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Identifying Employee Profiles that Drive Projects Performance: A Data Mining Approach Based on Human Resource Survey Data

Abstract. *Identifying the factors that influence project performance is an important concern in human resource and project management. This study aims to identify the profiles of employees who contribute significantly to project performance, using an approach based on data mining techniques applied to data obtained through a questionnaire addressed to people involved in project activities. The questionnaire was designed to collect information on the professional characteristics of respondents, their skills, teamwork, and perception of factors that influence project outcomes. Based on the collected data, a data mining analysis was performed, which allowed the identification of relevant patterns and relationships between the analyzed variables. The results highlight the existence of distinct employee profiles, characterized by specific combinations of skills, experience, and organizational behaviors, which differently influence project performance. The study contributes to the literature by highlighting the potential of data analysis techniques in identifying employee profiles that impact project success and offers practical implications for organizations seeking to optimize human resource management in projects.*

Keywords: *projects performance, employee profile, data mining, human resources survey, project teams.*

JEL Classification: M12, M51, C38, C55.

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1. Introduction

Within projects, their performance is significantly influenced by the characteristics, skills, and level of involvement of team members. For this reason, identifying employee profiles that contribute to positive project outcomes is an important area of research in project management and human resource management. In this context, data analysis techniques and data mining methods provide useful tools for identifying patterns in the data collected from employees involved in project activities.

The purpose of this article is to identify employee profiles that influence project performance, using a data mining approach applied to data obtained through a questionnaire addressed to employees involved in projects. Following the application of the questionnaire, 164 valid responses were obtained, which formed the basis of the analysis carried out in the research.

Analysis of the dataset, which includes 50 attributes, led to the identification of four distinct clusters of respondents. The results highlight differences between groups in terms of project experience, education level, working style, and perception of project performance. Some groups include people with more project experience and involvement in larger teams, but they perceive the project experience less favorably and do not want to participate.

To identify and understand these nuanced patterns, the study employs advanced data mining techniques, going beyond the limitations of classical descriptive statistics. Data were collected using purposive sampling, strictly selecting employees with direct and active experience in project execution to ensure the relevance of the 164 responses. The analysis of the 50 attributes thus revealed latent relationships between demographic traits, interpersonal skills, and general work attitude, demonstrating that motivation and adaptability are often the decisive factors shaping performance, complementing purely technical competencies.

From a practical perspective, these findings provide a solid foundation for project managers and human resources departments to optimize recruitment strategies, team building, and resource allocation. The use of a data-driven approach facilitates an optimal mix of skills, minimizing internal conflicts and increasing project success rates. In the following sections, this paper explores the theoretical foundation, presents the methodological tools and algorithms applied to the dataset in detail, and finally discusses the identified profiles, offering applicable managerial recommendations and directions for the future.

To provide a detailed account of this approach, the paper continues with Chapter 2 (“Literature Review”), which examines the current state of knowledge in the field. Next, Chapter 3 (“Methodology Specification”) rigorously describes the analytical tools, followed by Chapter 4 and 5 (“Results and Discussion”), which provides a comprehensive interpretation of the profiles identified by the algorithms. Finally, there is a “Conclusions” section, which summarizes the practical utility of the study and proposes directions for future research.

2. Literature Review

Recent literature on human resource management and project performance shows a significant increase in interest in the use of data analysis techniques and data mining methods to identify employee profiles that contribute to organizational performance. The digital transformation of organizations and the increase in the volume of data generated by internal human resource management systems have facilitated the development of the concept of HR analytics, which allows organizational data to be leveraged to improve decision-making processes (Margherita, 2022; Phan & Teoh, 2024; Minbaeva, 2021). In this context, organizational questionnaires and internal databases become important sources for identifying behavioral patterns and developing predictive models of employee performance (Wamba et al., 2017; McCartney et al., 2021).

In project management, team performance is influenced by a complex combination of individual and organizational factors. Recent studies highlight that professional skills, collaboration skills, and adaptability to change are key determinants of project success (Ahmed et al., 2021; Maqbool & Sridhar, 2024). At the same time, research shows that employee engagement and the quality of the organizational environment influence individual performance and project outcomes (Nauman et al., 2024; Carnevale & Hatak, 2020). In the context of the expansion of remote work and the digitization of organizational activities, access to information resources and employee autonomy are becoming essential factors for maintaining performance (Ma et al., 2024; Liu et al., 2022; Medhi et al., 2024).

Another relevant area for analyzing employee profiles is represented by studies on employee well-being and job satisfaction. Research shows that variables such as occupational stress, work-life balance, and organizational communication significantly influence employee performance (Cooke et al., 2020; Muneer et al., 2022; Ipsen et al., 2021). In this context, profiling employees based on these variables can help identify patterns of behavior associated with high performance in project teams.

At the same time, methodological literature emphasizes the role of data analysis techniques and multi-criteria methods in personnel evaluation and selection. The use of data mining algorithms and predictive models allows the identification of relationships between employee characteristics and their performance (Keshavarz-Ghorabae et al., 2024; Shao, 2018; Müller et al., 2019). These methods are increasingly used to develop decision support systems in human resource management. Recent research highlights the importance of statistical analyses and decision models in assessing organizational performance and human capital. Studies show that the use of data analysis methods allows the identification of relationships between organizational variables and employee performance, contributing to the development of predictive models relevant to human resource management (Gabor et al., 2024; Keshavarz-Ghorabae et al., 2024; Barbalho et al., 2022; Vasilescu et al., 2025).

Overall, recent literature highlights that integrating data mining techniques into the analysis of human resource survey data is a promising direction for identifying employee profiles that contribute to project performance and increased organizational competitiveness.

The results of these studies are consistent with recent research highlighting the role of human resource analysis and data utilization in improving employee performance and the performance of projects implemented at the organizational level (Margherita, 2022; Duffour et al., 2024).

3. Methodology Specification

Methodology. The CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology is one of the most extensively used methodologies for data mining and data analysis systems. It has the goal to provide a standard frame that guides the entire analysis process, from defining the business problem up to the obtained results. The model was firstly developed in the 1990s by a several companies (like Daimler-Benz and SPSS) and is considered a standard in data mining analysis.

The CRISP-DM methodology comprises six main phases, which form an all-around iterative process. This means that the analysis could return to a previous phase when new information emerges or when the model needs to be improved (Provost & Fawcett, 2023; Martínez-Plumed et al. 2019; Gill et al., 2024; Ma et al., 2025).

1. Understanding the business problem and requests (Business Understanding phase). In this first phase, are defined the problem to be answered and the design objects from the perspective of the requests. Success criteria are also identified.
2. Understanding the data phase (Data Understanding phase). The necessary data is collected and an exploratory analysis of it's performed. The goal of this phase is to identify the types of data, their quality and any problems that may arise. Everything must be comment and understood by the people involved into the analysis.
3. Data Preparation phase. This phase involves preprocessing and cleaning data for the use in logical models. Preprocessing includes removing duplicates, handling missing values, homogenizing the data and obtaining applicable variables for the analysis.
4. Modeling phase. Data mining or machine learning algorithms (e.g. classification, clustering, etc.) are named and applied to make models that can identify patterns or make prognostications based on the analyzed data.
5. Evaluation phase. The developed models are created in order to meet the business requests. In this stage, the performance and practical obtained results are assessed.
6. Deployment phase. The results of the analysis are integrated into the association's processes, in order to illustrate a new model in a specific system or by developing reports and recommendations for decision- makers.

Thus, the CRISP-DM methodology provides a clear and flexible frame for carrying out data mining systems, easing the association of conditioning,

collaboration between teams and offering the results for the decision-making process.

The used software. WEKA Software (Waikato Environment for Knowledge Analysis) is an open-source software for data analysis, data mining and machine learning, software developed by the University of Waikato, New Zealand. The operation provides a complete framework for data analysis, including tools for data preprocessing and selection, model structure and performance evaluation. The way indicated in the CRISP- DM methodology can be very easy applied within the WEKA platform. The platform includes several data mining and machine learning algorithms, similar as decision trees, Bayesian classifiers, k-Nearest neighbor's algorithm, neural networks, styles and clustering algorithms (Ian et al., 2016; Mark et al., 2009; Arora et al., 2025; Li (2023)).

Algorithms. The algorithms used in the present data mining analysis are both clustering (EM- Anticipation Maximization and Simple K- Means) and classification (PART) (Ian et al., 2016).

- EM is a probabilistic clustering algorithm that assumes that the data comes from a combination of statistical distributions (generally Gaussian). The algorithm works in an iterative way, first estimating the parameters of the distributions (Anticipation) and also maximizing the probability of the data given these distributions (Maximization). This algorithm also has the property that it can indicate the number of clusters into which the data set is to be divided. This can be done grounded on the parameter settings before running.
- Simple K-Means - centroid-based clustering algorithm that groups the data into k clusters grounded on the distances from the cluster center. The algorithm iteratively updates the centroids and point assignments until they no longer update.
- PART is a rule-based algorithm. This algorithm builds a set of "IF-THEN" rules by generating partial decision trees. Each rule is then applied in order to classify new cases, combining the simplicity of the rules with the performance of decision trees. Within this algorithm, values that could describe the algorithm are:
 - TP Rate (True Positive Rate) – it represents the proportion of positive cases that were classified in a right manner by the model.
 - FP Rate (False Positive Rate) – it indicates the proportion of negative cases that were classified wrong as positive.
 - Precision – it measures the proportion of cases classified by the algorithm as being as positive that are really positive.
 - Recall – indicates the proportion of real positive cases that were correctly identified by the model.
 - F-Measure – represents the harmonious mean between Precision and Recall, providing a balanced assessment of the model's performance.
 - MCC (Matthews Correlation Measure) – measure that evaluates the quality of the classification, taking into account all the values from the confusion matrix.

- ROC Area – the area under the ROC curve, which reflects the model's capability to distinguish between positive and negative classes.
- PRC Area – the area under the Precision- Recall curve, used especially in the case of unstable data sets.
- Class – it represents the class label for which the performance criteria are computed.

Figure 1 shows the steps taken within WEKA to obtain the results.

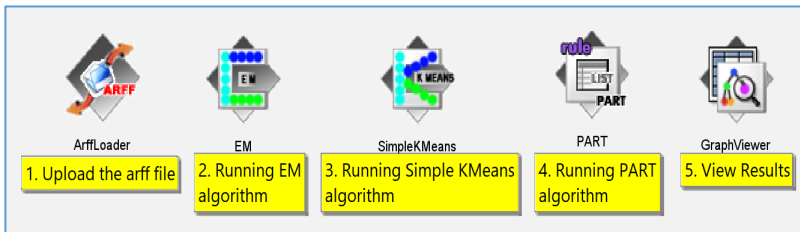


Figure 1. Work stages within WEKA

Source: Authors' own creation.

Data. The dataset contains 164 records, 50 attributes and 6 sections. In the data preprocessing stage, responses that had the same meaning but were written in a different manner were standardized. No other interventions were made on the dataset. The degree of filling for the attributes was representative, without many missing values. There were no outliers or deviant values that needed to be corrected or records required to be eliminated. All attributes are mentioned in ANNEX 1 together with the values they can take. The questions in the questionnaire were divided into the following sections:

- Section A – Respondent profile and project context
- Section B – Project-relevant professional competences
- Section C – Socio-emotional competences in project activity
- Section D – Digital competences and project collaboration
- Section E – Organizational context and project leadership
- Section F – Results: project performance and engagement

The dataset used in the study comprises 164 respondents, consisting of employees and entrepreneurs who were involved in project activities, regardless of their field of work or role within the projects. Data collection took place in early March 2026 via an online questionnaire distributed by email and through professional groups comprising individuals with project experience. This distribution method allowed for the inclusion of a diverse range of respondents involved in managing, implementing, or participating in projects.

The research instrument was structured into *six main sections*, designed to capture both the respondents' characteristics and their perceptions regarding the competencies required for project work, the organizational context, and the performance of the projects in which they were involved.

The first section, titled “*Respondent Profile and Project Context*”, included 12 questions regarding the respondents’ socio-demographic and professional characteristics, such as age, education level, project experience, the size of the teams they were part of, and how project activities were carried out.

The second section, “*Professional Skills Relevant to Projects*”, consisted of 10 items rated on a Likert scale, designed to measure respondents’ perceptions of the professional skills necessary for the effective implementation of project activities.

The third section, “*Social-emotional skills in project work*”, included 10 questions formulated on a Likert scale, addressing aspects such as communication, collaboration, adaptability, conflict management, and other interpersonal skills relevant to project success.

The fourth section, “*Digital Skills and Collaboration in Projects*”, comprised 5 items that assessed respondents’ digital skills and their ability to use technological tools for collaboration and coordination of project activities.

The fifth section, “*Organizational Context and Leadership in Projects*”, included 7 Likert-scale questions focused on analyzing the organizational environment, the support provided by the organization, and the leadership characteristics that influence project implementation.

The final section, “*Results: Project Performance and Engagement*”, consisted of six items rated on a Likert scale and was designed to measure respondents’ perceptions of project performance, the value generated for the organization, as well as their level of satisfaction and involvement in project activities.

In total, the questionnaire included 50 questions, 38 of which were formulated on a Likert scale, allowing for the analysis of respondents’ perceptions regarding the main factors influencing performance and engagement in projects. The collected data formed the basis for statistical analyses and the clustering process, which enabled the identification of distinct profiles of individuals involved in project activities.

4. Results

1.A. First direction of analysis: identification of groups of employees working in projects.

Within the first direction of analysis, the main categories of employees are identified. For this profile, all attribute categories (Sections A, B, C, D, E, F) and all attributes involved in the analysis (from A1 to F6) were taken into account.

This first analysis provides an answer to the first research question, namely “RQ1: What are the main categories of employees involved in projects identified based on the data set?”

To provide an answer to this question, the EM algorithm was run on the entire data set. It indicated a number of 4 clusters as being relevant for the data set. Based on this number of clusters, the Simple KMeans algorithm was run (Fig. 2). The results obtained by this are shown in Table 1 from Appendix. In relation to this table,

the main notable differences in relation to the other clusters are mentioned below for each cluster:

1-st Cluster:

- number of instances: contains the smallest number of instances, namely 2 (1% of the entire data set)
- A2: main role in projects that the respondent had: Team coordinator
- A3: number of projects in which he was involved: 4-5 projects
- A4: number of projects in which they were involved: 3-6 months
- A5: average size of the project team: 11-20 members
- A8: mode of project activity: mostly remote
- A9: experience in projects: 4-7 years
- A10: latest completed studies: Master studies
- A11: age between 35 and 44 years
- D2: are not willing to use digital tools to organize their activities
- E1: do not consider that their role in projects was well defined
- F5: do not consider that the projects generated real value for the organization
- F6: do not want to participate at all in similar projects in the future

For Cluster 1, the results reveal a profile consisting of individuals with significant project experience who hold coordinating roles and work primarily remotely, but who express a low level of satisfaction with their past experiences and a low intention to participate in similar projects in the future. The literature indicates that a lack of clarity regarding roles and responsibilities within projects can reduce team members' level of engagement and negatively influence their perception of project success and their willingness to participate in future initiatives (Abakpa and Dvouletý, 2025).

At the same time, recent studies highlight that, in the context of virtual teams and remote work, the perception that projects generate real value for the organization is a key determinant of participants' engagement and motivation. When the project's contribution to organizational objectives is not clearly perceived, satisfaction levels and willingness to participate in future projects tend to decline, even among experienced individuals and those in leadership roles (Cortellazzo et al., 2019; Abakpa and Dvouletý, 2025).

For the rest of the attributes, the approach is neutral, with most values being 3.

2-nd and 4-th Clusters:

These two clusters are quite similar in terms of values, the main differences between them being:

- number of instances: in Cluster 2 approximately one third of the total instances (55 instances) were distributed and in Cluster 4 approximately two thirds (92 instances)
- A7: type of institution in which they worked on projects (Cluster 2 – Private organization and Cluster 4 – Public institution)

For the rest of the attributes (those with values 1,2,3,4,5) it can be seen that those in Cluster 2 had a preference of value 4 (i.e. they agreed with the statement related to the attribute) and those in Cluster 4 had a preference of value 5 (i.e. they totally agreed with the statement related to the attribute).

For clusters 2 and 4, the results indicate high levels of agreement and strong agreement regarding competencies, organizational conditions, and project outcomes, with the main difference being the type of organization in which the respondents work (private versus public), a finding that confirms the conclusions of recent studies suggesting that a positive perception of the organizational environment, management support, and the value generated by projects significantly contributes to increased participant satisfaction and engagement, regardless of the sector of activity (Mansor et al., 2023).

3-rd Cluster:

Respondents assigned to cluster three have the following characteristics:

- number of instances: this category includes a number of 15 instances;
- A3: participated in more projects than those in clusters 2 and 4 but fewer than those in cluster 1
- A8: would work more on site
- A9: have more experience in projects than those in clusters 2 and 4 but less than those in cluster 1
- A10: bachelor degree
- B6: do not constantly monitor their progress and do not intervene with new methods when they deviate from the initial planning

For Cluster 3, characterized by a moderate level of project experience, a preference for on-site work, and a limited tendency to monitor and adapt work processes, the results are consistent with the literature, which highlights that managerial flexibility, continuous progress monitoring, and the ability to adapt to change are essential factors for improving project performance and team member engagement (Shen and Ying, 2022).

The other attribute values (those with values 1,2,3,4 and 5) have most of the values equal to 3, this representing that they basically agree with the aspect mentioned in the attribute title but do not necessarily apply it.

1.B. Second direction of analysis: identifying profiles of employees working on projects in relation to engagement and satisfaction (attribute F6).

This analysis aims to obtain the answer to the second research question, namely: *“RQ2: What are the profiles (conditions that are simultaneously met) for a certain degree of engagement and satisfaction in projects?”*

To provide the answer to this question, the PART algorithm was used to obtain a set of decision rules. All attributes from the data set were used and the class attribute used was F6, respectively the one that targets the desire to participate in similar projects in the future (F6 – ENGAGEMENT AND SATISFACTION IN

PROJECTS – I would like to participate in similar projects in the future). The results obtained consist of a set of 21 rules (Fig. 3). Below are some of the most relevant ones.

1-st Rule:

B5 TAKING RESPONSIBILITY I take responsibility for the deliverables and results of my project activities = 5 AND

F5 PROJECT PERFORMANCE The projects generated real value for the organization = 5 AND

B3 TIME MANAGEMENT I manage my time effectively to cope with the workload of projects = 5: 5 (36.0)

Comment:

IF the respondent takes responsibility for deliverables and results to a very high degree

AND believes that the project generates value for the organization to a high degree

AND believes that he manages his time efficiently to a high degree

THEN he will want to participate in other similar projects in the future (Value 5 for attribute class F6)

The other rules will be interpreted in a similar manner.

B5 TAKING RESPONSIBILITY I take responsibility for the deliverables and results of my project activities = 5 AND

A12 Gender = Female: 5 (36.0/7.0)

B5 TAKING RESPONSIBILITY I take responsibility for the deliverables and results of my project activities = 4 AND

F4 PROJECT PERFORMANCE The project beneficiaries were satisfied with the results = 5 AND

F2 PROJECT PERFORMANCE The projects respected the planned budget or resources = 5: 5 (9.0)

B5 TAKING RESPONSIBILITY I take responsibility for the deliverables and results of my project activities = 5 AND

A4 Average duration of the projects you worked on = Under 3 Months AND

D1 USE OF DIGITAL TOOLS Effectively use digital collaboration tools in project work = 5 AND

F5 PROJECT PERFORMANCE The projects generated real value for the organization = 5: 5 (5.0/1.0)

B5 TAKING RESPONSIBILITY I take responsibility for the deliverables and results of my project activities = 5 AND

A4 Average duration of the projects you worked on = 3_6 Months: 5 (4.0)

B5 TAKING RESPONSIBILITY I take responsibility for the deliverables and results of my project activities = 5 AND

A11 Age = Under 25 Years AND

E3_MANAGERIAL_SUPPORT_The_project_manager_provides_support_when_difficulties_arise = 5 AND

A2_Main_role_in_the_projects_you_have_been_involved_in = Project_Team_Member: 3 (4.0)

B5_TAKING_RESPONSIBILITY_I_take_responsibility_for_the_deliverables_and_results_of_my_project_activities = 2 AND

B7_MAKING_DECISIONS_I_am_able_to_make_quick_and_effective_decisions_when_the_project_requires_it = 1: 5 (2.0)

B5_TAKING_RESPONSIBILITY_I_take_responsibility_for_the_deliverables_and_results_of_my_project_activities = 2 AND

A2_Main_role_in_the_projects_you_have_been_involved_in = Team_Coordinator: 1 (2.0/1.0)

B5_TAKING_RESPONSIBILITY_I_take_responsibility_for_the_deliverables_and_results_of_my_project_activities = 4 AND

A6_Activity_Domain = Marketing_Communication AND

E2_CLARITY_OF_OBJECTIVES_The_project_objectives_are_clearly_communicated_and_are_easy_to_understand_for_all_team_members = 3: 3 (4.0/1.0)

B5_TAKING_RESPONSIBILITY_I_take_responsibility_for_the_deliverables_and_results_of_my_project_activities = 4 AND

A6_Activity_Domain = Marketing_Communication AND

A3_Number_of_projects_have_you_participated_in_the_last_12_months = 1_Project: 5 (5.0/1.0)

E7_RECOGNITION_OF_CONTRIBUTIONS_The_efforts_and_contributions_of_team_members_are_recognized_and_appreciated = 4 AND

A6_Activity_Domain = Marketing_Communication AND

B4_CLARITY_OF_OBJECTIVES_I_understand_the_project_objectives_and_how_my_contribution_supports_their_achievement = 4: 4 (4.0)

The values related to running the PART algorithm for the second direction of analysis are shown below.

Correctly Classified Instances	135	82.3171 %
Incorrectly Classified Instances	29	17.6829 %
Kappa statistic	0.6073	
Mean absolute error	0.0942	
Root mean squared error	0.217	
Relative absolute error	44.9352 %	
Root relative squared error	67.5617 %	
Total Number of Instances	164	

Detailed Accuracy By Class

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class	
	1,000	0,019	0,500	1,000	0,667	0,700	0,991	0,500	1
	0,600	0,000	1,000	0,600	0,750	0,770	0,972	0,738	2
	0,591	0,007	0,929	0,591	0,722	0,712	0,952	0,789	3
	0,400	0,007	0,909	0,400	0,556	0,564	0,915	0,668	4
	0,972	0,436	0,815	0,972	0,887	0,624	0,924	0,946	5

Weighted Avg.

0,823	0,292	0,845	0,823	0,806	0,633	0,929	0,868
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Confusion Matrix

a	b	c	d	e	<-- classified as
3	0	0	0	0	a = 1
1	3	0	0	1	b = 2
1	0	13	0	8	c = 3
0	0	0	10	15	d = 4
1	0	1	1	106	e = 5

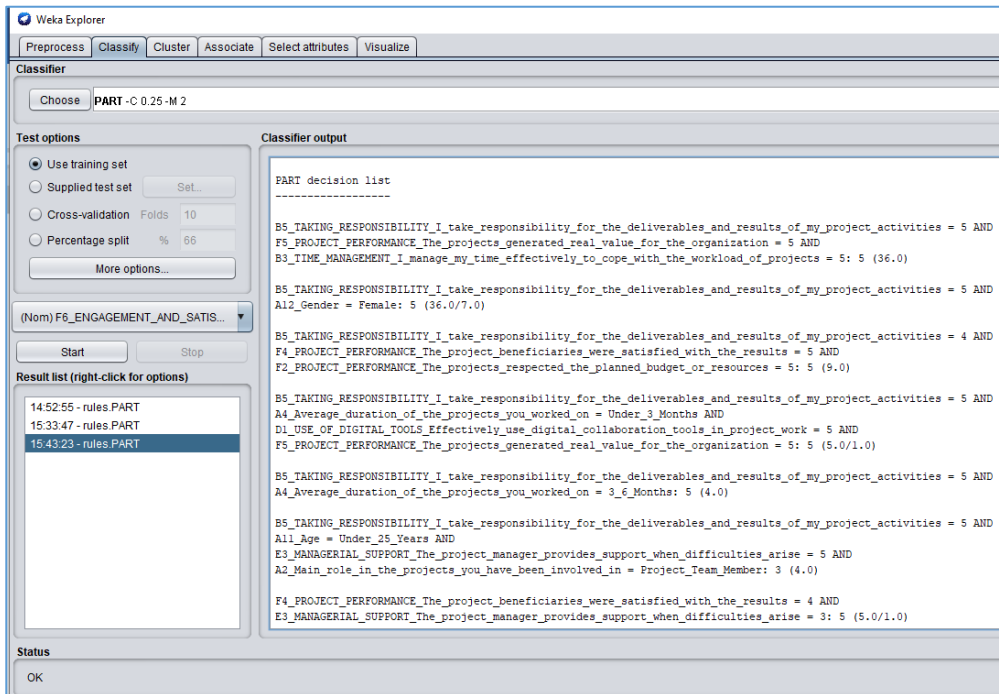


Figure 2. Running the PART algorithm

Source: Authors' own creation.

For the second line of analysis, which aims to identify employee profiles based on their level of engagement and satisfaction with project participation, the use of decision rules generated by the PART algorithm is consistent with the literature,

which highlights that the intention to participate in future projects is influenced by a set of individual, organizational, and project-experience-related factors, with engagement considered an important predictor of participants' future performance and involvement (Saks, 2022).

2.A Third direction of analysis: Clustering - Performance correlation (all attributes F1 – F6).

The third analysis aims to find the answer to the third research question, namely "RQ3 - What are the main categories of employees involved in projects identified solely on the basis of performance and engagement?".

To find the answer to this question, the Simple KMeans algorithm was applied. The results are shown in Table 2.

Table 2. Clustering process results for Performance, Engagement and satisfaction in projects

Attribute	1-st Cluster (53 instances – 32%)	2-nd Cluster (11 instances – 7%)	3-rd Cluster (16 instances – 10%)	4-rd Cluster (84 instances – 51%)
F1 PROJECT PERFORMANCE The projects I was involved in were completed on time	4	4	3	5
F2 PROJECT PERFORMANCE The projects respected the planned budget or resources	4	4	3	5
F3 PROJECT PERFORMANCE The project objectives were achieved according to the initial planning	4	4	3	5
F4 PROJECT PERFORMANCE The project beneficiaries were satisfied with the results	4	4	3	5
F5 PROJECT PERFORMANCE The projects generated real value for the organization	4	5	3	5
F6 ENGAGEMENT AND SATISFACTION IN PROJECTS I would like to participate in similar projects in the future	5	4	3	5

Source: Authors' processing.

Based on Table 2, the following can be deduced:

- Clusters 1 and 2 have similar approaches regarding performance, engagement and satisfaction in projects. More precisely, they would agree to a large extent to participate in other similar projects in the future. This is mainly due to the positive results they had in the ones they were part of.
- Cluster 3 – has the most neutral approach regarding the analyzed aspects. More precisely, those in this cluster did not have such good results in the projects and therefore do not really want to participate in others.
- Cluster 4 – a situation that characterizes almost half of the respondents in the data set. They had very good results in the projects they had and therefore would really like to participate in other similar projects.

For the third area of analysis, the clustering results highlight the existence of distinct respondent profiles based on their perceptions of project performance and level of engagement, with respondents in Cluster 4 recording the highest ratings across all performance dimensions (meeting deadlines, staying within budget, achieving objectives, beneficiary satisfaction, and value generated for the organization), along with the highest intention to participate in future projects, which confirms the conclusions of the literature that the perception of project success directly influences participants' satisfaction and commitment, and the value created for the organization is one of the most important predictors of future involvement in projects (Ika & Pinto, 2022; Schaufeli, 2021).

2.B. Fourth research direction: identifying correlations between performance-related aspects (attributes F1-F5) and engagement and satisfaction in projects (F6).

This analysis aims to obtain the answer to the third research question, namely: *"RQ4: What are the performance conditions for project employees to want to participate in similar projects in the future?"*

To find the answer to this question, the PART algorithm was used to obtain a set of decision rules. The rules obtained are 10 in number and are presented below.

1st Rule:

F3_PROJECT_PERFORMANCE_The_project_objectives_were_achieved_according_to_the_initial_planning = 4 AND

F4_PROJECT_PERFORMANCE_The_project_beneficiaries_were_satisfied_with_the_results = 4: 5 (24.0/11.0)

Comment:

IF the project objectives were met according to plan

AND the beneficiaries were satisfied with the results

THEN it is very likely that the respondent will participate in other similar projects in the future.

Some other rules:

F5_PROJECT_PERFORMANCE_The_projects_generated_real_value_for_the_or_ganization = 5: 5 (90.0/12.0)

F5_PROJECT_PERFORMANCE_The_projects_generated_real_value_for_the_or_ganization = 3 AND

F3_PROJECT_PERFORMANCE_The_project_objectives_were_achieved_accordi ng_to_the_initial_planning = 3: 3 (8.0/3.0)

F5_PROJECT_PERFORMANCE_The_projects_generated_real_value_for_the_or_ganization = 3: 5 (6.0/1.0)

F3_PROJECT_PERFORMANCE_The_project_objectives_were_achieved_accordi ng_to_the_initial_planning = 5: 5 (15.0/7.0)

F5_PROJECT_PERFORMANCE_The_projects_generated_real_value_for_the_or_ganization = 4 AND

F2_PROJECT_PERFORMANCE_The_projects_respected_the_planned_budget_o r_resources = 4: 4 (8.0/4.0)

F4_PROJECT_PERFORMANCE_The_project_beneficiaries_were_satisfied_with_the_results = 4 AND

F2_PROJECT_PERFORMANCE_The_projects_respected_the_planned_budget_o r_resources = 3: 4 (3.0/1.0)

F4_PROJECT_PERFORMANCE_The_project_beneficiaries_were_satisfied_with_the_results = 3: 2 (4.0/2.0)

F3_PROJECT_PERFORMANCE_The_project_objectives_were_achieved_accordi ng_to_the_initial_planning = 4: 5 (3.0/1.0)

The values related to running the PART algorithm for the second direction of analysis are shown below.

Correctly Classified Instances	104	63.4146 %
Incorrectly Classified Instances	60	36.5854 %
Kappa statistic	0.1652	
Mean absolute error	0.1818	
Root mean squared error	0.3195	
Relative absolute error	86.4821 %	
Root relative squared error	99.3569 %	
Total Number of Instances	164	

=== Detailed Accuracy By Class ===

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0,000	0,006	0,000	0,000	0,000	-0,011	0,756	0,114	1
0,000	0,000	?	0,000	?	?	0,483	0,074	2
0,227	0,099	0,263	0,227	0,244	0,137	0,548	0,208	3
0,080	0,072	0,167	0,080	0,108	0,011	0,575	0,236	4
0,890	0,636	0,735	0,890	0,805	0,302	0,718	0,795	5

Weighted Avg.
 0,634 0,447 ? 0,634 ? ? 0,667 0,597

=== Confusion Matrix ===

```

a b c d e <-- classified as
0 0 1 0 2 | a = 1
0 0 3 1 1 | b = 2
1 0 5 3 13 | c = 3
0 0 4 2 19 | d = 4
0 0 6 6 97 | e = 5
    
```

For the fourth research direction, the decision rules obtained highlight that achieving project objectives as planned, beneficiary satisfaction, and the perception that projects generate real value for the organization are key determinants of engagement and the intention to participate in similar projects in the future—a finding that confirms recent literature on project success, according to which organizational benefits and stakeholder satisfaction constitute essential dimensions of performance and important predictors of participants’ future involvement (Ika & Pinto, 2022).

5. Discussion

First analysis direction (I.A.) - identification of groups of employees working in projects - the results of the clustering analysis for the entire data set using the Simple K-Means algorithm highlight four distinct typologies of respondents. This highlight validates the theoretical correlations between group structure and project management performance. Cluster 1 outlines a profile of “experienced but demotivated coordinators”, characterized by solid expertise and teleworking activity. The scores on post-project satisfaction and future retention are minimal. In specialized terminology, this behavioral anomaly is attributed to role ambiguity and lack of clear responsibilities, factors that erode organizational commitment. Moreover, in the case of virtual teams, the fragmentation of interaction and the absence of a clear metric of added value discourage participation, even among segments with leadership functions.

In contrast, Clusters 2 and 4 reveal a high homogeneity of the characteristic vectors, recording maximum values (strong link) on the dimensions of skills, organizational climate and performance. The splitting criterion between these two subgroups is exclusively the nature of the sector of activity (private versus public). This convergence empirically demonstrates that managerial support and positive organizational culture act as universal predictors of satisfaction, neutralizing sector-specific variations. Finally, Cluster 3 defines a segment of respondents with moderate experience and a preference for on-site interaction, but with a deficit in the monitoring and process resilience characteristic. For this last category, the relevant literature confirms that the flexibility of the management architecture and the agility

in adapting processes constitute the critical levers for optimizing performance indicators.

Second analysis direction (1.B.), identifies profiles of employees working on projects in relation to engagement and satisfaction. The analysis is based on generating a set of IF-THEN decision rules, extracted using the PART classification algorithm. In this algorithm, the central predictor in most scenarios is assuming responsibility for results (attribute B5). It is observed that a maximum level of responsibility (attribute B5=5), combined with the perception of the project value and efficient time management, determines a firm intention to participate in the future (attribute F6=5). Also, high project performance (budget compliance and beneficiary satisfaction) and the efficient use of digital tools on short projects greatly influence the maximum retention scores. The rules also identify situations that aim for neutrality. Some examples of this category would be, for example, young people under 25 years old with the role of a simple team member who show moderate interest (score 3) even when receiving managerial support. Finally, the Marketing/Communication segment tends towards medium to high predictable behavior, strongly influenced by clarity of objectives and recognition of team merit.

The third analysis direction (2.A) identifies clearly defined categories in terms of respondents. The categories are differentiated by their level of engagement and how they evaluate the success of internal projects. Within this analysis, Cluster 4 stands out, which positions itself as the group with top performances (high-performers), recording maximum scores on all key performance indicators (KPIs). From a strategic point of view, this segment also reports the greatest openness to getting involved in future projects. The results confirm a direct correlation validated many times in the industry: the perception of the success of a project directly maximizes the satisfaction and retention of the team, and the real value that the project generates for the company represents the strongest predictor and driver for attracting talent in the organization's future initiatives.

The fourth analysis direction (2.B) identifies the determinants of future project participation intention, with key performance indicators (KPIs) as the main predictors. The analysis highlights that the perception of generating real value for the organization (attribute F5=5) represents the most robust rule in the model, recording the highest support in the data set, with 90 instances predicting a maximum retention intention. Also, achieving objectives according to the initial plan (attribute F3) and high satisfaction of beneficiaries (attribute F4) act as strong catalysts, creating the premises for obtaining maximum future involvement scores. In contrast, the model identifies an area of neutrality or uncertainty when both the value brought and compliance with the plan stagnate at an average level (score 3), generating a similarly neutral reaction from respondents. The decrease in beneficiary satisfaction to a moderate level (attribute F4=3) directly alters predictive behavior, greatly lowering the retention score towards minimum values (score 2). In conclusion, the

classification model demonstrates that the loyalty of human resources in project structures is closely conditioned by the delivery of tangible value and the quality of results perceived by stakeholders.

6. Conclusions

Based on the results obtained from the data analysis and the responses to the first two research questions, it can be concluded that the sample under investigation is structured into **four distinct clusters**, resulting from the consideration of all **50 attributes analyzed**. These clusters highlight the existence of different profiles among individuals involved in projects, differentiated by their accumulated experience, work style, level of education, perception of project performance, and willingness to participate in similar projects in the future.

The first cluster comprises respondents with greater project experience compared to the other groups. They have worked remotely to a greater extent and have been part of larger teams. In terms of education, the most recent degree completed is, in most cases, a master's degree, and the predominant age range is between 35 and 44 years old. Although they have significant experience in project activities, their perception of past experiences is not entirely positive. This is also reflected in their reduced willingness to engage in similar projects in the future, suggesting the existence of factors that have diminished the overall satisfaction associated with participating in projects.

The second and fourth clusters account for the largest share of the dataset and exhibit very similar characteristics. The respondents in these two groups had no prior project experience and were primarily involved in small teams. Their work took place both in-person and remotely, and their educational background is predominantly high school. The evaluation of the projects is favorable, with participants believing that they were managed efficiently and that the initial objectives were achieved. In their view, beneficiaries were satisfied with the results achieved, resources and budgets were used appropriately, and the projects generated real value for the organization. These positive perceptions are also reflected in the level of satisfaction and commitment, with respondents from both clusters stating that they would gladly participate in similar projects in the future. For these groups, one of the most important factors influencing the decision to participate in future projects is taking responsibility for deliverables and results, an aspect highlighted by attribute B5.

The third cluster consists of respondents with moderate project experience. The teams they have been part of have already developed collaborative relationships and well-established working mechanisms among members, indicating a certain level of organizational maturity. In terms of education, most respondents in this cluster hold a bachelor's degree and prefer to carry out activities at the organization's headquarters. Regarding project performance, their assessments are more reserved compared to those made by respondents in clusters 2 and 4. The lower level of perceived performance also influences willingness to participate in the future, as

these respondents show a lower desire to participate in similar projects. Furthermore, their perception of satisfaction and commitment based on past experiences is less favorable than that of groups characterized by positive performance evaluations.

The analysis conducted for research questions 3 and 4 confirms the existence of the same four clusters and reinforces the conclusions drawn previously. The results highlight that groups 1 and 2 exhibit similar characteristics in terms of the level of agreement and strong agreement regarding the aspects analyzed, suggesting a similar perception of the experience of participating in projects. At the same time, respondents in cluster 4 stand out for their highest ratings of project performance, which explains their high willingness to get involved in similar initiatives in the future. At the opposite end of the spectrum, respondents in Cluster 3 believe that the projects in which they were involved did not achieve a satisfactory level of performance, a fact that reduces their intention to participate in future project activities.

Another important result of the analysis is the identification of the main factor influencing participants' engagement and satisfaction. Thus, the perception that the project generates real value for the organization, reflected by attribute F5, is the most relevant factor in determining the level of involvement and the desire to participate in future projects. This result highlights the fact that, beyond a project's operational success, participants place particular importance on the concrete impact and benefits generated for the organization.

Overall, the results of the analysis demonstrate the existence of distinct profiles among individuals involved in projects, differentiated by professional experience, educational level, perception of performance, and the degree of satisfaction associated with participating in project activities. At the same time, the study highlights that the perception of value created for the organization and the assumption of responsibility for deliverables and results are essential factors influencing participants' commitment and their willingness to engage in similar projects in the future.

These conclusions provide a clear picture of how past experiences and individual perceptions shape the behavior and motivation of those involved in project activities, contributing to a better understanding of the factors that support participation and performance in the organizational environment.

References

- [1] Abakpa, A., Dvouletý, O. (2025), *Navigating the digital era: the role of virtual teams in organizational transformation*. *Asia Pacific Journal of Innovation and Entrepreneurship*, 19(3), 208-233.
- [2] Ahmed, R., Philbin, S.P., Cheema, F.E.A. (2021), *Systematic literature review of project manager's leadership competencies*. *Engineering, Construction and Architectural Management*, 28(1), 1-30, DOI: <https://doi.org/10.1108/ECAM-05-2019-0276>.

- [3] Arora, P., Kaur, J., Anshu (2025), *Mining Social Media Data: A Practical Approach with Weka*. *International Journal of Scientific Research in Science and Technology*, 12(3), 1012-1019, DOI:10.32628/IJSRST25123108.
- [4] Barbalho, S.C.M., Carlos de Toledo, J., Cintra Faria, A.C. (2022), *Transitions in project management offices: a framework relating functions, success factors and project performance in a high-technology company*. *Engineering Management Journal*, 34(3), 357-373, DOI: <https://doi.org/10.1080/10429247.2021.1925497>.
- [5] Carnevale, J.B., Hatak, I. (2020), *Employee adjustment and well-being in the era of COVID-19: Implications for human resource management*. *Journal of business research*, 116, 183-187, DOI: <https://doi.org/10.1016/j.jbusres.2020.05.037>.
- [6] Cooke, F.L., Dickmann, M., Parry, E. (2020), *Important issues in human resource management: introduction to the 2020 review issue*. *The International Journal of Human Resource Management*, 31(1), 1-5, DOI: <https://doi.org/10.1080/09585192.2020.1691353>.
- [7] Cortellazzo, L., Bruni, E., Zampieri, R. (2019), *The role of leadership in a digitalized world: A review*. *Frontiers in Psychology*, 10, 1938, <https://doi.org/10.3389/fpsyg.2019.01938>.
- [8] Duffour, K.A., Atiim, E., Batuuuro, E. (2024), *The mediation effect of employee engagement on the relationship between employee relations and organizational performance*. *Journal of Business and Management Review*, 5(11), 1030-1045, DOI: 10.47153/jbmr.v5i11.1192.
- [9] Gabor, M.R., Dimbean, C.A., Kardos, M., Banacu, C.S. (2024), *Statistical Modelling for Synergic Well-Being and Company Performance Based on Psychological Constructs as Predictors of Employee Satisfaction*. *Economic Computation & Economic Cybernetics Studies & Research*, 58(1), 280-297.
- [10] Gill, M.S., Westermann, T., Steindl, G., Gehlhoff, F., Fay, A. (2024), *Integrating Ontology Design with the CRISP-DM in the Context of Cyber-Physical Systems Maintenance*. arXiv, <https://arxiv.org/html/2407.06930v1>.
- [11] Hall, M.A., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., Witten, I.H. (2009), *The WEKA Data Mining Software: An Update*. *Machine Learning*, 11(1), 10-18.
- [12] Ika, L.A., Pinto, J.K. (2022), *The “re-meaning” of project success: Updating and recalibrating for a modern project management*. *International Journal of Project Management*, 40(7), 835-848.
- [13] Ipsen, C., Van Veldhoven, M., Kirchner, K., Hansen, J.P. (2021), *Six key advantages and disadvantages of working from home in Europe during COVID-19*. *International journal of environmental research and public health*, 18(4), 1826, DOI: <https://doi.org/10.3390/ijerph18041826>.
- [14] Keshavraz-Ghorabae, M., Rastegar, A., Amiri, M., Zavadskas, E.K., Antucheviciene, J. (2024), *Multi-Criteria Personnel Evaluation and Objective Pairwise Adjusted Ratio Analysis (OPARA)*. *Economic Computation and Economic Cybernetics Studies and Research*, 58(2), 23-45, DOI: 10.24818/18423264/58.2.24.02.
- [15] Liu, H., Zhang, H., Zhang, R., Jiang, H., Ju, Q. (2022), *Competence model of construction project manager in the digital era—The case from China*. *Buildings*, 12(9), 1385, DOI: <https://doi.org/10.3390/buildings12091385>.

- [16] Ma, Q., Cheung, S.O., Zhu, L. (2024), *Empowering project team to perform: directive and facilitative antecedents*. *International journal of project management*, 42(8), 102651, DOI: <https://doi.org/10.1016/j.ijproman.2024.102651>.
- [17] Ma, Z., Jørgensen, B.N., Ma, Z. (2025), *DataPro—A Standardized Data Understanding and Processing Procedure*. arXiv, <https://arxiv.org/abs/2501.12176>.
- [18] Mansor, F.A., Jusoh, Y.H.M., Hashim, M.Z., Muhammad, N., Omar, S.N.Z. (2023), *Employee engagement and organizational performance*. *International Journal of Accounting, Finance and Business*, 8(50), 69-80.
- [19] Maqbool, R., Sridhar, H. (2024), *Governing public–private partnerships of sustainable construction projects in an opportunistic setting*. *Project management journal*, 55(1), 86-101, DOI: <https://doi.org/10.1177/87569728231214227>.
- [20] Margherita, A. (2022), *Human resources analytics: A systematization of research topics and directions for future research*. *Human Resource Management Review*, 32(2), 100795, DOI: <https://doi.org/10.1016/j.hrmr.2020.100795>.
- [21] Martínez-Plumed, F., Contreras-Ochando, L., Ferri, C., Hernández-Orallo, J., Kull, M., Lachiche, N., ... & Flach, P. (2019), *CRISP-DM twenty years later: From data mining processes to data science trajectories*. *IEEE transactions on knowledge and data engineering*, 33(8), 3048-3061, DOI: 10.1109/TKDE.2019.2962680.
- [22] McCartney, S., Murphy, C., Mccarthy, J. (2021), *21st century HR: a competency model for the emerging role of HR Analysts*. *Personnel review*, 50(6), 1495-1513, DOI: <https://doi.org/10.1108/PR-12-2019-0670>.
- [23] Mehdi, K.G., Abdolghani, R., Maghsoud, A., Zavadskas, E.K., Antuchevičienė, J. (2024), *Multi-Criteria personnel evaluation and selection using an objective pairwise adjusted ratio analysis (OPARA)*. *Economic computation and economic cybernetics studies and research.*, 58(2), 23-45, DOI: 10.24818/18423264/58.2.24.02.
- [24] Minbaeva, D. (2021), *Disrupted HR?*. *Human Resource Management Review*, 31(4), 100820, DOI: <https://doi.org/10.1016/j.hrmr.2020.100820>.
- [25] Müller, R., Drouin, N., Sankaran, S. (2019), *Modeling organizational project management*. *Project Management Journal*, 50(4), 499-513, DOI: <https://doi.org/10.1177/8756972819847876>.
- [26] Muneer, M., Khan, N., Awais Hussain, M., Shuai, Z., Khan, A.A., Farooq, R., Tariq, M. A.U.R. (2022), *A quantitative study of the impact of organizational culture, communication management, and clarity in project scope on constructions' project success with moderating role of project manager's competencies to enhance constructions management practices*. *Buildings*, 12(11), 1856, DOI: <https://doi.org/10.3390/buildings12111856>.
- [27] Nauman, S., Musawir, A.U., Riaz, M.B.E. (2024), *Leveraging organizational social capital in construction projects to enhance project success: the enabling role of transformational leadership*. *Project Management Journal*, 55(4), 352-371, DOI: <https://doi.org/10.1177/87569728231221544>.
- [28] Phan, K.Y., Teoh, A.P. (2024), *Systematic literature review on the influence of business intelligence capabilities on BI systems success and firm performance: an Asian perspective*. *International Journal of Business Information Systems*, 47(2), 227-254, DOI: <https://doi.org/10.1504/IJBIS.2024.142289>.

- [29] Provost, F., Fawcett, T. (2023), *Data Science for Business* (2nd ed.). O’Reilly Media.
- [30] Saks, A.M. (2022), *Caring human resources management and employee engagement. Human resource management review*, 32(3), 100835.
- [31] Schaufeli, W. (2021), *Engaging leadership: how to promote work engagement?. Frontiers in psychology*, 12, 754556.
- [32] Shao, J. (2018), *The moderating effect of program context on the relationship between program managers' leadership competences and program success. International Journal of Project Management*, 36(1), 108-120, DOI: <https://doi.org/10.1016/j.ijproman.2017.05.004>.
- [33] Shen, W., Ying, W. (2022), *Large-scale construction programme resilience against creeping disruptions: Towards inter-project coordination. International Journal of Project Management*, 40(6), 671-684.
- [34] Vasilescu, M.D., Stănilă, L., Crivoi, S., Belu, M.B. (2025), *Investigating employment patterns and determinants in the European Union through panel data insights. Management & Marketing*, 20(1), 1-14, DOI: 10.2478/mmcks-2025-0005.
- [35] Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J.F., Dubey, R., Childe, S.J. (2017), *Big data analytics and firm performance: Effects of dynamic capabilities. Journal of business research*, 70, 356-365, DOI: <https://doi.org/10.1016/j.jbusres.2016.08.009>.
- [36] Witten, I.H., Frank, E., Hall, M.A., Pall, C.J. (2016), *Data Mining: Practical Machine Learning Tools and Techniques. Morgan Kaufmann, Elsevier: Cambridge, MA, USA*.
- [37] Li, Y. (2023), *Application of Data Mining Technology Based on Weka in Student Management*. In: Jan, M.A., Khan, F. (eds) *Application of Big Data, Blockchain, and Internet of Things for Education Informatization*. BigIoT-EDU 2022. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, vol 465. Springer, Cham, DOI: https://doi.org/10.1007/978-3-031-23950-2_25.

Appendix 1 –

Table 1. Centroids for the entire dataset based on Simple KMeans

Attribute	1-st Cluster (2 instances – 1%)	2-nd Cluster (55 instances – 34%)	3-rd Cluster (15 instances – 9%)	4-rd Cluster (92 instances – 56%)
A1 Involvement in projects in the last 12 months	Yes	Yes	Yes	Yes
A2 Main role in the projects you have been involved in	Team Coordinator	Project Team Member	Project Team Member	Project Team Member
A3 Number of projects have you participated in the last 12 months	4 -5 Projects	1 Project	2-3 Projects	1 Project
A4 Average duration of the projects you worked on	3-6 Months	Under 3 Months	Under 3 Months	Under 3 Months
A5 The average size of the project teams	11-20 Members	1-5 Members	1-5 Members	1-5 Members
A6 Activity Domain	Marketing and Communication	Marketing and Communication	Marketing and Communication	Marketing and Communication
A7 Organization type you work for	Public Institution	Private Organization	Public Institution	Public Institution

Attribute	1-st Cluster (2 instances – 1%)	2-nd Cluster (55 instances – 34%)	3-rd Cluster (15 instances – 9%)	4-rd Cluster (92 instances – 56%)
A8 How is project activity predominantly carried out	Mostly Remote	Hybrid OnSite and Remote	Mostly OnSite	Hybrid OnSite and Remote
A9 Years you have been involved in project activities	4-7 Years	Under 1 Year	1-3 Years	Under 1 Year
A10 Level of completed studies	Master Studies	Secondary Education	Bachelor Degree	Secondary Education
A11 Age	35-44 Years	Under 25 Years	Under 25 Years	Under 25 Years
A12 Gender	Female	Male	Male	Female
B1 PLANNING I plan my project activities so that we meet the established deadlines	2	4	3	5
B2 PRIORITIZING TASKS I can effectively prioritize tasks when unforeseen situations arise in the project	3	4	4	5
B3 TIME MANAGEMENT I manage my time effectively to cope with the workload of projects	3	4	3	5
B4 CLARITY OF OBJECTIVES I understand the project objectives and how my contribution supports their achievement	3	4	4	5
B5 TAKING RESPONSIBILITY I take responsibility for the deliverables and results of my project activities	3	4	3	5
B6 MONITORING PROGRESS I constantly monitor my progress and adjust my work method when deviations from the plan occur	3	4	2	5
B7 MAKING DECISIONS I am able to make quick and effective decisions when the project requires it	3	4	3	5
B8 RESPECTING PROCEDURES I respect the procedures standards and rules established within the projects	3	4	4	5
B9 COLLABORATION Cross functional I collaborate effectively with people from other departments or functions involved in the project	3	4	4	5
B10 RESULT ORIENTATION I am oriented towards achieving the project results and objectives even under pressure	3	4	3	5
C1 EMOTIONAL MANAGEMENT Manage my emotions in tense situations within projects	2	4	3	5
C2 STRESS MANAGEMENT Cope effectively with the stress generated by deadlines and pressure in projects	3	4	3	5

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Attribute	1-st Cluster (2 instances – 1%)	2-nd Cluster (55 instances – 34%)	3-rd Cluster (15 instances – 9%)	4-rd Cluster (92 instances – 56%)
C3 SELF CONTROL Maintain my calm even when unforeseen problems arise in the project	Totally Agree	Totally Agree	Totally Agree	Totally Agree
C4 ADAPTABILITY Adapt quickly to changes in project requirements or priorities	Totally Agree	Totally Agree	Totally Agree	Totally Agree
C5 MOTIVATION AND PERSEVERANCE Manage to maintain my motivation even during difficult periods of the project	2	4	3	5
C6 EMOTIONAL COMMUNICATION Communicate clearly and respectfully with team members including in conflict situations	3	4	3	5
C7 ACTIVE LISTENING Actively listen to the opinions of others and try to understand their perspectives	3	4	3	5
C8 EMPATHY Show empathy towards my colleagues when they are facing difficulties in the project	3	4	3	5
C9 CONSTRUCTIVE FEEDBACK Provide constructive feedback to my colleagues to improve the team performance	3	4	4	5
C10 ACCEPTING FEEDBACK Accept the feedback I receive without perceiving it as personal criticism	2	4	4	5
D1 USE OF DIGITAL TOOLS Effectively use digital collaboration tools in project work	3	4	3	5
D2 PROJECT MANAGEMENT TOOLS Use digital project management tools to organize activities	1	3	3	3
D3 ADAPTATION TO NEW TECHNOLOGIES Quickly adapt to the use of new digital tools when the project requires it	3	4	3	5
D4 COLLABORATION IN THE ONLINE ENVIRONMENT Collaborate effectively with team members in projects carried out online or in hybrid format	3	4	3	5
D5 DIGITAL INFORMATION MANAGEMENT Manage to organize and share digital information and documents in the project efficiently	3	4	3	5
E1 ROLE CLARITY My role and responsibilities within the project are clearly defined	1	4	3	5
E2 CLARITY OF OBJECTIVES The project objectives are clearly communicated and are easy to understand for all team members	2	4	3	5

Attribute	1-st Cluster (2 instances – 1%)	2-nd Cluster (55 instances – 34%)	3-rd Cluster (15 instances – 9%)	4-rd Cluster (92 instances – 56%)
E3 MANAGERIAL SUPPORT The project manager provides support when difficulties arise	4	4	3	5
E4 MANAGERIAL FEEDBACK I receive regular and constructive feedback from the project manager	2	4	3	5
E5 LEADERSHIP AND DECISION MAKING The project manager makes effective decisions	3	4	3	5
E6 CONFLICT MANAGEMENT Conflicts within the team are managed constructively by the project management	4	4	3	5
E7 RECOGNITION OF CONTRIBUTIONS The efforts and contributions of team members are recognized and appreciated	2	4	3	5
F1 PROJECT PERFORMANCE The projects I was involved in were completed on time	2	5	3	5
F2 PROJECT PERFORMANCE The projects respected the planned budget or resources	3	4	3	5
F3 PROJECT PERFORMANCE The project objectives were achieved according to the initial planning	4	4	3	5
F4 PROJECT PERFORMANCE The project beneficiaries were satisfied with the results	4	4	3	5
F5 PROJECT PERFORMANCE The projects generated real value for the organization	1	4	3	5
F6 ENGAGEMENT AND SATISFACTION IN PROJECTS I would like to participate in similar projects in the future	1	5	3	5

Source: Authors` processing.