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Use of Machine Learning to Validate an Intelligent Framework to Support Decision Making in the Public Sector

Álvaro Farias Pinheiro*, Wylliams Barbosa Santos and Fernando Buarque de Lima Neto

University of Pernambuco, Recife, Brazil

ABSTRACT

Problem: Currently, many public organizations have adopted applications for process automation to avoid repetitive work and produce more efficient results; however, the development of intelligent mechanisms to support complex decision-making is not often observed. In public services, in particular, difficulties may be related to the abundance of data sources and the number of legal norms to comply with.

Objective: A formal specification of a framework for the application and service layer suitable for public services with machine learning to support decision-making by technology and business experts.

Method: In this study, the Design Science Research Methodology (DSRM) method was used, dividing the work into the following stages: (i) identification of the problem and motivation; (ii) definition of the objectives; (iii) planning, design, and development; (iv) demonstrations of the simulations; (v) verification and validation of the experiments; and (vi) communication of results. Interspersed with Domain Engineering (DE) in three stages: (i) Domain Analysis, (ii) Domain Design, and (iii) Domain Implementation. Results: This research was carried out: (i) elicitation of characteristics for an Intelligent Framework for the Public Sector, (ii) execution of Domain Engineering in Public Sector projects to obtain the characteristics, (iii) construction of an architectural model with machine learning by reinforcement, and (iv) instantiation of the framework for its validation using five experimental cases.

***Corresponding author**
Alvaro Pinheiro, PhD, University of Pernambuco, Recife, Brazil.

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Introduction

Currently, the development of complex and interactive systems is a reality in society, with a high level of penetration into the daily lives of people and companies. According to Prencipe, integration of the quality of these systems is necessary, which is a challenge for computing. This is a fertile field for the application of Artificial Intelligence [1].

According to Kuhl, Artificial Intelligence algorithms are the main technological facilitators because, owing to the inherent complexity of these technologies, they are suitable for solving problems in the Public Sector [2].

Based on a study by Saltz, Artificial Intelligence is becoming an important strategic asset, as it enables organizations to offer new products and services based on data, achieving greater agility in decision-making [3].

In addition, as organizations increasingly use Artificial Intelligence, they need new theories, methodologies, and frameworks. Organizations are beginning to need critical meta-information capture and management processes that allow them to establish policies and a culture designed to ensure adherence to the highest standards of management and the deployment of predictive models [4].

According to these authors, this attraction, in many cases, is due to advances in Machine Learning techniques, and despite the potential of Artificial Intelligence technologies, there are still problems that do not make practical use of these technologies, especially strategically in the Public Sector.

In this context, this research aims to instantiate an Intelligent Framework to support the activities of the public service, making use of a kernel that learns based on the formalism of Safe Reinforcement Learning, so that with the inferences of technology experts, this Artificial Intelligence can recommend more appropriate techniques to solve problems in the Public Sector.

Methodology

To conduct this research, the Design Science Research Methodology (DSRM) was used to guide the research construction process. This method was applied because of the studies by Freitas, who reported on technological research that has been increasingly used in academia, especially in engineering, with a focus on applied research [5].

Technological research cannot be considered simply with the application of scientific methods, as many of its results do not come from classical science. Scientific knowledge differs from technological knowledge because the former proposes a broad application, whereas the latter proposes a restricted application, that is, it focuses on the solution of specific problems [6].

Based on the authors, it is possible to understand that this technological research aims to solve specific problems with a focus on the artifacts to be developed. With the caveat that the artifact is not necessarily something material, but a project, scientific knowledge is limited by theory, whereas technological knowledge is limited by the task [5].

Thus, the DSRM was applied to the construction of knowledge because, according to Lacerda, it is a process of designing artifacts to solve problems, evaluating what was designed or what is working, and communicating the results obtained through the instantiation of the constructed model [7].

We also used the methods proposed by Hevner to evaluate the artifacts developed from the DSRM using a descriptive evaluation by scenario, with the aim of demonstrating the usefulness of the artifact through simulations [8].

Associated with the DSRM method, Domain Engineering (DE) was used with its phases of analysis, design, and implementation to discover the features and implementation in the framework [9].

This association of the DSRM method with the DE aimed to methodologically structure the discovery of features in the analysis phase of the integrated domain and stages of definition and development of the DSRM.

Model the framework in the domain design phase linked to the stages of development and demonstration of DSRM. Finally, an instance was built in the implementation phase associated with the DSRM demonstration and evaluation steps.

Framework

The process of analysis and construction of the features at the conceptual level was carried out through a survey of requirements, reengineering of Artificial and Computational Intelligence projects, and application of the DE associated with the DSRM method to these requirements, which aimed to propose a framework to support decision-making related to activities in the Public Sector.

To this end, DE and DSRM concepts were used to devise a framework to support technology experts and business experts from the Public Sector in the tasks of verification and validation of conformities, among others, of public management.

To obtain requirements with Domain Engineering, we describe the work carried out in three applications of Machine Learning in decision-making problems in the Government of the State of Pernambuco. The three selected projects were conducted by the Artificial Intelligence, Computational Intelligence, and Compliance research team of the University of Pernambuco, Brazil.

The following identified elements are also considered for the construction of a structural set that allows experts to extend the features, thus characterizing a white-box framework:

Identification and Definition

The first work selected with the title "Selection of characteristics of process models using Artificial Intelligence techniques" dealt with the modeling of processes that can be used in organizations to guide and optimize business processes [16].

The second paper selected with the title "Detecting anomalies of multiple classes" dealt with the discovery of contours that could be used to find patterns of deviation [17]. The author of this work found that defining rules for auditing has always been important; however, defining them in advance and considering event patterns relevant to the topic, particularly in critical applications, would be an important step.

The third paper selected with the title "A model for selecting relevant themes in documents applied to conformity" dealt with natural language processing, one of the fields of Artificial Intelligence research that aimed to process the meaning of words in natural language [18].

The features were elicited based on the re-engineering process applied to the three works, resulting in class diagrams. In addition to the survey of requirements resulting from the interviews conducted with the stakeholders, it was possible to conduct Domain Engineering associated with the method for the survey of the features.

It is noteworthy that the framework will not only solve problems related to the areas of process mining, anomaly detection, and rule extraction, as it was complemented with other areas, such as fraud detection, risk management, and not only these, since the problems in the Public Sector are the most diverse, such as active debt collection, generation of policies for the economy, and compliance analysis in document generation, among others, all requiring support for technology and business experts.

Development and Demonstration

The process of building the framework model consisted of defining the conceptual framework and developing an instance of the model to perform the demonstration step based on the DSRM method. With this applicability, we seek to propose an improvement in the planning of actions with the use of process optimization, improve communication between citizens, perform classification and prediction to better solve current problems and avoid problems that may occur, group and associate data to be able to understand and identify them, and finally, automate the processes so that specialists stop performing repetitive processes and focus on cognitive processes.

The adopted architecture was the Model-View-Controller (MVC), a software architecture pattern focused on reusing code and separating concepts into three interconnected layers [11-13,19]. Then, with the increase in the applications developed aiming at object-oriented programming, it is shown to be applicable to the separation between the data and presentation, thus allowing the changes in the layout to not affect the manipulation of the data, which can be reorganized without changing the layout.

Because the Framework makes the proposition of connectors, the facade pattern was used to provide a single point of access. A bridge pattern was applied to connect the vision, model, and control layers. Owing to the purpose of building the Whitebox Framework, the Template Method, Factory Method, and Abstract Factory standards are being applied, as recommended for this type of structure [15].

Mediate and Command patterns were applied between the model and control layers. The interconnection between the transversal components of the architecture was applied to the Chain of Responsibility standards [10,14,15].

The differential of the Machine Learning Framework for the Public Sector is the availability of a kernel that performs Learning by Reinforcement, being a formalism of Artificial Intelligence that allows an agent to learn from the interaction with the environment in which it is inserted.

Learning occurs through knowledge of the State of the Agent inserted in the environment, the actions performed by the agent in the instance of the Framework and the State changes resulting from these actions.

This technique is indicated when you want to obtain an optimal policy, being the policy of how the behavior of the agent, a technology and business expert, uses the environment (instance of the framework) to achieve a goal by a function that will model the policy.

Thus, the Agent will interact with its environment directly, obtaining information that will be processed by the algorithm to perform actions that lead to achieving the objectives, that is, to use the best technique known by the instance of the framework to solve a problem in the Public Sector.

To completely avoid undesirable situations in risky environments, an external knowledge base is necessary, because without it, the Agent would need to visit the dangerous state at least once before labeling it as "dangerous," so to minimize these risks of the exploitation process, the Framework Kernel used the mechanism called Learning with Demonstrations.

With the application of Demonstration Learning, we now have Safe Reinforcement Learning to generate online learning with real-time self-correction capability. The Intelligent Framework for the Public Sector with an emphasis on the Public Sector will behave as a Recommendation System and thus become customized for each technology or business expert who uses the instantiation of the framework.

Systems and Recommendation are a form of personalized presentation of data to its users, which in the case of this research, will allow connecting the technology experts with the business experts to achieve the effectiveness of the objectives of the instantiation of the framework so that there is interest in the knowledge made available, with all the logic behind the recommendation algorithms being controlled by Artificial Intelligence.

Recommendation Systems are divided into two main categories: collaborative filtering and content based.

Evaluation and Communication

To demonstrate the effectiveness of the framework, instantiation was performed. In this section, we demonstrate the process of construction of instantiation through its prototyping, so that the proposed simulations were performed with the application of Safe Reinforcement Learning.

It is derived from the learning feature that is responsible for learning the best algorithm for solving problems in the Public Sector and recommending them to experts.

The Kernel feature was implemented to represent the formalism of reinforcement learning, where the agent, the expert who interacts with the environment or the decision maker, receives a recommendation.

The recommendation is the most optimized or best policy action based on the actions performed by the Agent in the Environment, being the instance of the framework, aiming to modify the current behavior of the Agent in the Environment.

The Kernel has the responsibility of generating a new reward, the value that represents the feedback of the environment after the execution of an action, providing a reinforcement (reward) as a stimulus for a technology or business expert to change their behavior in decision-making.

The Kernel is the core of the framework that aggregates the Machine Learning feature providing adaptive learning, that is, reinforcement learning, through the Q-learning algorithm, which can be used to solve Public Sector problems through trial and error.

Q-Learning is an algorithm of the Reinforcement Learning formalism, a technique that allows an Agent to learn in the Environment using feedback from their own actions.

The collaboration methods of the instance were separated into three parts: (i) learning, which learns the action policy from the iteration of the algorithm with the prototype, making it seek the optimal policy that maximizes the reward received by the agent. (ii) Adjustment, which consists of the choice of hyperparameters (reward function, learning rate, etc.) used to evaluate the learning performance of the algorithm. (iii) Inference, in which the Agent already knows, what action to take, and no longer learns from his actions, final mode in which the instance provides a "like" or "dislike" for the actions proposed by the experts in technology and / or business.

Results of Framework Kernel

Kernel recommendation methods are based on obtaining a dataset composed of the main techniques used in Artificial and Computational Intelligence provided by technology experts.

With this set of data, a tensor was generated with the dimensions state, actions, and techniques, where the states the rows and actions, the columns of the tensor, and its cells, the matrices with the techniques.

The Kernel uses three methods of "filtering" or "recommendation," aiming to make the process more secure. The first is called the Content-Based Recommendation (RBC), the second is called the Memory-Based Collaborative Recommendation (RCBM), and the third Content-Based Collaborative Recommendation (RCBC).

The RBC method is based on the similarity of data and is an algorithm that solves the same class of problems. The method works using data collected from technology experts, obtaining the algorithms most searched by experts, which results in the recommendations shown in Table 1.

Table 1: Search Frequency of Algorithms

Problem	Algorithms (Search Frequency)
Classify	RF=6003; SVM=2375; MLP=559; DT=325; KNN=68
Predict	MLP=3480; LIR=3350; LOR=1893; DT=1691; RF=823
Group	KM=7694; HCA=4071; SOM=304
Cause	NB=6461
Optimize	GA=7694; PSO=1425; ACO=797; ABC=235; FSS=39; AIS=38; NSGA=32
Search	TS=4869; LB=2064; HC=512; ILS=304

Experimental Cases

Five experimental cases were planned and executed to validate the instantiation of the framework with simulations related to the Public Sector with an emphasis on auditing and control, and data were obtained from the databases of the Attorney General's Office of the State of Pernambuco.

Seeking each case to meet an area of diverse nature, to demonstrate the portability to users, scalability of use, multimodality, comparability, and Multiobjectivity of the Framework, with each case having a simulation with three scenarios to perform the checks to evaluate the assertiveness, regularity, predictability, probability, and enforceability of the framework. Here are the results.

Case-1: Portability to User

The experimental case portability of users demonstrated the ability of the framework to serve many users with different purposes, enabling the flexibility of the inputs of the framework instantiation. To prove the framework's ability in this case, it is possible to solve the problem related to the dynamism of the state's active debt data to identify the best form of collection.

To achieve this objective, we propose a prediction of the best form of collection of the state's active debt, whether protest or electronic filing, thus aiming to obtain a greater recovery of credit.

Simulation Best Way to Collect Debt

The first simulation consisted of classifying the data of the state's active debt using the formalism of Supervised Machine Learning so that the machine learns the best form of collection, whether judicialized or protested.

The need to use this formalism lies in the amount of debt data and its dynamism; therefore, today, debt that may have protest characteristics tomorrow can be indicated for filing and vice versa. This simulation used 2000 episodes to evaluate the recommendation of the technique; that is, if the algorithm recommended by the Framework Kernel was compared with two others randomly chosen but appropriate to solve the same class of problem, better indicators were obtained in relation to the metrics specified in this research.

Scenario-1: "RF"

The recommendation made by the prototype for this problem in the Public Sector was the use of the Random Forest (RF) algorithm, an algorithm used to solve the classification problem class in supervised machine-learning formalism. RF is a learning method used for classification and regression. The algorithm scans and randomly selects the characteristics and then constructs a collection of decision trees with controlled variance [20].

Scenario-2: "KNN"

The first random choice for verification and validation of the Framework Kernel choice was the K-Nearest Neighbors (KNN) algorithm, which is a nonparametric classification method used for classification and regression. In both cases, the input consists of the closest K training examples in a dataset, with the output depending on whether the KNN is being used for classification or regression [21].

Scenario-3: "SVM"

The second random choice for the verification and validation of the choice of the Framework Kernel was the Support Vector Machine (SVM) algorithm, which allows the generation of a representation of examples as points in space, mapped so that the examples in each category are divided clearly and accurately. Thus, the new input cases are properly mapped as belonging to one of the output space categories [22].

Data Mining

For the application of data mining, the cross-industry standard process for data mining (CRISP/DM) technique was used to perform the following activities described by Chapman et al.: (1) business understanding, (2) understanding the data, (3) data preparation, (4) data modeling, (5) data evaluation, and (6) implementation. The process was repeated until the extracted data were satisfactory, aiming to extract the appropriate dataset to solve the problem and then standardize and balance them [23].

For this simulation, the following data were selected: (i) debt identifier, anonymized field corresponding to CDA (target); (ii) amount of debt, total in reais of the debt with the government (feature); (iii) type of person, whether physical or legal (feature); (iv) type of debt, constitution of the debt, whether tax or not (feature); (v) debt situation, whether subpoenaed or not (feature); and (vi) type of charge, if protested or filed (target).

Hyperparameter Configuration

To apply the evaluation factors, in addition to data preparation, it was necessary to define the hyperparameters used by the models in the simulation to obtain the maximum proportion between them.

Table 2: Simulation-1 Hyperparameters

RF	KNN	SVM
n_estimators=10 criterion='gini' max_depth=None min_samples_split=2 min_samples_leaf=1 min_weight_ fraction_leaf=0.0 max_features='auto' max_leaf_ nodes=None bootstrap=True oob_score=False n_jobs=1 random_state=None verbose=0 class_weight=None preprocessors=None	n_neighbors=3 metric='euclidean' weights='distance' algorithm='auto' metric_ params=None preprocessors=None	C=1.0 kernel='rbf' degree=3 gamma='auto' coef0=0.0 shrinking=True probability=False tol=0.001 cache_size=2000 max_iter=-1 preprocessors=None

For this simulation, the dataset used 3,990 records from the Active Debt Registry of the State of Pernambuco with six fields, in which one field is the identifier used as a goal, four fields used for extraction of characteristics, one field of the numerical type, three of the categorical type, and one objective field.

For this dataset, 70% were used for training and testing, resulting in 2,793 records, and 30% for validation, resulting in 1,197 records, using a five-fold cross-validation technique with five folds.

Cross-validation is a technique used to evaluate the generalization capacity of a model from a set of data, seeking to estimate the accuracy of the model, that is, how it is performed in relation to a new set of data [24].

Evaluation Factors

Assertiveness Factor (AF): the level of accuracy of the model recommended by the Kernel compared to the randomly chosen models that can solve the same class of problem, using the same number of iterations through the metrics of Accuracy (A), Precision (P), Recall (R) and F1 (F).

Table 3: Simulation-1 Assertiveness of Models

Scenario	Model	(A)	(P)	(R)	(F)	Ranking
1	RF	0.843	0.853	0.831	0.842	1
2	KNN	0.728	0.747	0.697	0.721	3
3	SVM	0.743	0.755	0.726	0.740	2

Regularity Factor (RF): This evaluation verifies the percentage of correct answers of the models based on a new set of data, that is, it verifies how the model behaves with data that were never used in the training and testing phases.

Table 4: Simulation-1 Regularity of Models

Scenario	Model	(A)	(P)	(R)	(F)	Ranking
1	RF	0.921	0.922	0.921	0.921	2
2	KNN	0.999	0.999	0.999	0.999	1
3	SVM	0.647	0.679	0.647	0.628	3

Predictability Factor (PF): allows the visualization of the two dimensions, "current" and "predicted," through the combination of the dimensions and thus verifies the performance of the model for the classes.

Table 5: Simulation-1 Model Performance

<table>
<tr><th>Scenario</th><th>Model</th><th colspan="3">Confusion Matrix</th><th>Ranking</th></tr>
<tr><td rowspan="3">1</td><td rowspan="3">RF</td><td></td><td>Judge</td><td>Protest</td><td rowspan="3">1</td></tr>
<tr><td>Judge</td><td>1713</td><td>265</td></tr>
<tr><td>Protest</td><td>341</td><td>1671</td></tr>
<tr><td rowspan="3">2</td><td rowspan="3">KNN</td><td></td><td>Judge</td><td>Protest</td><td rowspan="3">2</td></tr>
<tr><td>Judge</td><td>1489</td><td>489</td></tr>
<tr><td>Protest</td><td>618</td><td>1394</td></tr>
<tr><td rowspan="3">3</td><td rowspan="3">SVM</td><td></td><td>Judge</td><td>Protest</td><td rowspan="3">3</td></tr>
<tr><td>Judge</td><td>1277</td><td>701</td></tr>
<tr><td>Protest</td><td>598</td><td>1414</td></tr>
</table>

Probability Factor (OF): displays the comparison model of the area over the ROC curve, with the score of the model in the row when it is greater than that of the model in the column.

Table 6: Simulation-1 Probability of Models

Scenario	Color	Model	KNN	SVM	RF	Ranking
1	Purple	RF	0.994	1.000		1
2	Orange	KNN		0.040	0.006	3
3	Green	SVM	0.960		0.000	2

Executable Factor (EF): execution time in seconds of training and testing performed by the model recommended by the kernel compared to randomly chosen models that can solve the same class of problems.

Table 7: Simulation-1 Executable Models

Scenario	Model	Training	Test	Ranking
1	RF	0.169	0.044	2
2	KNN	0.095	0.816	1
3	SVM	0.169	0.044	3

Case-2: Scalability of Use

The experimental use scalability case served to demonstrate the framework's ability to use Machine Learning by offering scalability for instance use; therefore, even if it exponentially increases data inputs, the processing time will not increase exponentially.

To prove the ability of the framework for this case, the possibility of solving a problem that deals with the difference in the application of penalties in the methods of collection, differentiating debtors from evaders, was proposed as an objective.

To achieve this objective, we grouped the data of individuals and legal entities that comprise the state's active debt registry into two groups: debtors and tax evaders. Consequently, legal penalties were applied correctly.

Debtor Profile Discovery Simulation

The second simulation involved grouping the data of the individuals and legal entities that make up the state's active debt registry to use the formalism of Unsupervised Machine Learning.

This is so that the machine groups the data that have common characteristics, and then, with the support of business experts, can identify the groups of evaders or debtors and label them. This identification is important for taking appropriate legal action for each taxpayer group.

Moreover, due to the amount of data from the debt register and the change in the behavior of the data in relation to the characterization of debtors and tax evaders resulting from changes in the economy and politics of the country, it becomes difficult to create a rule that separates these two profiles, requiring this rule to be found by the algorithm itself.

This simulation used 2000 episodes with random initialization to evaluate the recommendation of the technique; that is, if the algorithm recommended by the kernel was compared with two others randomly chosen, but appropriate to solve the same class of problem, it obtained better indicators in relation to the metrics used in this research.

Scenario-1: "KM"
The recommendation made by the Framework Kernel for this problem in the Public Sector was the use of the K-means (KM) algorithm, an algorithm used to solve the class of clustering problems in Unsupervised Machine Learning formalism [25].

Scenario-2: "HCA"
The first random choice for verification and validation of the Framework Kernel was the Hierarchical Clustering (HCA) algorithm. The hierarchical clustering algorithm or hierarchical cluster analysis is used in data mining and statistics and is usually presented in a dendrogram [26].

Scenario-3: "SOM"
The second random choice for verification and validation of the choice of the framework kernel is the Self-Organizing Map (SOM) algorithm, an algorithm used to solve the grouping problem class in Unsupervised Machine Learning formalism, which is a technique that aims to produce a low-dimensional representation of a higher-dimensional dataset, preserving the topological structure of data [27].

Data Mining
For the application of data mining, the cross-industry standard process for data mining (CRISP/DM) technique was used, repeating the process until the extracted data were satisfactory [23].

For this simulation, the following data were selected: (i) debt identifier, anonymized field corresponding to the CDA (target); (ii) name of the debtor, anonymized field (meta); (iii) type of person, whether physical or legal (feature); (iv) UF, Federative Unit of the Debtor (feature); (v) modality, form of debt collection (feature); (vi) type, type of debt (feature); (vii) situation, debt situation (feature); and (viii) cause, amount of debt (feature).

Hyperparameter Configuration
To apply the evaluation factors, in addition to data preparation, it was necessary to define the hyperparameters used by the models in the simulation to obtain the maximum proportion between them.

Table 8: Simulation-2 Hyperparameters

KM	HCA	SOM
n_clusters=2 init='k-means++' n_init=10 max_iter=200 tol=0.0001 random_state=None preprocessors=None compute_ silhouette=None	n_clusters=2 linkage=AVERAGE calable='euclidean' memorystr=None connectivity=None compute='auto' distancet=None distanceb=False	size=(5, 5) trainer=LinearDecaySom call-backs=[] loss=mean_quantization_err

For this simulation, the dataset used 4,130 records from the Active Debt Registry of the State of Pernambuco with eight fields, of which two fields, the identifier and name, were used as a goal, six fields were used for the extraction of characteristics, one field of the numerical type, and five fields of the categorical type.

For this dataset, 70% was used for training and testing, resulting in 2,891 records, and 30% was used for validation, resulting in 1,239 records.

For Scenario-1, the KM model recommended by the kernel was applied, which generated 1,436 records for Cluster-1 and 1,455 records for Cluster-2. For Scenario-2, a randomly chosen HCA model was applied, which generated 2,886 records for Cluster-1 and five records for Cluster-2. For Scenario-3, a randomly chosen SOM model was applied, which generated 712 records for Cluster-1 and 548 records for Cluster-2.

As the objective of Unsupervised Machine Learning is to group the data by similarities, for the application of the Evaluation Factors, the data of the three scenarios were labeled based on the knowledge of the business experts, obtaining the label of debtors the data of Cluster-1 and with the label of evaders, the data of Cluster-2.

Evaluation Factors
Assertiveness Factor (AF): level of accuracy of the model recommended by the Kernel compared to the randomly chosen models using the same number of iterations through the metrics of Accuracy (A), Precision (P), Recall (R) and F1 (F).

Table 9: Simulation-2 Assertiveness of Models after Labeling

Scenario	Model	(A)	(P)	(R)	(F)	Ranking
1	KM	0.498	0.622	0.498	0.532	2
2	HCA	0.752	0.566	0.752	0.646	1
3	SOM	0.343	0.614	0.342	0.326	3

Regularity Factor (RF): This evaluation verifies the percentage of correct answers of the models based on a new set of data, that is, it verifies how the model behaves with data that were never used in the training and testing phases.

Table 10: Simulation-2 Regularity of Models after Labeling

Scenario	Model	(A)	(P)	(R)	(F)	Ranking
1	KM	49%	62%	49%	53%	2
2	HCA	75%	56%	75%	64%	1
3	SOM	34%	61%	34%	32%	3

Predictability Factor (PF): allows the visualization of the two dimensions, the "current" and "predicted," through the combination of the dimensions and thus verify the performance of the model for the classes.

Table 11: Simulation-2 Performance of Models after Labeling

Scenario	Model	Confusion Matrix			Ranking
1	KM		Cluster1	Cluster2	1
		Cluster1	469	463	
		Cluster2	159	148	
2	HCA		Cluster1	Cluster2	2
		Cluster1	932	0	
		Cluster2	307	0	
3	SOM		Cluster1	Cluster2	3
		Cluster1	184	748	
		Cluster2	66	241	

Probability Factor (OF): displays the comparison model of the area over the ROC curve, with the score of the model in the row when it is greater than that of the model in the column.

Table 12: Simulation-2 Probability of Models after Labeling

Scenario	Color	Model	ROC	Ranking
1	Purple	KM	0.488	3
2	Orange	HCA	0.503	1
3	Verde	SOM	0.490	2

Case-3: Multimodality
The multimodal experimental case demonstrated the ability of the framework to generate multimodal recommendations (outputs), enabling experts to obtain several results with the same input.

To prove the framework's ability for the case, it was proposed as an objective to solve the problem related to the specificities of the documents that must be followed by specialists who have proper competence in their analysis.

To achieve this objective, learning was used with the classification of the document in its correct direction according to its area of specialty, obtaining greater efficiency in the procedural analysis.

Simulation Document Selection by Features
The third simulation consisted of identifying which documents should follow the nuclei of specialized prosecutors' offices. For example, in a specialized farm, there are nuclei, active debt, tax information, tax execution, and priority processes. In litigation, there are nuclei of servers, acts, and taxes. In the consultative, hiring takes care of the contracts and agreements, and personnel matters that deal with the processes that involve the servers.

Servers and commissioned positions analyze documents to carry out their forwarding, specialized work, repetitive, voluminous, tiring, and subject to errors.

The gain will be significant, since there are many data and the identification of the correct destination of these documents is carried out with human expertise; if by some claim, one of these business specialists leaves the process, until the formation of a new manager who can perform the correct direction, there will be a long learning curve, denoting the importance of a Machine Learning solution.

This simulation used 2000 episodes with random initialization to evaluate the recommendation of the technique; that is, if the algorithm recommended by the Framework Kernel was compared with two others randomly chosen but appropriate to solve the same class of problem, it obtained better indicators in relation to the metrics cited in this research.

Scenario-1: "MLP"
The recommendation made by the prototype for this problem in the Public Sector is the use of the MultiLayer Perceptron (MLP) algorithm. MLP can be used to solve problems of classification, regression, or prediction, and is a class of artificial neural networks of the feedforward type. It is restricted to a network composed of multiple layers of perceptrons using a threshold activation function consisting of at least three layers of nodes, the first of which is the input layer, the second is the middle or hidden layer, and the third is the output layer [28].

Scenario-2: "LOR"
The first random choice for verification and validation of the Framework Kernel was the Logistic Regression (LOR) algorithm, an algorithm used to solve the prediction problem class in Supervised Machine Learning formalism. The LOR in statistics is used to model the probability of a given class existing in a win-lose event, which is then used to model various classes of events by classifying them [29].

Scenario-3: "NB"
The second random choice for the verification and validation of the choice of the Framework Kernel was the Naive Bayes (NB) algorithm, an algorithm used to solve the prediction problem class in Supervised Machine Learning formalism.

Data Mining
For the application of data mining, the cross-industry standard process for data mining (CRISP/DM) technique was used, repeating the process until the extracted data were satisfactory [23].

For this simulation, the following data were selected: (i) identifier, anonymized field (meta); (ii) object, text with the data extracted from the advisory (meta); (iii) year, year corresponding to the extraction of the data (target); (iv) agency, secretariat, or government agency of the extracted object (feature); (v) class, type of document extracted from the object (feature); (vi) modality, type of subject extracted from the object (feature); and (vii) core, target area of the object (target).

Hyperparameter Configuration
To apply the evaluation factors, in addition to data preparation, it was necessary to define the hyperparameters used by the models in the simulation to obtain the maximum proportion between them.

Table 13: Simulation-3 Hyperparameters

MLP	LOR	NB
hidden_layer_ sizes=(64,64), activation='relu', solver='sgd', alpha=0.0001, batch_size='auto', learning_ rate='constant', learning_rate_ init=0.001, power_t=0.5, max_ iter=2000, shuffle=True, random_state=None, tol=0.0001, verbose=False, warm_start=False, momentum=0.9, nesterovs_ momentum=True, early_ stopping=False, validation_ fraction=0.1, beta_1=0.9, beta_2=0.999, epsilon=1e-08, preprocessors=None	penalty='l2', dual=False, tol=0.0001, C=1.0, fit_intercept=True, intercept_scaling=1, class_weight=None, random_state=None, solver='auto', max_iter=2000, multi_class='auto', verbose=0, n_jobs=1, preprocessors=None	preprocessors=None

For this simulation, the dataset used 2,803 records from the Register of Documents of the Consultative of the State of Pernambuco with seven fields, in which three fields, the identifier, year, and object used as goals, three fields were used for extraction of characteristics: the three fields of the categorical type and one field of the target type also categorical, the core.

For this dataset, 70% were used for training and testing, resulting in 1,962 records, and 30% were used for validation, resulting in 840 records.

Evaluation Factors

Assertiveness Factor (AF): level of accuracy of the model recommended by the Kernel compared to the randomly chosen models using the same number of iterations through the metrics of Accuracy (A), Precision (P), Recall (R) and F1 (F).

Table 14: Simulation-3 Assertiveness of Models

Scenario	Model	(A)	(P)	(R)	(F)	Ranking
1	MLP	0.956	0.914	0.956	0.935	3
2	LOR	0.999	0.999	0.999	0.999	1
3	NB	0.993	0.993	0.993	0.993	2

Regularity Factor (RF): This evaluation verifies the percentage of correct answers of the models based on a new set of data, that is, it verifies how the model behaves with data that were never used in the training and testing phases.

Table 15: Simulation-3 Regularity of Models

Scenario	Model	(A)	(P)	(R)	(F)	Ranking
1	MLP	95%	91%	95%	93%	3
2	LOR	99%	99%	99%	99%	1
3	NB	99%	99%	99%	99%	2

Predictability Factor (PF): allows the visualization of the two dimensions, the "current" and "predicted," through the combination of the dimensions and thus verify the performance of the model for the classes.

Table 16: Simulation-3 Model Performance

Scenario	Model	Confusion Matrix			Ranking
1	MLP		Contract	Matter	3
		Contract	2680	0	
		Matter	123	0	
2	LOR		Contract	Matter	1
		Contract	2679	1	
		Matter	2	121	
3	NB		Contract	Matter	2
		Contract	2662	18	
		Matter	3	120	

Probability Factor (OF): displays the comparison model of the area over the ROC curve, with the score of the model in the row when it is greater than that of the model in the column.

Table 17: Simulation-3 Probability of Models

Scenario	Color	Model	ROC	Ranking
1	Orange	MLP	0.680	3
2	Green	LOR	0.993	2
3	Purple	NB	0.999	1

Executable Factor (EF): execution time in seconds of training and testing performed by the model recommended by the kernel compared to randomly chosen models that can solve the same class of problems.

Table 18: Simulation-3 Executability of Models

Scenario	Model	Training	Test	Ranking
1	MLP	3.131	0.147	3
2	LOR	0.341	0.116	2
3	NB	0.026	0.004	1

Case-4: Comparability

Experimental case comparability was used to demonstrate the ability of the framework to analyze the quality of the results in relation to learning by observing the convergence curve, as the prototype prioritizes scalable techniques.

To prove the ability of the framework for the case was proposed as an objective, the possibility of solving the problem related to many processes, and the small number of specialists for its analysis, thus making it necessary for its prioritization.

To achieve the objective of optimizing the process of document selection in the previous phase (document analysis) with the aim of gaining more effectiveness in procedural analysis.

Simulation Process Selection for Analysis

The fourth simulation consisted of identifying the process that should be analyzed first among several distinct characteristics. For example, in the specialized consultative, there are several processes that arrive for analysis with the characteristics of complexity (very low, low, medium, high, and very high), number of pages, delivery time, and number of reviews (quotas), among others, that hinder efficient and effective selection.

Performing a correct ordering of which process should be analyzed first, among many others, that provides more efficiency and effectiveness to the consultative process is necessary to optimize this selection because the number of processes, dimensions, and variety of situations make it impossible to easily understand these data. With the use of an optimization technique, there is a gain in time for the selection of the process and, consequently, its delivery by the prosecutors in its analysis.

This simulation used 2000 episodes with random initialization to evaluate the recommendation of the technique; that is, if the algorithm recommended by the kernel compared with two others randomly chosen, but appropriate to solve the same class of problem, obtained better indicators in relation to the metrics cited in this research.

Scenario-1: "PSO"

The recommendation made by the prototype for this problem in the Public Sectorit was the use of the Particle Swarm Optimization (PSO) algorithm. PSO or Particle Swarm Optimization is a method proposed by Kennedy and Eberhart in 1995 to solve optimization problems inspired by the behavior of particles, seeking to improve the candidate solution by applying a given quality measure [30].

Scenario-2: "FSS"

The first random choice for the verification and validation of the kernel choice was the Fish School Search (FSS) algorithm, which is an algorithm used to solve the optimization problem class in

Swarm Intelligence formalism. The FSS or Shoal Research method was proposed by Fernando Buarque and Carmelo Filho in 2008 to solve optimization problems inspired by the behavior of shoals, in which the coordinated feeding and movement mechanisms of the fish were used as inspiration to create the search operators, having as a central idea to make the fish swim towards the positive gradient to feed and gain weight [31].

Scenario-3: "ABC"

The second random choice for the verification and validation of the kernel choice was the Artificial Bee Colony (ABC) algorithm, which is an algorithm used to solve the optimization problem class in Swarm Intelligence formalism. The ABC or Artificial Bee Colony method was proposed by Derviş Karaboğa in 2005 to solve optimization problems inspired by the behavior of intelligent foraging by bees, seeking to improve the candidate solution in relation to a goal [32].

Data Mining

For the application of data mining, the cross-industry standard process for data mining (CRISP/DM) technique was used, repeating the process until the extracted data were satisfactory [23].

For this simulation, the following data were selected: (i) process, anonymized process identifier (meta); (ii) year, date of entry of the process (feature); (iii) complexity, level of complexity of the process (feature); (iv) page, number of pages of the process (feature); (v) deadline, maximum period to perform the analysis of the process (feature); and (vi) priority, whether it is prioritized based on optimization (target).

Hyperparameter Configuration

To apply the evaluation factors, in addition to data preparation, it was necessary to define the hyperparameters used by the models in the simulation to obtain the maximum proportion between them.

Table 19: Simulation-4 Hyperparameters

PSO	FSS	ABC
projection = '3d' dimensions = 3 iterations = 2000 population = 20 bounds = [e1,e2] cost = 'weighting' ci = 0.8 (w) fi = 2.05 ($c1$) particles = []	projection = '3d' dimensions = 3 iterations = 2000 school = 20 bounds = [e1,e2] cost = 'weighting' initial step = 0.01 final step = 0.000001 fish = []	projection = '3d' dimensions = 3 iterations = 2000 swarm = 40 bounds = [e1,e2] cycles = 10 cost = 'weighting' power supplies = int(swarm/2) bees = []

For this simulation, the dataset used 1,013 records from the Register of Documents of the Consultative of the State of Pernambuco with seven fields, in which one field, the identifier of the type goals, and six fields were used to extract the characteristics and all numerical types.

Evaluation Factors

Assertiveness Factor (AF): level of accuracy of the model recommended by the Kernel compared to the randomly chosen models using the same number of iterations through the metrics of Accuracy (A), Precision (P), Recall (R) and F1 (F).

Table 20: Simulation-4 Assertiveness of Models

Scenario	Model	(A)	(P)	(R)	(F)	Ranking
1	PSO	0.20	0.03	0.05	0.04	2
2	FSS	1.00	1.00	1.00	1.00	1
3	ABC	0.00	0.00	0.00	0.00	3

Convergence Factor (CF): shows the convergence curve of the model between time and interactions.

Table 21: Simulation-4 Model Convergence

Scenario	Model	Convergence	Ranking
1	PSO	09	1
2	FSS	60	2
3	ABC	80	3

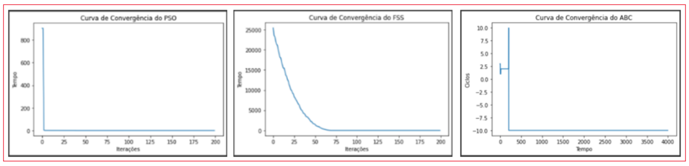

Figure 9: Simulation-4 Model Convergence

Executable Factor (EF): is the execution time in seconds of the optimization process performed by the kernel-recommended model compared to randomly chosen models that can solve the same class of problems.

Table 22: Simulation-4 Executable Models

Scenario	Model	Optimization	Ranking
1	PSO	38.767	2
2	FSS	37.879	1
3	ABC	39.758	3

Case-5: Multiobjectivity

The multiobjectivity experimental case demonstrated the framework's ability to address multiobjectivity by demonstrating that instantiation can resolve conflicting objectives.

To prove the framework's ability for the case, a solution to the existence of two or more distinct objectives for the analysis of the productivity of prosecutors was proposed as a problem objective. To achieve the objective of seeking the optimal point between the objectives of efficiency and effectiveness, we obtained the result of making the evaluation process fairer.

Simulation Productivity Analysis

The fifth simulation involved identifying the optimum point between two distinct objectives, efficiency and effectiveness, in the productivity of the performance of the procedural analysis tasks performed by the prosecutors.

Allowing a fairer evaluation of the productivity of prosecutors since the objectives that guide this analysis are efficiency, speed of analysis, delivery of processes, and effectiveness in the correctness of this analysis.

Using a multi-objective optimization technique, the optimum point between the objectives was obtained, allowing a fairer evaluation.

This simulation used 2000 episodes with random initialization to evaluate the recommendation of the technique, that is, if the algorithm recommended by the Framework Kernel compared with two others randomly chosen, but appropriate to solve the same class of problem, obtained better indicators in relation to the metrics cited in this research.

Scenario-1: "NSGA2"
The recommendation made by the Framework Kernel for this problem in the Public Sector is the use of the Non-dominated Sorting Genetic Algorithm (NSGA). The NSGA2 or Unmastered Classification Genetic Algorithm is a metaheuristic for multi-objective optimization that can be termed "multiobjective programming" or "vector optimization" or "multicriteria optimization" or " multi-attribute optimization" or "Pareto optimization," being a decision-making area with multiple objectives to be optimized simultaneously from two or more conflicting objectives [33].

Scenario-2: "AGEMODEA"
The first random choice for the verification and validation of the choice of the Framework Kernel was the AGEMODEA algorithm, an algorithm used to solve the optimization problem class in Swarm Intelligence formalism. Adaptive geometry estimation for multi-objective optimization is a metaheuristic for multi-objective optimization [34].

Scenario-3: "CTAEA"
The second random choice for the verification and validation of the choice of the Framework Kernel was the CTAEA algorithm, which is an algorithm used to solve the optimization problem class in Swarm Intelligence formalism. The two-archive evolutionary algorithm for constrained multi-objective optimization is a metaheuristic for multi-objective optimization [35].

Data Mining
For the application of data mining, the cross-industry standard process for data mining (CRISP/DM) technique was used, repeating the process until the extracted data were satisfactory [23].

For this simulation, the following data were selected: (i) prosecutor, identification of the anonymized prosecutor (meta); (ii) process, anonymized process identifier (meta); (iii) complexity, level of complexity of the process (feature); (iv) page, number of pages of the process (feature); (v) deadline, maximum period to perform the analysis of the process (feature); (vi) review, number of revisions already made in the process (feature); (vii) delivery, number of days elapsed in the analysis (feature); and (viii) value and value of the cause (feature).

Hyperparameter Configuration
To apply the evaluation factors, in addition to data preparation, it was necessary to define the hyperparameters used by the models in the simulation to obtain the maximum proportion between them.

Table 23: Simulation-5 Hyperparameters

NSGA2	AGEMODEA	CTAEA
projection = '3d' dimensions = 3 iterations = 2000 population = 20 bounds = [e1, e4] cost = 'weighting' seed=1 verbo=false call = '' weight = [0.2,0.2,0.1] individuals = []	projection = '3d' dimensions = 3 iterations = 2000 population = 20 bounds = [e1, e4] cost = 'weighting' seed=1 verbo=false call = '' weight = [0.2,0.2,0.1] individuals = []	projection = '3d' dimensions = 3 iterations = 2000 population = 20 bounds = [e1, e4] cost = 'weighting' seed=1 verbo=false call = '' weight = [0.2,0.2,0.1] individuals = []

For this simulation, the dataset used 1,013 records from the Register of Documents of the Consultative of the State of Pernambuco with eight fields, in which two fields, the identifier of the type goals, and six fields were used for the extraction of characteristics, all numerical types.

Evaluation Factors
Assertiveness Factor (AF): level of accuracy of the model recommended by the Kernel compared to the randomly chosen models using the same number of iterations through the metrics of Accuracy (A), Precision (P), Recall (R) and F1 (F).

Table 24: Simulation-5 Assertiveness of Models

Scenario	Model	(A)	(P)	(R)	(F)	Ranking
1	NSGA2	0.20	0.03	0.05	0.04	1
2	AGEMODEA	1.00	1.00	1.00	1.00	2
3	CTAE	0.00	0.00	0.00	0.00	3

Convergence Factor (CF): shows the convergence curve of the model between time and interactions.

Table 25: Simulation-5 Convergence of Models

Scenario	Model	Convergence	Ranking
1	NSGA2	10	1
2	AGEMODEA	80	2
3	CTAE	90	3

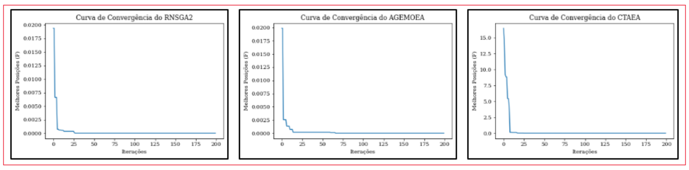

Figure 11: Simulation-5 Convergence of Models

Executable Factor (EF): is the execution time in seconds of the optimization process performed by the kernel-recommended model compared to randomly chosen models that can solve the same class of problems.

Table 26: Simulation-5 Executable Models

Scenario	Model	Optimization	Ranking
1	NSGA2	0.46	1
2	AGEMODEA	0.52	3
3	CTAE	0.49	2

Conclusion

To test the instantiation of the framework to verify and validate the features elicited for its construction, five experimental cases were proposed: "Case-1: portability for user," "Case-2: Scalability of Use"; "Case-3: multimodality‘; "Case-4: comparability’; and “Case-5: Multiobjectivity".

The prototyping of the application performed the verification and validation of five simulations: "simulation-1: identification of the best form of debt collection"; "simulation-2: debtor profile discovery"; "simulation-3: selection of documents by characteristics"; "simulation-4: selection of priority processes"; and “Simulation-5: Productivity Evaluation".

For each simulation, three scenarios were used, allowing the application of the evaluation factors in the framework in relation to the recommendations arising from Machine Learning with the formalism by reinforcement in the safe modality for verification and validation of the features elicited and built. Table 27 summarizes the results.

Table 27: Cases, Simulations and Scenarios

#	Cases	Simulations	Sn.1	Sn.2	Sn.3
1	Portability for User	Identification of the best collect the debt	RF	KNN	SVM
2	Scalability of Use	Debtor profile discovery	KM	HCA	SOM
3	Multimodality	Selection of docs by characteristics	MLP	LOR	NB
4	Comparability	Selection of priority processes	PSO	FSS	ABC
5	Multiobjectivity	Productivity evaluation	NSGA2	AGEMODEA	CTAEA

Case 1, called User Portability, aimed to verify the framework’s ability to serve different specialists simultaneously. For validation, a simulation was used to propose better ways of collecting active debt based on the formalism of Supervised Machine Learning, solving the problem of the prediction class using statistical algorithms, namely Random Forest (RF), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM).

The problem sought to be solved was the dynamism of the data on the active debt of the state, generating the need to identify the best form of collection, aiming to predict the best form of redemption of the active debt of the state, whether protest or electronic filing, and thus obtain a greater recovery of credit.

Using three scenarios with the application of the evaluation factors, it was possible to observe through the results obtained and displayed in the general table of evaluations (Table 28) that the algorithm recommended by the Kernel, RF, obtained the best general evaluation based on the factors evaluated, followed by KNN and SVM.

Table 28: Simulation-1 General Framework of Evaluation Factors

Scenario	Model	AF	RF	PF	OF	EF	Ranking
1	RF	1	2	3	1	2	1
2	KNN	2	2	1	3	1	2
3	SVM	3	1	2	2	3	3

After applying learning with the technique recommended for technology specialists, the Framework Kernel used these data to recommend the best form of collection for active debts, which provided more assertive recommendations for business experts.

Thus, we argue that the recommendation process of the Framework Kernel, even though it does not yet have a knowledge base with a volume in the house of thousands of collaborations, relying more on learning-by-demonstration, which was the startup base provided by the experts, has already presented satisfactory results. However, greater collaboration of experts will enrich the knowledge base and confidence in the recommendations.

With this simulation, we proved that the framework can serve users of different types simultaneously. In this case, technology experts (developers) and business experts (public servants) have different needs, but use the same data to solve them.

Case 2, called Scalability of Use, aimed to verify the ability of the framework to enable the processing of high-dimensional data. For validation, the simulation was used to propose the discovery of the debtors' profile, based on the formalism of Unsupervised Machine Learning, to solve the problem of the grouping class using neural and statistical algorithms, such as Self-Organizing Map (SOM), K-means (KM), and Hierarchical Clustering (HCA).

The problem that was solved was the difference in the application of penalties in the collection methods in which it is necessary to differentiate debtors from tax evaders, aiming to group the data of the individuals and legal entities that make up the register of the active debt of the state into two groups, that of debtors and that of evaders, and thus correctly apply the legal penalties.

Using three scenarios with the application of the evaluation factors, it was possible to observe through the results obtained and displayed in the general table of evaluations (Table 29) that the algorithm recommended by the Kernel, KM obtained the second-best general evaluation based on the factors evaluated, followed by the SOM, obtaining the best evaluation of the HCA.

Table 29: Simulation-2 General Framework of Evaluation Factors

Scenario	Model	AF	RF	PF	OF	EF	Ranking
1	KM	2	2	1	3	-	2
2	HCA	1	1	3	1	-	1
3	SOM	3	3	2	2	-	3

We emphasize that the kernel recommendation process, because it does not yet have a reasonable knowledge base and relies more on learning-by-demonstration, which is the startup base provided by the technology experts, needs more collaboration on the part of the experts to enrich the knowledge base and generate more assertive recommendations.

However, even if the recommendation of the kernel to the technology expert was not the most convergent, the ones recommended randomly, but that solved the same class of problem, served to indicate the best technique for this type of problem, thus generating this learning for the kernel. After the data were used by the Q-Deep Learning technique, it was shown that the recommendation of documents by characteristics was more assertive for business experts.

With this simulation, we were able to prove that the framework can process data with high dimensionality and deliver satisfactory results, even if they result from data processing with high dimensionality.

Case 3, called multimodality, aimed to verify the ability of the framework to recommend multiple actions using the same data. For its validation, the simulation was used to select documents with variability of characteristics, based on the formalism of Supervised Machine Learning, to solve a problem of the classification class with the use of neural and statistical algorithms, which were: Multilayer Perceptron (MLP); Logistic Regression (LOR); and, Naive Bayes (NB).

The problem that was solved was the need to learn about the specificities of the documents that must follow the correct specialized ones, which have the proper competence for their analysis, aiming to classify the document in the correct direction according to its area of expertise, and thus gain more efficiency in procedural analysis.

Using three scenarios with the application of the factors, it was possible to observe through the results obtained and displayed in the general table of evaluations (Table 30) that the algorithm recommended by the Kernel, the MLP, obtained the worst performance in the general evaluation with, having the best evaluation of the LOR followed by the NB.

Table 30: Simulation-3 General Framework of Evaluation Factors

Scenario	Model	AF	RF	PF	OF	EF	Ranking
1	MLP	3	3	1	3	3	3
2	LOR	1	1	3	2	2	1
3	NB	2	2	2	1	3	2

We assessed that the need to adjust the hyperparameters, which can be performed in real time (one of the features of the framework), may result in more assertive recommendations, which adds to a larger collaboration base. However, because the framework does not yet have a reasonable knowledge base, the simulation would require further experimentation to re-evaluate the results.

With this simulation, we proved that the framework can recommend different actions using the same data, enabling framework users to receive multiple recommendations for the problems addressed. Case 4, called comparability, aimed to verify the ability of the framework to enable solutions to complex problems for numerous dimensions. For validation, the simulation was used for the selection of priority processes based on the formalism of Swarm Intelligence to solve the problem of the optimization class using swarm algorithms, namely, Particle Swarm Optimization (PSO), Fish School Search (FSS), and Artificial Bee Colony (ABC).

The problem that was aimed at solving was the number of processes and the small number of specialists. For its analysis, it is necessary to prioritize, aiming to optimize the process of selecting documents in the phase prior to document analysis and thus gain more effectiveness in procedural analysis.

Using three scenarios with the application of the evaluation factors, it was possible to observe through the results obtained and displayed in the general table of evaluations (Table 32) that the algorithm recommended by the Kernel, the PSO, was behind the FSS followed by the ABC. Thus, we evaluated that even with the balance of the hyperparameters, the framework recommended PSO, but with the data used, the overall performance of the FSS was better, which indicates the need for more interactions of agents with the environment to enrich learning.

Table 31: Simulation-4 General Framework of Evaluation Factors

Scenario	Model	AF	CF	EF	Ranking
1	PSO	2	2	1	2
2	FSS	1	1	2	1
3	ABC	3	3	3	3

With this simulation, we proved that the framework can address complex problems with N dimensions, enabling framework users to work with many dimensions.

Case-5 called Multiobjectivity, aimed to verify the ability of the framework to provide problem solutions to numerous conflicting objectives.

For validation, we used the simulation of productivity evaluation of the prosecutors based on the formalism of Swarm Intelligence to solve the problem of the optimization class with the use of evolutionary algorithms: Non-dominated Genetic Algorithm (NSGA), Adaptive Geometry Estimation for Objective (AGEMOEA), and Two-Archive Evolutionary Algorithm (CTAEA).

The problem that was solved was the existence of two distinct objectives that characterize productivity, so it is necessary to determine how to evaluate it, aiming to seek the optimal point between the objectives of efficiency and effectiveness, making the evaluation process fairer.

Using three scenarios with application of the evaluation factors, it was possible to observe through the results obtained and displayed in the general table of evaluations, Table 32, that the NSGA2 algorithm had a better performance than the AGEMODEA followed by the CTAE. Thus, we evaluated that, with the balance of the hyperparameters, the Framework recommended NSGA2, which had the best evaluation among the three scenarios.

Table 32: Simulation-5 General Framework of Evaluation Factors

Scenario	Model	AF	CF	EF	Ranking
1	NSGA2	1	1	1	1
2	AGEMODEA	2	2	3	2
3	CTAE	3	3	2	3

With this simulation, we were able to prove that the framework can meet complex problems with N dimensions, enabling users to work with many dimensions.

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