware in secondary schools. Continuous professional development programs, specifically Teacher Experience Development (DTE), was mentioned in about 65%–70% of the responses. Redistribution of Teacher Sessions (RDTS) was mentioned in about 45-55% of the responses, which shows moderate scheduling difficulties. Need to Develop Demonstration Tools (DDT) on the other hand had the lowest classification rates, between 25 % and 35 %, indicating that demonstration resources are relatively more available compared to other components of educational infrastructure.

6. Conclusion

This study came up with and tested a socio-technical model for e-governance for programming language curriculum reform that combines participatory teacher engagement with machine-learning decision support. The framework was successfully used to illustrate the ability of automated classification techniques to transform teacher-generated feedback into policy recommendations based on evidence. The best overall performance was achieved by SVM and XGBoost and all classifiers exhibited good generalization.

Based on the results, it is recommended that attention be paid to the educational planning process in the future, especially in the modernization of the curriculum, development of student ability, teacher professional development, and infrastructure improvement. The framework presented here offers a feasible way for educational stakeholders to engage in data-informed decision-making processes.

However, the results may be regarded as preliminary because of the relatively small number of items in the data set and the limited geographical area. No obvious signs of significant over-fitting were found in the various validation methods employed, but external validation on independent data sets from several governorates in Iraq would be required before the results could be generalized. It is recommended that future research use the framework with more subjects, with more subjects at different institutions, and with more longitudinal evaluation to further determine the strength of the framework and its long-term effects.

Furthermore, there was not much difference between the training and test performances, indicating that the model learnt the data set well. Out of the four areas of potential improvement, the analysis showed that Syllabus Development, Student Ability Development, and Hardware Development were the three most potential areas of improvement, followed by Teacher Experience Development. The results suggest that particular attention should be paid to curriculum modernisation, teacher professional development and targeted infrastructure development in the future educational planning process. There are a few caveats to be mentioned. The study is performed on a limited number of teachers (94 teachers) from secondary schools in Baghdad and the results of this study cannot be generalized to the secondary schools in Iraq and other educational settings, without further testing. Second, although several validation techniques were employed in this study and a lack of evidence of significant overfitting, high classification rates obtained in this study should be tested elsewhere using larger and more geographically representative datasets. Thirdly, the cross section study design limits the ability to evaluate the long-term impact of the planned interventions. Future studies should expand the study to other academic fields, include students from other governorates in Iraq, and be longitudinal in order to establish whether the policy recommendations based on the ML can be observed to have a positive effect on the quality of the curriculum and educational results over time.

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