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Design Science Research Framework for Performance Analysis Using Machine Learning Techniques

Mihaela Muntean * and Florin Daniel Militaru

Business Information Systems Department, Faculty of Economics and Business Administration, West University of Timisoara, 300223 Timisoara, Romania
* Correspondence: mihaela.muntean@e-uvt.ro

Abstract: We propose a methodological framework based on design science research for the design and development of data and information artifacts in data analysis projects, particularly managerial performance analysis. Design science research methodology is an artifact-centric creation and evaluation approach. Artifacts are used to solve real-life business problems. These are key elements of the proposed approach. Starting from the main current approaches of design science research, we propose a framework that contains artifact engineering aspects for a class of problems, namely data analysis using machine learning techniques. Several classification algorithms were applied to previously labelled datasets through clustering. The datasets contain values for eight competencies that define a manager's profile. These values were obtained through a 360 feedback evaluation. A set of metrics for evaluating the performance of the classifiers was introduced, and a general algorithm was described. Our initiative has a predominant practical relevance but also ensures a theoretical contribution to the domain of study. The proposed framework can be applied to any problem involving data analysis using machine learning techniques.

Keywords: design science research; performance analysis; machine learning; classification algorithms; clustering algorithms

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Citation: Muntean, M.; Militaru, F.D. Design Science Research Framework for Performance Analysis Using Machine Learning Techniques. *Electronics* **2022**, *11*, 2504. https://doi.org/10.3390/electronics11162504

Academic Editors: Taiyong Li, Wu Deng and Jiang Wu

Received: 20 July 2022
Accepted: 8 August 2022
Published: 11 August 2022

1. Introduction

Design science research is a research paradigm with well-established conceptualizations applicable in engineering and, more recently, in the field of information systems.

According to Pfeffers et al. [1], design science research (DSR) is important in disciplines oriented towards the creation of successful artifacts. In data analysis, key artifacts are the "useful data artifacts" (UDA) and data-related information artifacts [2]. UDAs are "nonrandom subsets or derivative digital products of a data source, created by an intelligent agent (human or software) after performing a task on the data source", e.g., a labelled dataset or train and test dataset, while information artifacts refer to the objectives of the solution and requirements for final data visualizations or data specifications. Based on the importance of data/information artifacts in data analysis, we propose the design and development of a DSR process in this field of investigation.

Performance measurement is "the process of collecting, analyzing, and/or reporting information regarding the performance of an individual, group, organization, system, or component" [3]. According to Stroet [4], performance measuring is influenced by the usage of machine learning (ML) techniques "in a way that it becomes more accurate through the use of more current and accurately collected data, performance data are gathered easier, is done more continuous, is less biased and done with a more proactive attitude than before ML was implemented in the process". Managers and employees are frequently evaluated using 360-degree feedback. In general, 360 feedback focuses on behaviors and competencies more than basic skills, job requirements, and performance objectives. Therefore, the 360 feedback is incorporated into a larger performance management process and it is clearly "communicated on how the 360 feedback will be used". Because 360-feedback is time-consuming, the use of machine learning techniques for analyzing performance data determines the fluidization of the entire process, and the evaluation results are obtained in real time [4,5].

The process is a priori reviewed with staff members, and is started by collecting confidential information from managers' colleagues and sending the evaluation form to be completed by the employees [6]. Data are automatically collected and integrated into a single dataset. Further, mean values for each competence for all evaluated managers are calculated. The resulting dataset is subjected to analysis using machine learning algorithms.

The paper develops a theoretical applied research discourse based on:

- a methodological framework using design science research (DSR) for data analysis with machine learning techniques, such as classification algorithms;
- a theoretical approach to classification evaluation metrics;
- a set of competencies for evaluating the managers' performance using 360 feedback;
- an approach to apply the methodological framework to a performance related dataset.

2. Materials and Methods

2.1. Machine Learning Techniques—Clustering and Classification

The study of machine learning (ML) led to the development of many methods depending on the purpose, data representation, and learning strategy. Depending on the experience gained during the learning, we distinguish supervised, unsupervised, or semi-supervised learning methods. In addition, learning can occur through reinforcement or through "learning" [7]. According to El Bouchefry and De Souza [8], "ML algorithms are programs of data-driven inference tools that offer an automated means of recognizing patterns in high-dimensional data". Supervised algorithms search for inherited structures in a dataset, whereas unsupervised algorithms provide the correct labels or function values.

Both clustering and classification algorithms are proven to be successful in different analyses [9]. Classification algorithms require labelled datasets to perform the learning process. We proposed applying classification algorithms to datasets that were previously subjected to a clustering process. According to Alapati and Sindhu [10], the accuracy of a classifier can be improved by applying a classification algorithm to clustered data. We propose the following phases for the prediction analysis and performance prediction (Figure 1).

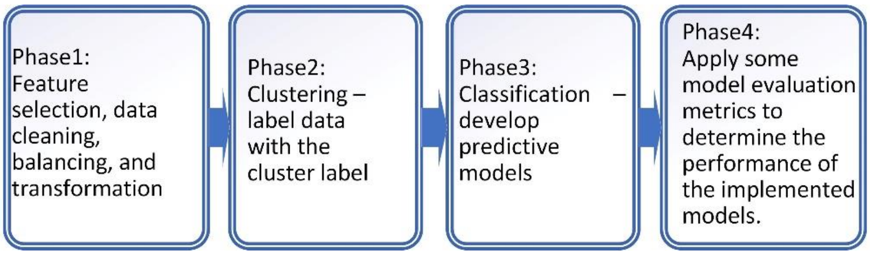

Phase1: Feature selection, data cleaning, balancing, and transformation
Phase2: Clustering – label data with the cluster label
Phase3: Classification – develop predictive models
Phase4: Apply some model evaluation metrics to determine the performance of the implemented models.

Figure 1. Prediction analysis phases.

To evaluate the quality of the classification, the performance of the classifier was analyzed, regardless of whether it may be, with the help of the following measures: sensitivity, specificity, accuracy, and F1 score [11,12].

2.1.1. Feature Selection

Not all attributes or features are important for a specific learning task. The challenging task in feature selection is to obtain an optimal subset of relevant and non-redundant features, which will provide an optimal solution without increasing the complexity of the modelling task [13]. According to Dash and Koot [14], for clustering tasks, it is not so obvious which features are to be selected: some of the features may be redundant, some are irrelevant, and others may be "weakly relevant". In the context of classification, feature selection techniques can be categorized as filter methods (ANOVA, Pearson correlation, and variance thresholding), wrapper methods (forward, backward, and stepwise selection), embedded methods (LASSO, RIDGE, and decision tree), and hybrid methods [15]. All feature selection methods help reduce the dimensionality of the data and the number of variables, while preserving the variance of the data.

2.1.2. Clustering

Clustering is an unsupervised learning problem that involves finding a structure in a collection of unlabelled data. A cluster is "a collection of objects that are similar between them and dissimilar to objects belonging to other clusters" [16]. Clustering algorithms can be classified as hierarchical, partitioning, density, grid, or model-based (Figure 2). According to Witten, Frank, Hall, and Pal [17], a cluster contains instances that bear a stronger resemblance to each other than to other instances.

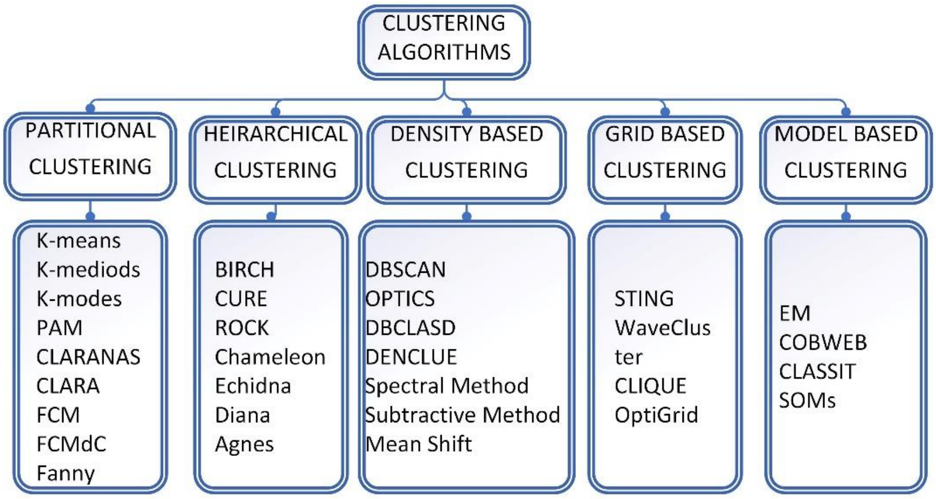


Figure 2. Clustering algorithms [18].

Partitional clustering algorithms divide datasets into mutually disjointed partitions. Data points are assigned to K clusters using an iterative process [19]. The partitional clustering techniques start with randomly chosen clustering, and then optimize the clustering according to the accuracy measurements. Owing to its simplicity and low time complexity, the K-means algorithm is commonly used for mining data and labeling them with cluster labels [20]. This requires pre-defining the number of clusters K, and the optimal K value is determined a priori [21]. Determining the optimal number of clusters is fundamental for clustering. According to Loukas [22], the optimal number of clusters depends on the method used for measuring similarities and the parameters used for partitioning (the elbow method, silhouette analysis, and gap statistics method).

Hierarchical clustering can be divided into two types: agglomerative (bottom-up) and divisive (top-down) clustering. Data objects (instances) are organized into a tree of clusters called a dendrogram. Each intermediate level can be viewed as combining two clusters from the next lower level (bottom-up) or splitting a cluster from the next higher level (top-down) [23]. Frequently applied in the construction of taxonomies, hierarchical clustering requires considerable computational and storage resources for deploying the dendrogram. Unfortunately, once a merge or split step is performed, it cannot be undone. Therefore, it is recommended to integrate hierarchical clustering with other techniques for multi-phase clustering.

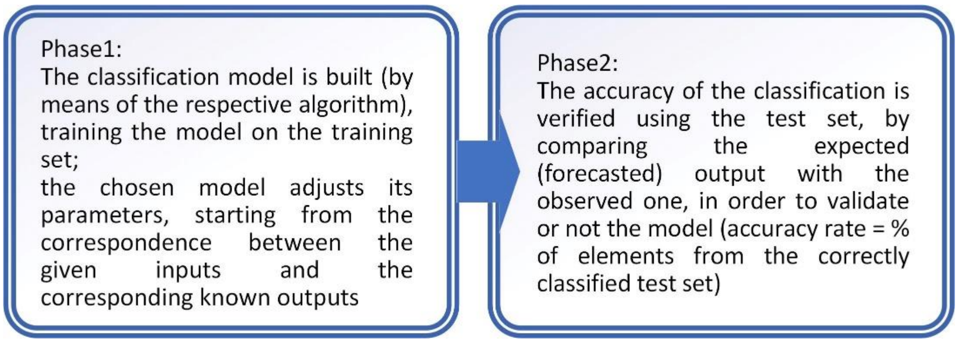
Density-based clustering algorithms identify distinctive clusters in the data based on the idea that "a cluster in a data space is a contiguous region of high point density", separated from other such clusters by contiguous regions of low point density [24]. The algorithms detect areas where points are concentrated, and where they are separated by areas that are empty or sparse.

Grid-based approaches are popular for mining clusters in large multidimensional spaces, in which clusters are regarded as denser regions than their surroundings. Such an algorithm is concerned not with data points but with the value space that surrounds them [25].

Finally, model-based clustering assumes that data are generated by a model, and attempts to recover the original model from the data.

2.1.3. Classification

Classification algorithms are supervised learning techniques that are used to identify the category (class) of new data. The classification involves the following processing phases (Figure 3).



Phase1:
The classification model is built (by means of the respective algorithm), training the model on the training set;
the chosen model adjusts its parameters, starting from the correspondence between the given inputs and the corresponding known outputs

Phase2:
The accuracy of the classification is verified using the test set, by comparing the expected (forecasted) output with the observed one, in order to validate or not the model (accuracy rate = % of elements from the correctly classified test set)

Figure 3. Classification process.

Among the most well-known models (methods) used for classification, we can mention the following [26]: decision trees, Bayesian classifiers, neural networks, k-nearest neighbor classifiers, statistical analysis, genetic algorithms, rough sets, rule-based classifiers, memory-based reasoning, support vector machines (SVMs), and boosting algorithms.

Binary classification (Figure 4) refers to classification tasks that have only two class labels (k-nearest neighbors, decision trees, support vector machines, and naive Bayes), whereas multiclass classification refers to classification tasks that have more than two class labels (k-nearest neighbors, decision trees, naive Bayes, random forest, and gradient boosting).

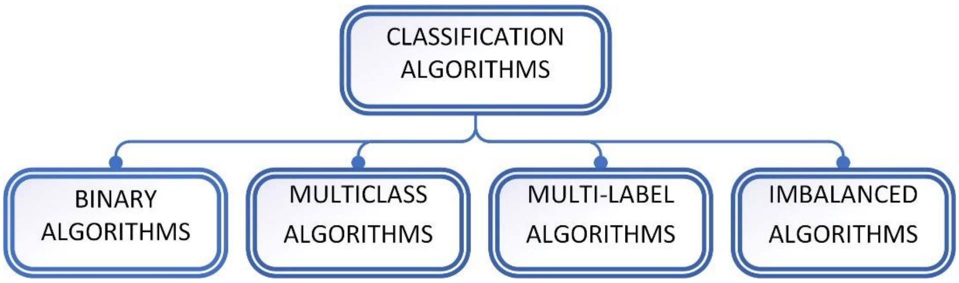


Figure 4. Classification algorithms.

A multi-label classifier can predict one or more labels for each data instance (multi-label decision trees, multi-label random forests, and multi-label gradient boosting). Unbalanced classification processes determine the classification of an unequal number of instances into classes (cost-sensitive logistic regression, cost-sensitive decision trees, and cost-sensitive support vector machines).

According to [27], it is necessary to first identify business needs and then map them to the corresponding machine learning tasks (Figure 5). After establishing the business requirements, the requirements for the machine learning algorithm were established. Characteristics, such as the accuracy of the algorithm, training time, linearity, number of parameters, and number of features influence the classifier selection [5]. The accuracy reflects the effectiveness of a model, that is, the proportion of true results in all cases. The training time varies from one classifier to another. Many machine learning algorithms use linearity. The parameters are the values that determine the algorithm behavior, and a large number of features substantially influence the training time [28]. Classification performance can be improved by mixed approaches [29].

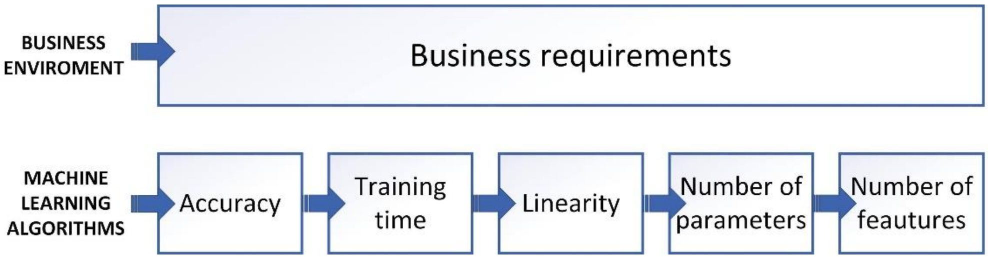


Figure 5. Criteria for selecting machine learning algorithms [28].

2.2. Design Science Research

According to Nunamaker et al. [30], research is "represented by its objectives and methods, whereby the objectives require a methodological approach to integrate theory building, system development, and experimentation". On a theoretical scale (Figure 6), the degree of theoretical importance is represented on one side versus the practical relevance on the other side [31].

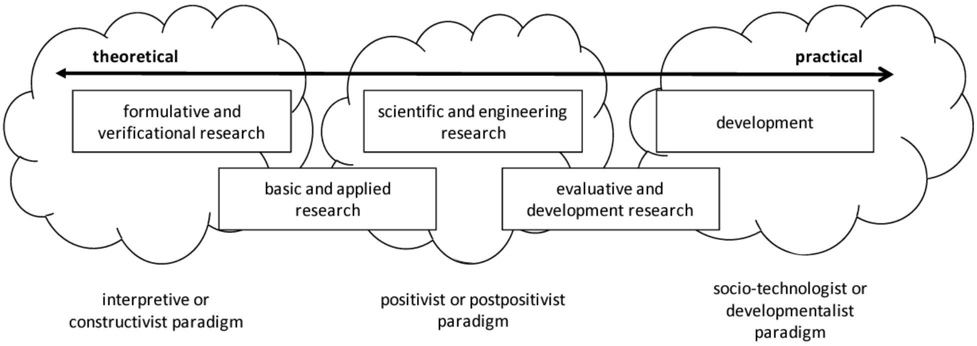

theoretical
practical
formulative and verificational research
scientific and engineering research
development
basic and applied research
evaluative and development research
interpretive or constructivist paradigm
positivist or postpositivist paradigm
socio-technologist or developmentalist paradigm

Figure 6. Research paradigm [30].

Research in information systems and data science implies an interdisciplinary research process that fits more than one paradigm [31].

Design science research (DSR) is a paradigm that is accepted in disciplines, such as engineering. This research paradigm is extended to information systems and data science [32]. As asserted by Hevner et al. [32], guidelines for design science research include methodological choices for the DSR process.

Several research methodologies were developed to support the DSR process [33]. The main methodologies are the systems development research methodology (SDRM) [30], DSR process model (DSRPM) [34], design science research methodology (DSRM) [7], action design research (ASR) [35], soft design science methodology (SDSM) [36], and participatory action design research (PADR) [37].

According to Nunamaker et al. [33], SDRM is a five-step research process that includes the following steps: constructing a conceptual framework, developing a system architecture, analyzing and designing the system, building the (prototype) system, and observing and evaluating the system.

In their "Design Research in Information Systems", Vaishnavi and Kuechler [34] explain the process steps of design research. By pointing out the importance of artifacts, the DSR process includes the following steps: awareness of the problem, suggestion, development, evaluation, and conclusion.

Peffers et al. [1] proposed a six-step design science research methodology: identifying the problem and motivation, defining the objectives of a solution, design and development, demonstration, evaluation, and communication. DSR methodology is "an artifact-centric creation and evaluation approach" [1,34]. The research methodology implies the design cycle of "artifacts of practical value to either the research or professional audience" [38,39]. Artifacts are systems, applications, methods, data models, data sets, and others "that could contribute to the efficacy of information systems and business analysis in organizations" [40].

ADR methodology combines action research with DSR [33]. It includes four phases: problem formulation, building intervention and evaluation, reflection and learning, and formalization of learning [35].

The eight activities of SDSM are: learning about a specific problem, inspiring and creating the general problem and general requirements, intuiting the general solution, general evaluation, designing specific solution for specific problem, specific evaluation, constructing specific solution, and post evaluation [33,36].

The PADR methodology is recommended for developing solutions to problems involving large heterogeneous groups of stakeholders [33,37]. It consists of the following steps: diagnosis and problem formulation, action planning, action taking: design, impact evaluation, and reflection and learning.

Based on the DSRM and DSRPM, we recommend the methodological framework shown in Figure 7 for performing data analysis.

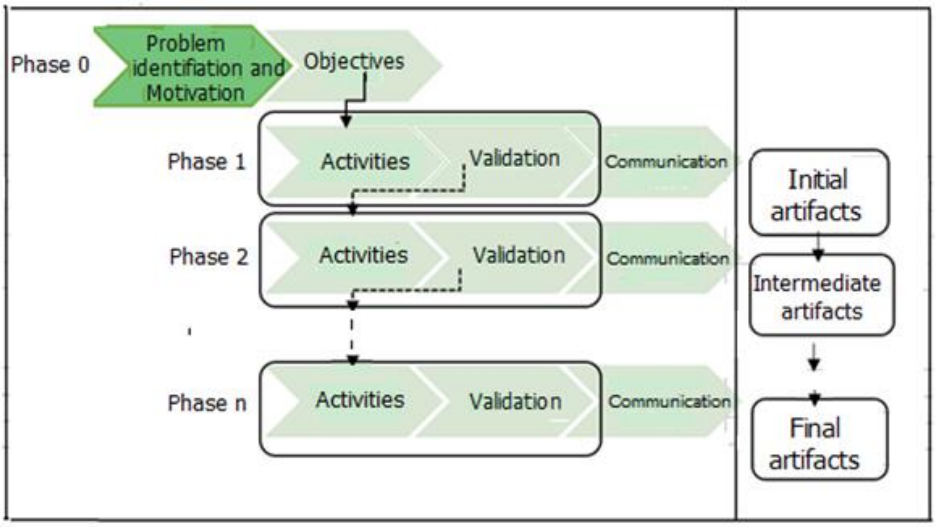


Figure 7. Design science research framework.

The activities shown in Figure 7 indicate the design and development of the artifacts. Furthermore, the artifacts are evaluated, and after validation, they are e communicated and processed in the next phase [41]. Artifact evaluation provides a better interpretation of the problem and feedback to improve the quality of designed artifacts [42].

Owing to its focus on developing information artifacts, DSR is a research approach with a predominant practical relevance. Artifacts are designed and developed in order to improve business activities, processes, or to support decisions. Therefore, the targeted business beneficiaries of the artifacts are involved in their testing and validation [31].

3. Methods

3.1. Artifacts Development in Design Science Research

"Current design science research method does not have a systematic methodological process to follow in order to produce artifacts" [43]. In general, the following research methods, techniques and tools are used for artifact design and development (Table 1).

Table 1. DSR process. Research methods, techniques and tools.

Phase	Activity	Research Methods, Techniques and Tools
Phase 0	Problem identification and Motivation Objectives establishment	Brainstorming, systems review and analysis, literature study, interviews, focus group
Phase 1 Phase n	Activities	Literature review, system analysis, field and case study. artifacts engineering
	Validation	Simulation, informed argument, controlled experiment, case study, field study
	Communication	Communication framework

We propose an approach to prediction analysis (Figure 1) in a DSR framework (Figure 7) using appropriate research methods, techniques and tools (Table 1).

Artifact engineering using machine learning techniques implies a set of activities and tasks that are highlighted in Table 2. The initial, intermediate, and final artifacts were established for each phase.

Table 2. DSR process. Using machine learning techniques.

Phase	Activity/Task	Artifact (Output)
Ph0. Phase 0	A01. Problem identification and Motivation A02. Objectives establishment	O01. Objectives of the solution O02. Requirements for final data visualizations
Ph1. Phase 1	A11. Understanding the data Task1. Establishing the data that are necessary for the business analysis, Task2. Identifying the issues that affect the data quality A12. Validation of the information artifacts A13. Communicating the result	O11. Data specifications
Ph2. Phase 2	A21. Data set design and development Task1. Accessing data sources and retrieving data Task2. Features selection Task3. Data cleaning Task4. Data transforming A22. Validation of the information artifact A23. Communication of the result	O21. Dataset
Ph3. Phase 3	A31. Data modelling through clustering Task1. Choosing the clustering algorithm depending on analysis objectives, type of data, size of the dataset, cleanliness of the data Task2. Performing the clustering A32. Validation of the information artifact A33. Communication of the result	O31. Labelled dataset
Ph4. Phase 4	A41. Data modelling through classification Task1. Establishing the training (80%) and test dataset (20%) Task2. Train the model for different classification algorithms Task3. Test the models Task4. Evaluate each model and select the best classification algorithm A42. Validation of the information artefacts A43. Communication of the result	O41. Training dataset O42. Test dataset O43. Classification data models O44. Results of the testing process O45. Evaluation metrics results
Ph5. Phase 5	A51. Prediction with the best classification algorithm	O51. Class labels and scores for the new dataset

Our proposal establishes all necessary processing to perform data analysis in general, and performance analysis in particular.

Data analysis is part of a larger business process, such as the process of evaluating performance, and is meant to add value to a business [7]. Data analysis takes primary information from the information flows and returns the information artifacts to the information flows in the corporate environment. As part of the performance management process, the proposed framework is closely linked to process elements downstream and upstream. This implies a scalable deployment approach containing the following stages: top management involvement, proper planning and scoping, introducing the data analysis in terms of a business case, implementing the DSR process, and maintaining a solid data governance program.

3.2. Metrics for Evaluating Classification Models

Classification algorithms are widely used to make predictions and meaningful decisions [42]. Once a classification algorithm produces a model, it is evaluated with respect to certain criteria such as accuracy, ROC curve, or F1 score [44].

According to the prediction approach (Figure 1), classification represents the third phase after feature selection and clustering [11]. A classification model is constructed by applying a classifier to the training dataset (80% of the data). Furthermore, classification accuracy was verified using a test set (20% of the data) by comparing the forecasted output (class label) with the observed output (cluster label provided by the clustering algorithm). Building acceptable classification models implies, despite accuracy and justifiability, that the model should be in line with the existing domain knowledge [45].

According to Choi et al. [46], six evaluation metrics are recommended to evaluate multilevel classification: accuracy, precision, recall, F1-score, receiver operating characteristic curve, and AUC. A greater number of indicators are used in specific contexts, such as software fault predictions [47]. In addition, the classification performance was measured using G-mean, J-coefficient, error rate, and balance. A review of evaluation metrics for data classification evaluations presented a set of suitable indicators for obtaining the optimal classifier: accuracy, error rate, sensitivity, specificity, precision, recall, F-score, geometric mean, average accuracy, average error rate, average precision, average recall, and average F-score [48].

In all approaches, the basic metrics are true positive (TP), true negative (TN), false positive (FP), and false negative (FN) [49]. A true positive is a predicted outcome that is similar to the actual class (cluster label). A false positive result occurs when the classifier labels (or categorizes) a data instance that it should not contain. A true negative result occurs when the classifier does not correctly label (or categorize) the output. A false negative result occurs when the classifier does not label a data instance but should have. Based on these considerations, we introduced the following metrics to evaluate the classification performance (Table 3).

Table 3. Classification model evaluation metrics (adapted from [49]).

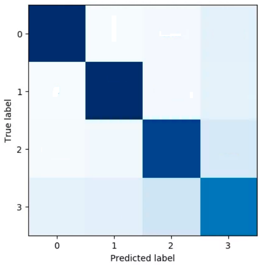
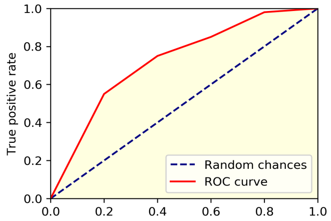
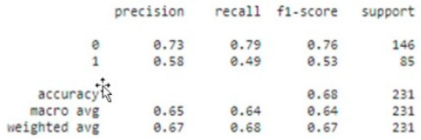
No.	Metric Name	Metric Description	
0	true positive (TP), true negative (TN), false positive (FP), false negative (FN)		
1	Confusion matrix (CM)	is a summary of the prediction results; the number of correct and incorrect predictions is summarized with count values and broken down by class	

Table 3. *Cont.*

<table>
<tr><th>No.</th><th>Metric Name</th><th>Metric Description</th><th></th></tr>
<tr><td>2</td><td>Precision (P)</td><td>is the number of correct classes returned by the classification model.</td><td>$Precision = \frac{TP}{TP+FP}$</td></tr>
<tr><td>3</td><td>Recall (R)</td><td>is the ability of a model to find all relevant cases within a dataset, and is the number of true positives divided by the number of true positives plus the number of false negatives</td><td>$Recall = \frac{TP}{TP+FN}$</td></tr>
<tr><td>4</td><td>F1 score</td><td>is the harmonic mean of precision and recall</td><td>$F1 = 2 \times \frac{Precision \times Recall}{Precision+Recall}$
$F1 = \frac{2TP}{2TP+FP+FN}$</td></tr>
<tr><td>5</td><td>Receiver operating characteristic (ROC) curve</td><td>the ROC curve shows how the recall vs. precision relationship changes as we vary the threshold for identifying a positive data point in our model</td><td>
</td></tr>
<tr><td>6</td><td>Area under the ROC curve (AOC)</td><td>is the measure of the ability of a classifier to (AOC) distinguish between classes and is used as a summary of the ROC curve.</td><td></td></tr>
<tr><td>7</td><td>Accuracy (A)</td><td>the number of correct predictions made as a ratio of all predictions made.</td><td>$Accuracy = \frac{TP+TN}{TP+FP+FN+TN}$</td></tr>
<tr><td>8</td><td>Classification report</td><td>is used to measure the quality of predictions from a classification algorithm; the following measures are displayed: precision, recall, F1, and support scores.</td><td>
<pre>
              precision   recall f1-score   support

           0   0.73   0.79   0.76   146
           1   0.58   0.49   0.53   85

    accuracy   0.68   231
   macro avg   0.65   0.64   0.64   231
weighted avg   0.67   0.68   0.67   231
</pre></td></tr>
</table>

Accuracy is widely used to evaluate the classification performance. Additionally, in the case of imbalanced datasets, the F1-score and metrics presented in Table 3 were used [49].

3.3. General Algorithm for Determining the Classification Model Evaluation Metrics

Let DS be a labelled dataset with N instances and different NC class labels. During the training phase, a classification model was generated, and predicted class labels were added during the testing phase (1).

$$Y_{Class(j)}, Y_{Predicted_{Class(j)}} \in \left\{ class_{label(i)} \right\}, \quad i = 1, NC; \; j = 1, N \tag{1}$$

Metrics TP(i), TN(i), FP(i), FN(i), Precision(i), Recall(i), Accuracy(i) and f1(i) were calculated for each class_label(i) according to Pseudocode 1.

The classification report was assembled, and the global metrics of precision, recall, accuracy, and F1 for the classification algorithm were determined, as indicated in Pseudocodes 2.

We recommend using MS Power BI to perform the data analysis. It is used in business and industry sectors as an integral part of the technological and information systems framework. In a self-service manner, business users can integrate data from a variety of sources, perform advanced analysis, and design dashboards for process tracking and decision support. Automated machine learning (AutoML) for dataflows enables business analysts to train, validate, and invoke machine learning models directly in MS Power BI. Pycaret, an open source, low-code machine learning library in Python, accessible from MS Power BI offers support for automated machine learning workflow.

Pseudocode 1

```
FOR i IN 1..NC DO
  FOR j IN 1..N DO
    IF Y_Predicted_Class(j) = Y_Class(j)  AND Y_Predicted_Class(j) =class_label(i)
    TP(i) = TP(i) + 1;
    IF Y_Predicted_Class(j)<>Y_Class(j)  AND Y_Class(j)<>class_label(i)
    FN(i) = FN(i) + 1;
    IF Y_Predicted_Class(j)<>class_label(i)  AND Y_Class(j)<>class_label(i)
    TN(i) = TN(i) + 1;
    IF Y_Predicted_Class(j) = class_label(i)  AND Y_Class(j)<>class_label(i)
    FP(i) = FP(i) + 1;
  IF TP(i) + FP(i)<>0
    Precision(i) = TP(i)/((TP(i) + FP(i)));
  ELSE
    Precision(i) = 0;
  IF TP(i) + FN(i)<>0
    Recall(i) = TP(i)/((TP(i) + FN(i)));
  ELSE
    Recall(i) = 0;
  IF TP(i) + TN(i) + FP(i) + FN(i)<>0
    Accuracy(i) = ((TP(i) + TN(i)))/((TP(i) + TN(i) + FP(i) + FN(i)));
  ELSE
    Accuracy(i) = 0;
  IF Precision(i) + Recall(i)<>0
    f1(i) = 2*(Precision(i)*Recall(i))/((Precision(i) + Recall(i)));
  ELSE
    f1(i) = 0;
```

Pseudocode 2

```
FOR i IN 1..NC DO
    classification_report(i,1) = Precision(i);
    classification_report(i,2) = Recall(i);
    classification_report(i,3) = Accuracy(i);
    classification_report(i,4) = f1(i);
    Global_precision = Global_precision + Precision(i);
    Global_recall = Global_recall + Recall(i);
    Global_accuracy = Global_accuracy + Accuracy(i);
    Global_f1 = Global_f1 + f1(i);
Global_precision = Global_precision/NC;
Global_recall = Global_recall/NC;
Global_accuracy = Global_accuracy/NC;
Global_f1 = Global_f1/NC;
```

4. Analysis and Results

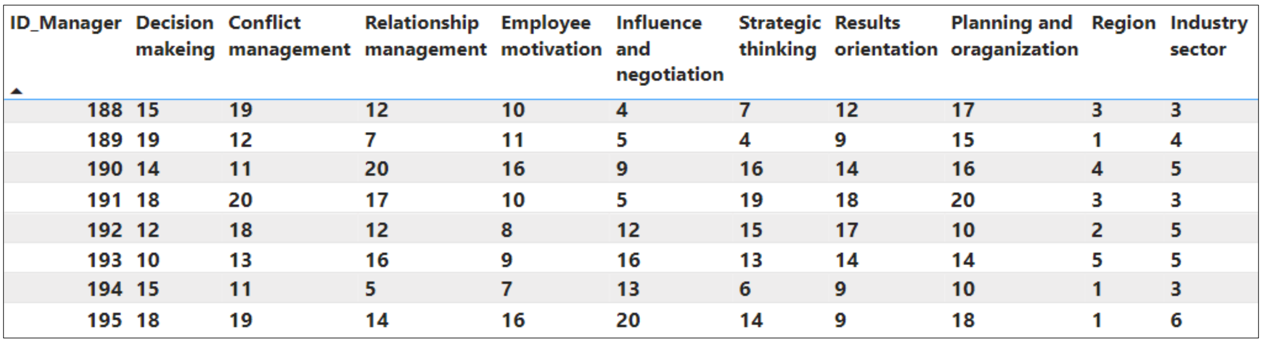
Right from the beginning, the objectives of our theoretical applied discourse were established. Objective one aims to the introduction of a methodological framework using design science research for data analysis. Based on relevant references on DSR [1,2,31–37], we propose a multi-phase framework (Figure 7). Further, the development of artifacts was systematized by establishing activities and tasks specific to each phase within the DSR framework (Table 2). Concrete specifications regarding the use of machine learning algorithms are formulated.

The second objective refers to the unitary approach of metrics for evaluating the performance of classification algorithms. The main evaluation metrics were briefly presented (Table 3) and a general algorithm for determining the classification model evaluation metrics was proposed (Pseudocodes 1 and 2).

The next two objectives, mentioned in the introductory chapter, aim at the application of the theoretical considerations for performance analysis.

The analysis regarding the "managerial capacity" of decision makers was performed using the DSR framework, in compliance with the phases listed in Table 2. A 360-degree evaluation form was chosen as the investigation tool and means of data collection [50]. The following competencies are evaluated: decision making ability, conflict management, relationship management, employee motivation, influence and negotiation, strategic thinking, results orientation, and last but not least planning and organization. Each competence was based on four statements, each of which was assessed by assigning a score on a scale of one to five. The resulting competency scores are in a range from 4 to 20 points (Appendix A).

The dataset centralizes the scores obtained by various managers and contains 195 final instances (Figure 8). Eight competencies (decision making ability, conflict management, relationship management, employee motivation, influence and negotiation, strategic thinking, result orientation, planning, and organization) were selected for data analysis using machine learning techniques, such as clustering and classification.



ID_Manager	Decision makeing	Conflict management	Relationship management	Employee motivation	Influence and negotiation	Strategic thinking	Results orientation	Planning and oraganization	Region	Industry sector
188	15	19	12	10	4	7	12	17	3	3
189	19	12	7	11	5	4	9	15	1	4
190	14	11	20	16	9	16	14	16	4	5
191	18	20	17	10	5	19	18	20	3	3
192	12	18	12	8	12	15	17	10	2	5
193	10	13	16	9	16	13	14	14	5	5
194	15	11	5	7	13	6	9	10	1	3
195	18	19	14	16	20	14	9	18	1	6

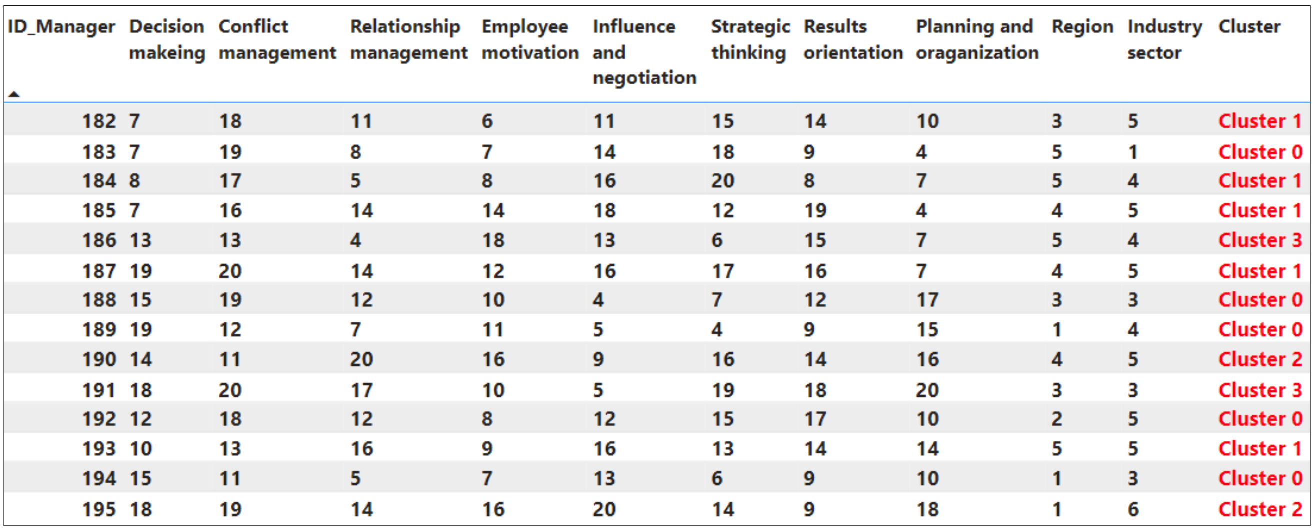
Figure 8. O21. Dataset. Partial data.

The dataset contained unlabeled data and required further annotation. This was achieved by modelling the data through clustering. PyCaret's clustering module is an unsupervised machine learning module that groups of a set of objects such that those in the same group (called a cluster) are more similar to each other than to those in other groups. Clustering was performed using the K-means algorithm (Script 1, Figure 9).

Script 1

```
from pycaret.clustering import *
dataset = get_clusters(dataset, num_clusters = 4, ignore_features = ['ID_Manager',
'Industry_sector', 'Region'])
```

The classification module is "a supervised machine learning module that is used for classifying elements into groups. The goal is to predict discrete and unordered categorical class labels" [26]. We used various classification algorithms (Table 2) and calculated evaluation metrics for each algorithm. The models were saved as pkl files. (Script 2).



ID_Manager	Decision makeing	Conflict management	Relationship management	Employee motivation	Influence and negotiation	Strategic thinking	Results orientation	Planning and oraganization	Region	Industry sector	Cluster
182	7	18	11	6	11	15	14	10	3	5	Cluster 1
183	7	19	8	7	14	18	9	4	5	1	Cluster 0
184	8	17	5	8	16	20	8	7	5	4	Cluster 1
185	7	16	14	14	18	12	19	4	4	5	Cluster 1
186	13	13	4	18	13	6	15	7	5	4	Cluster 3
187	19	20	14	12	16	17	16	7	4	5	Cluster 1
188	15	19	12	10	4	7	12	17	3	3	Cluster 0
189	19	12	7	11	5	4	9	15	1	4	Cluster 0
190	14	11	20	16	9	16	14	16	4	5	Cluster 2
191	18	20	17	10	5	19	18	20	3	3	Cluster 3
192	12	18	12	8	12	15	17	10	2	5	Cluster 0
193	10	13	16	9	16	13	14	14	5	5	Cluster 1
194	15	11	5	7	13	6	9	10	1	3	Cluster 0
195	18	19	14	16	20	14	9	18	1	6	Cluster 2

Figure 9. O31. Labelled dataset. Partial data.

Script 2

```
clf1 = setup(df, target = 'Cluster', silent = True, ignore_features = ['ID_Manager',
'Industry_sector','Region'])
# train multiple models
algorithms = ['knn','dt','catboost','nb','rbfsvm','lr','gpc','mlp','rf','qda','ada','gbc','lda','et',
'xgboost','lightgbm','svm','ridge']
models = [create_model(i) for i in algorithms]
final_models = [finalize_model(models[i]) for i in range(len(algorithms))]
for x in range(len(algorithms)):
save_model(final_models[x], 'D:/'+ algorithms [x])
```

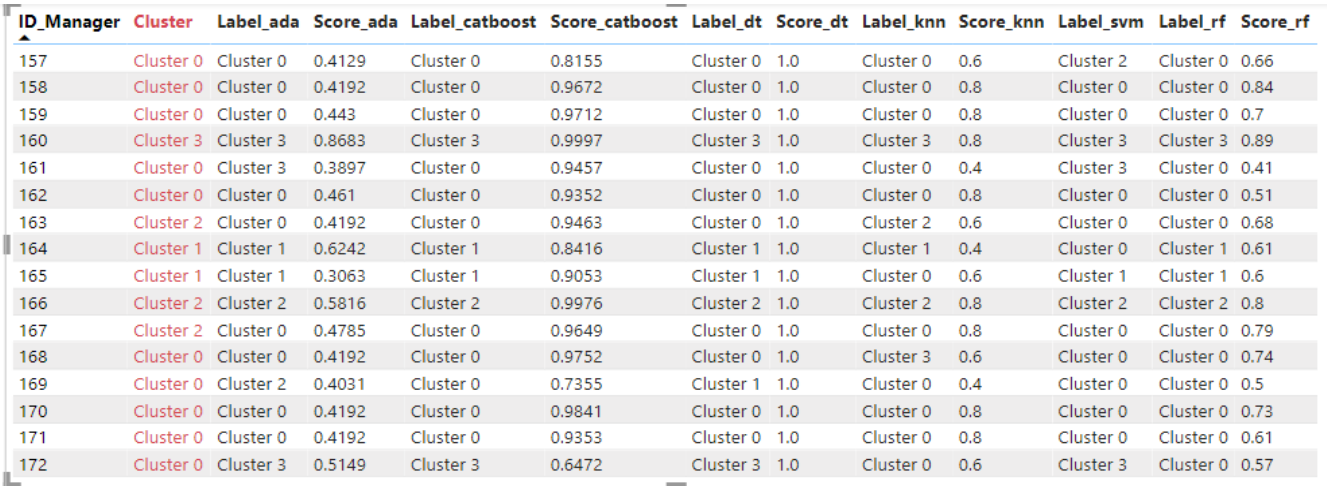
After training different classification algorithms, the models were tested (Script 3). The predicted class labels are associated with each instance of the test dataset (Figure 10).

Script 3

```
algorithms = ['knn','dt','catboost','nb','rbfsvm','lr','gpc','mlp','rf','qda','ada','gbc','lda','et',
'xgboost','lightgbm','svm','ridge']
from pycaret.classification import *
for i in range(len(algorithms)):
clasificator = load_model('D:/' + algorithms[i])
dataset = predict_model(clasificator, data = dataset)
dataset.rename(columns = {'Label':'Label_' + algorithms[i],'Score': 'Score_' + algorithms[i]},
inplace = True)
```

The evaluation metrics were calculated for each classification model according to the previously described "general algorithm for determining the classification model evaluation metrics" (Pseudocodes 1 and 2).

We created, trained, and deployed a machine leaning model for each classification algorithm available in PyCaret library. The following algorithms, which are listed in alphabetical order, were applied: adaboost (ada), cat booster classifier (catboost), decision tree (dt), extra tree classifier (et), extreme gradient boosting (xgboost), gaussian process classifier (gpc), gradient boosting classifier (gbc), light gradient boosting (lightgbm), linear disc analysis (lda), logistic regression (lr), k nearest neighbor (knn), multi level perceptron (mlp), naives bayes (nb), random forest (rf), ridge classifier (ridge), support vector machine (svm and rbfsvm), and quadratic disc analysis (qda) [26]. They are representative for all classification algorithm categories (Figure 4).



ID_Manager	Cluster	Label_ada	Score_ada	Label_catboost	Score_catboost	Label_dt	Score_dt	Label_knn	Score_knn	Label_svm	Label_rf	Score_rf
157	Cluster 0	Cluster 0	0.4129	Cluster 0	0.8155	Cluster 0	1.0	Cluster 0	0.6	Cluster 2	Cluster 0	0.66
158	Cluster 0	Cluster 0	0.4192	Cluster 0	0.9672	Cluster 0	1.0	Cluster 0	0.8	Cluster 0	Cluster 0	0.84
159	Cluster 0	Cluster 0	0.443	Cluster 0	0.9712	Cluster 0	1.0	Cluster 0	0.8	Cluster 0	Cluster 0	0.7
160	Cluster 3	Cluster 3	0.8683	Cluster 3	0.9997	Cluster 3	1.0	Cluster 3	0.8	Cluster 3	Cluster 3	0.89
161	Cluster 0	Cluster 3	0.3897	Cluster 0	0.9457	Cluster 0	1.0	Cluster 0	0.4	Cluster 3	Cluster 0	0.41
162	Cluster 0	Cluster 0	0.461	Cluster 0	0.9352	Cluster 0	1.0	Cluster 0	0.8	Cluster 0	Cluster 0	0.51
163	Cluster 2	Cluster 0	0.4192	Cluster 0	0.9463	Cluster 0	1.0	Cluster 2	0.6	Cluster 0	Cluster 0	0.68
164	Cluster 1	Cluster 1	0.6242	Cluster 1	0.8416	Cluster 1	1.0	Cluster 1	0.4	Cluster 0	Cluster 1	0.61
165	Cluster 1	Cluster 1	0.3063	Cluster 1	0.9053	Cluster 1	1.0	Cluster 0	0.6	Cluster 1	Cluster 1	0.6
166	Cluster 2	Cluster 2	0.5816	Cluster 2	0.9976	Cluster 2	1.0	Cluster 2	0.8	Cluster 2	Cluster 2	0.8
167	Cluster 2	Cluster 0	0.4785	Cluster 0	0.9649	Cluster 0	1.0	Cluster 0	0.8	Cluster 0	Cluster 0	0.79
168	Cluster 0	Cluster 0	0.4192	Cluster 0	0.9752	Cluster 0	1.0	Cluster 3	0.6	Cluster 0	Cluster 0	0.74
169	Cluster 0	Cluster 2	0.4031	Cluster 0	0.7355	Cluster 1	1.0	Cluster 0	0.4	Cluster 0	Cluster 0	0.5
170	Cluster 0	Cluster 0	0.4192	Cluster 0	0.9841	Cluster 0	1.0	Cluster 0	0.8	Cluster 0	Cluster 0	0.73
171	Cluster 0	Cluster 0	0.4192	Cluster 0	0.9353	Cluster 0	1.0	Cluster 0	0.8	Cluster 0	Cluster 0	0.61
172	Cluster 0	Cluster 3	0.5149	Cluster 3	0.6472	Cluster 3	1.0	Cluster 0	0.6	Cluster 3	Cluster 0	0.57

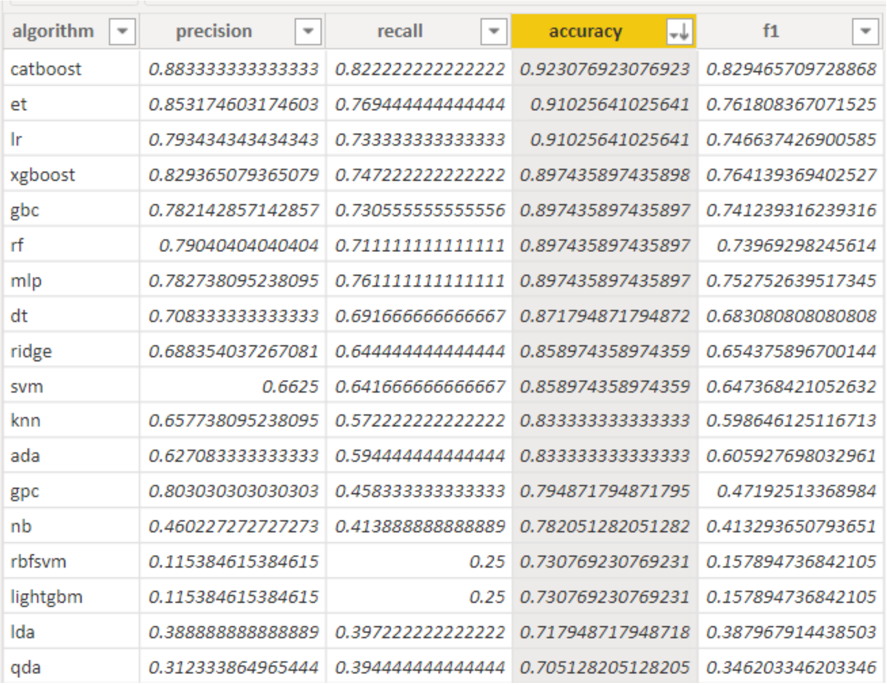
Figure 10. O44. Results of the testing process.

The automated machine learning (AutoML) workflow implemented by Scripts 2 and 3 generated the data artifacts specified in Table 2.

Further, the evaluation metrics for each algorithm were processed, namely precision, recall, accuracy, and f1 metric (Figure 11). Script 4 is part of the Auto ML approach.

Script 4

```
algorithms = [‘knn’,’dt’,’catboost’,’nb’,’rbfsvm’,’lr’,’gpc’,’mlp’,’rf’,’qda’,’ada’,’gbc’,’lda’,’et’,
‘xgboost’,’lightgbm’,’svm’,’ridge’]
final_models = [finalize_model(models[i]) for i in range(len(al))]
for x in range(len(al)):
save_model(final_models[x], ‘D:/[x])
best = compare_models(include = al)
results = pull()
print(results)
```



algorithm	precision	recall	accuracy	f1
catboost	0.883333333333333	0.822222222222222	0.923076923076923	0.829465709728868
et	0.853174603174603	0.769444444444444	0.91025641025641	0.761808367071525
lr	0.793434343434343	0.733333333333333	0.91025641025641	0.746637426900585
xgboost	0.829365079365079	0.747222222222222	0.897435897435898	0.764139369402527
gbc	0.782142857142857	0.730555555555556	0.897435897435897	0.741239316239316
rf	0.79040404040404	0.711111111111111	0.897435897435897	0.73969298245614
mlp	0.782738095238095	0.761111111111111	0.897435897435897	0.752752639517345
dt	0.708333333333333	0.691666666666667	0.871794871794872	0.683080808080808
ridge	0.688354037267081	0.644444444444444	0.858974358974359	0.654375896700144
svm	0.6625	0.641666666666667	0.858974358974359	0.647368421052632
knn	0.657738095238095	0.572222222222222	0.833333333333333	0.598646125116713
ada	0.627083333333333	0.594444444444444	0.833333333333333	0.605927698032961
gpc	0.803030303030303	0.458333333333333	0.794871794871795	0.47192513368984
nb	0.460227272727273	0.413888888888889	0.782051282051282	0.413293650793651
rbfsvm	0.115384615384615	0.25	0.730769230769231	0.157894736842105
lightgbm	0.115384615384615	0.25	0.730769230769231	0.157894736842105
lda	0.388888888888889	0.397222222222222	0.717948717948718	0.387967914438503
qda	0.312333864965444	0.394444444444444	0.705128205128205	0.346203346203346

Figure 11. O45. Evaluation metrics synthesis.

According to the values obtained for accuracy, as well as for the other metrics, the CatBoost algorithm proved to be the best performant classification algorithm in our analysis. Therefore, this will be investigated further (Figure 12). CatBoost is an algorithm for gradient boosting of decision trees. According to Pramoditha [51], CatBoost is one of the best machine learning models for tabular heterogeneous datasets.

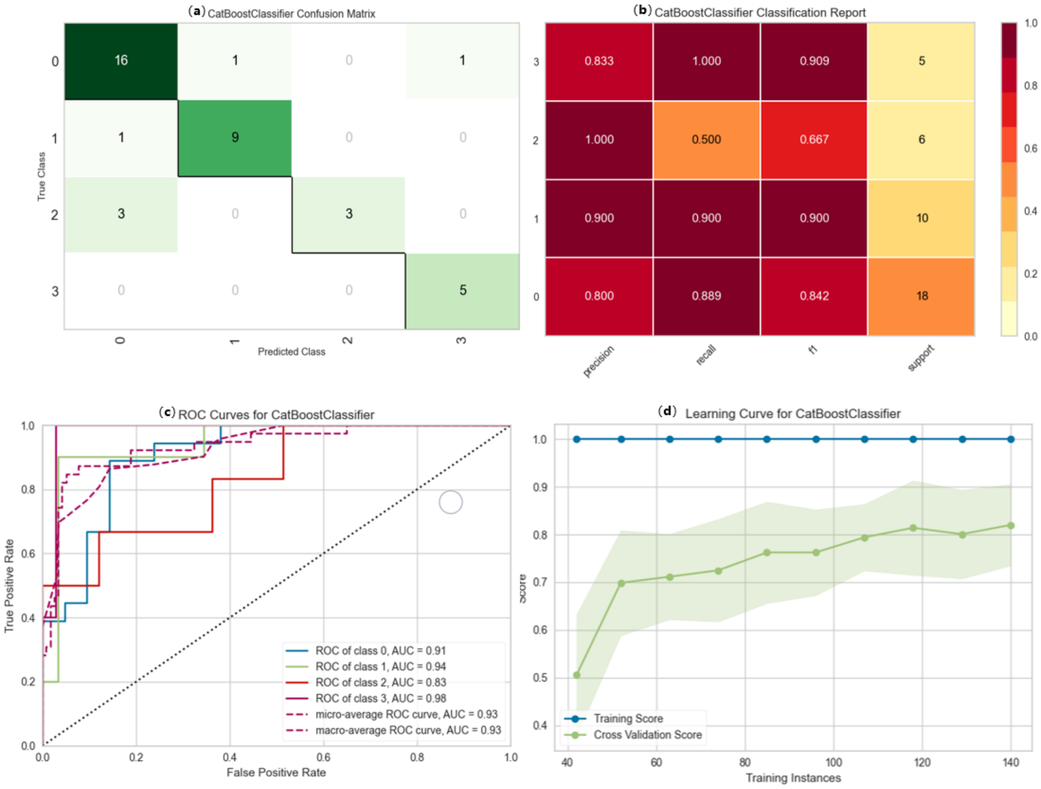


Figure 12. CatBoost algorithm. Evaluation metrics.

The confusion matrix contains the values of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) calculated for each class (Figure 12a). We observed that most instances were correctly labelled. Most instances that were incorrectly labelled belonged to class 0 (cluster 0).

The classification report presents the main classification matrices, namely, precision, recall, and F1 score for each class (Figure 12b). We can notice that:

- The algorithm has a significant ability to label instances correctly, particularly in classes 1 and 2.
- For classes 0, 1, and 3, the algorithm had a high capacity to find all instances; however, it correctly labelled only half of the instances in class 2.
- The values of f1 for classes 0, 1, and 3 are appropriate and approximately equal to an average of 0.9; however, for class 2, f1 is only 0.667. Although the precision of the classification of the instances in class 2 was 1, the algorithm identified only three out of the six instances of class 2.

The graph of the ROC curve shows that the classification model can place the instances in a single class (Figure 12c). The graph shows that the instances of classes 0, 1, and 3 are approximately equal to the algorithm average of 0.93, indicating that these classes are well-separated. The only class for which a lower score was obtained was class 2, which had a score of 0.83. However, even for this class, the model provides a good measure of the separability.

The learning curve for the CatBoost classifier indicated that increasing the number of instances in the training set led to an increase in the validation score (Figure 12d). The training score maintains a value of one, which indicates that the model perfectly integrates each newly added instance.

According to Huilgol [52], accuracy is used when true positives and true negatives are decisive in the analysis, whereas the F1-score is used when false negatives and false positives are the most important. Furthermore, the accuracy can be used when the class distribution is similar, whereas the F1-score is a better metric when dealing with imbalanced classes.

The use of machine learning techniques for performance analysis makes a significant contribution when operating with large datasets [27]. We identified concrete applications of our proposal, namely: the application of the procedure within a multinational company or in statistical research studies on companies.

The Power BI application integrates the data obtained through 360-feeback and performs the analysis. The results are available to the management boards and research coordinators.

DSR is applied in various business and industrial engineering areas [53]. The literature indicates different approaches to designing artifacts [31–41]. Our proposal comes to offer a framework for data analysis using machine learning techniques. The theoretical discourse was applied to a performance analysis.

5. Conclusions

DSR opens new research perspectives in information systems and data analysis. We managed to complete an artifact design-centric approach adapted for data analysis. The proposed DSR framework describes a multi-phase process containing activities and tasks that allow the design, development, testing, validation, and communication of the considered data and information artifacts.

Artifacts engineering is performed using machine learning techniques. We recommend the use of AutoML to automate the iterative tasks of machine learning model development. Mainly based on classification algorithms, the workflow also provides for the evaluation of the applied algorithms.

The proposed design science research was applied in a managerial performance evaluation project. Further steps are necessary to define a secure connection to the operational HR database, where performance data are stored. In this sense, we are concerned to respect all internal regulations and data governance prescriptions.

Author Contributions: Conceptualization, M.M.; methodology, M.M.; software, F.D.M.; validation, M.M. and F.D.M.; writing—review and editing, M.M. and F.D.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Acknowledgments: This study was conducted by Muntean Mihaela, associate member of the East European Center for Research in Economics and Business (ECREB) at the Faculty of Economics and Business Administration, West University of Timisoara. Florin Daniel Militaru, contributed to the completion of the paper, with the results of research undertaken within the Business Information Systems Department.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. The 360 feedback form for measuring a manager's performance [51].

Competence	Statements	Evaluation Scale				
Decision making capacity	Assess the implications of a strategic or potentially risky decision and the impact it may have on the organization	1	2	3	4	5
	Make good decisions based on a mix of analysis, intuition, experience and logic.	1	2	3	4	5
	Most of the solutions and suggestions offered by him/her prove to be correct and precise in time.	1	2	3	4	5
	It takes less popular measures when the situation demands it or implements decisions even if it does not have the consent of all its subordinates.	1	2	3	4	5
Conflict management	Manage issues firmly, directly and in a timely manner.	1	2	3	4	5
	He/she is an active listener, able to understand the source of conflicts and to suggest proper solutions.	1	2	3	4	5
	It easily reaches armistices and agreements, with the involvement of a minimum number of third parties.	1	2	3	4	5
	He/she finds ways out of difficult situations and manages to value the disputes.	1	2	3	4	5
Relationships management	It relates well to all categories of people, regardless of the hierarchical level, both inside and outside the company.	1	2	3	4	5
	Communication with colleagues is clear and efficient.	1	2	3	4	5
	Provides current, direct, complete, actionable, positive and/or corrective feedback to others.	1	2	3	4	5
	Encourages open dialogue within the team.	1	2	3	4	5
Employee motivation	Maintains a constant dialogue with the team members for whom he is responsible for the quality and quantity of work and results	1	2	3	4	5
	Appreciate the extra effort and communicate its recognition	1	2	3	4	5
	He/she is actively concerned with the development of the staff for whose performance he/she is responsible	1	2	3	4	5
	Request input from each person in the team, support visibility and invest in the right people with authority	1	2	3	4	5
Influence and negotiation	He convinces others and gains their support	1	2	3	4	5
	Use convincing arguments and ideas	1	2	3	4	5
	He/she tends to negotiate whenever he/she has the opportunity	1	2	3	4	5
	It is not discouraged by arguments against its objectives	1	2	3	4	5
Strategic thinking	Is capable to formulate new strategies and competitive plans.	1	2	3	4	5
	Can accurately anticipate future consequences and trends.	1	2	3	4	5
	Can draw up a realistic and motivating strategic plan.	1	2	3	4	5
	Think long-term, corroborating information and market trends, anticipating possible developments and alternative action plans.	1	2	3	4	5
Results orientation	He focuses his efforts on priority tasks, reserving time for other activities as well.	1	2	3	4	5
	Shows a passion for business, reflected in a "can-do" attitude	1	2	3	4	5
	Helps others manage priorities by focusing on critical activities for success.	1	2	3	4	5
	Do not get lost in irrelevant details by quickly finding the shortest path to the result.	1	2	3	4	5
Planning and organization	Can organize people, activities and resources to finish projects successfully.	1	2	3	4	5
	Can coordinate multiple activities at once to accomplish one goal.	1	2	3	4	5
	He plans his activity ahead of time and sets realistic deadlines.	1	2	3	4	5
	He is a systematic and well-organized person who sets clear priorities.	1	2	3	4	5

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