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Using Data Mining to Improve Decision-Making: Case Study of A Recommendation System Development

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Background and purpose: This study aims to provide a practical perspective on how data mining techniques are used in the home appliance after-sales services. Study investigates on how can a recommendation system help a customer service company that plans to use data mining to improve decision making during its digital transformation process. In addition, study provides a detailed outline on the process for developing and analyzing platforms to improve data analytics for such companies.
Methodology: Case study approach is used for evaluating the usability of recommendation systems based on data mining approach in the context of home appliance after-sales services. We selected the latest platforms based on their relevance to the recommender system and their applicability to the functionality of the data mining system as trends in the system design.
Results: Evaluation of the impact on decision making shows how the application of data mining techniques in organizations can increase efficiency. Evaluation of the time taken to resolve the complaint, as a key attribute of service quality that affects customer satisfaction, and the positive results achieved by the recommendation system are presented.
Conclusion: This paper increases the understanding of the benefits of the data mining approach in the context of recommender systems. The benefits of data mining, an important component of advanced analytics, lead to an increase in business productivity through predictive analytics. For future research, other attributes or factors useful for the recommender systems can be considered to improve the quality of the results.
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***Keywords:** Digital transformation, Data mining, Decision tree algorithm, Decision-making, Home appliances after-sales services*

1 Introduction

Nowadays, the digital transformation of the enterprise has become very important as it affects various facets of the business as the potential for adopting innovative technologies grows, including Big Data analytics, social media, mobile technologies, the Internet of Things, and cloud technologies (Morakanyane, 2017; Mydyti and Kadriu, 2021c). Artificial intelligence and advanced analytics are robust digital technologies that drive business and information analytics, prediction, and business process monitoring (West and Allen, 2018).

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The analytics systems and smart applications used by organizations demonstrate the importance of delivering results to improve decision making, productivity, and effectiveness (Bughin et al., 2017). Organizations are using technology to perform analytics, such as simple reports and a dashboard that present past performance reviews and investigation reports. (Bumblauskas et al., 2017). Organizations share a common goal of using digital technology to improve their decision-making capabilities as they continue their digital journey (Schwertner, 2017). Data mining, where statistics intersect with machine learning, will enable companies to reduce costs and improve the customer experience (Sima et al., 2020; Chen et al., 2015; Palmer et al., 2011), especially in the era of Big Data (Pejic-Bach et al., 2019).

Digitalization is driving huge improvements in aftermarket services. With prescriptive and predictive analytics, companies can reduce and optimize spending (Rudnick et al., 2020). Rapid technological development, high competitiveness, and increasing benefits mean that after-sales services are reshaping business traditions (Othman et al., 2020; Guzovski et al., 2022). The customer experience goes beyond the point of sale, with digital technologies transforming customer service strategies (Gimpel et al., 2018; Jintana et al., 2021; Phorncharoen, 2020) by leveraging various drivers for market analysis, such as sentiment analysis (Nguyen et al., 2021). Data mining is becoming increasingly relevant for SMEs (Pejić Bach et al., 2022; Topalović et al., 2020).

In the current business environment, digital transformation has emerged as a strategic imperative for organizations seeking better decision making. Organizations are increasingly using data mining to extract useful insights from big data so they can make informed, evidence-based decisions instead of making assumptions, resulting in a better customer experience. For companies to fully benefit from data mining, they can use the insights from data mining to create personalized customer experiences to improve customer satisfaction.

The data mining approach that establishes links between companies and customers has been identified as very important for this work. The research study aims to fill the knowledge gap on how customer service companies can effectively connect with their customers through a data mining approach. More specifically, the study aims to close the knowledge gap by proposing and providing a research methodology for building a recommendation system that can simplify decision making, provide accurate predictions, and help companies strengthen new experiences for their customers.

The results of this study will help companies improve their decision-making processes and adapt data mining approaches to digital transformation. The research questions posed in this study are:

RQ1: How can a recommendation system help a customer service company that plans to use data mining to improve decision making during its digital transformation process?

RQ2: What is the process for developing and analyzing platforms to improve data analytics for such companies?

The introduction is followed by the literature review, followed by the methodology for implementing the recommendation system, discussion of the results, conclusions of the research, and recommendations for future research. The methodology includes a case study approach in home appliance customer service, focusing on a selected company that provides repairs and installations. The research study uses a data mining approach and a recommendation system developed using the Python programming language. The system aims to predict product repairs based on user requirements and targets home appliance service users. The development of the system includes business observation, usability and API design. The main layers of the system are the application layer, the knowledge layer, and the source layer. The proposed model provides comprehensive prediction probability and is easy to understand and operate.

2 Literature Review

The researchers developed several perspectives on after-sales service for home appliances. The literature review conducted for the study includes an analysis of several key areas, including digital technologies, data mining technologies, algorithms, tools, and advanced analytics techniques. It also examines the various dimensions of digital transformation in the digital maturity model, customer service quality characteristics, and the benefits and challenges of applying data mining. This section discusses the relevant research that can effectively answer the research question of the study.

2.1 Home Appliances After-sales Services

Household appliance customers are demanding and require a comprehensive range of after-sales services. Home appliances are considered durable products that are expected to function for an extended period of time (Murali et al., 2018). After-sales services for home appliances are considered a highly profitable business that accounts for a larger portion of the business and company profits (Altekin et al., 2017). After-sales services are a key concept in the home appliance industry to build strong relationships with customers that improve performance and deliver reliable results. The authors highlight the impact that after-sales services have on customer satisfaction through research according to three different viewpoints (Wickramasinghe and Mathusinghe, 2016).

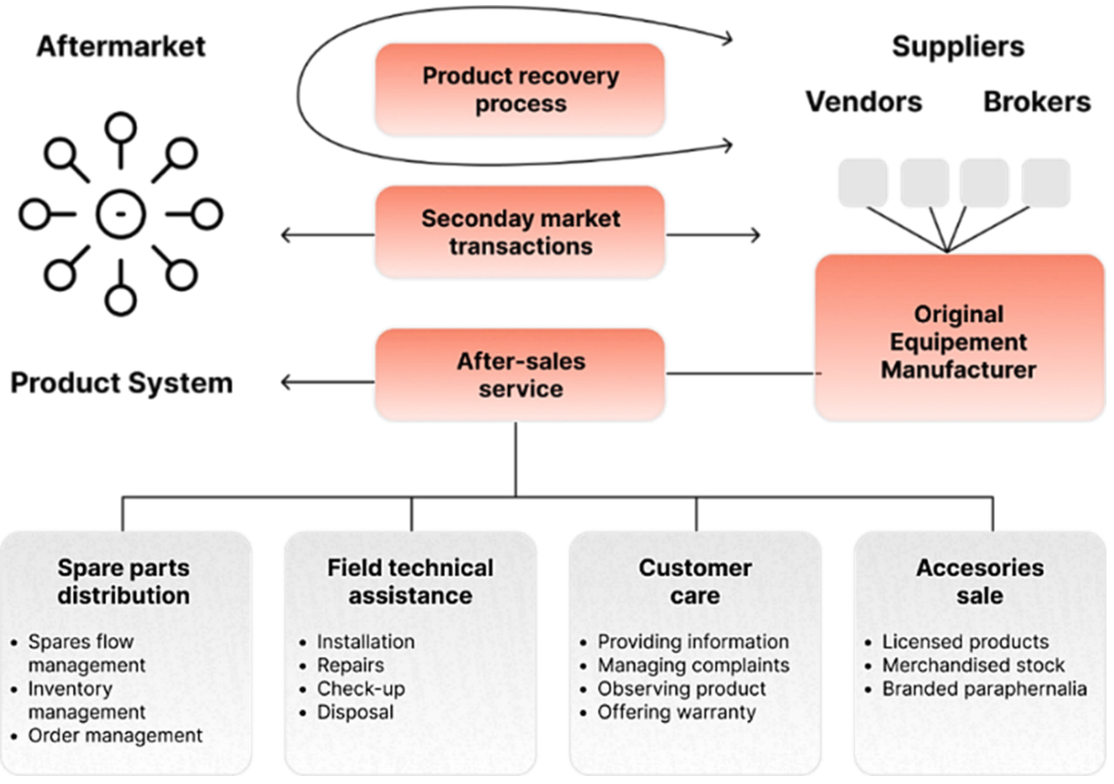


Figure 1: After-sales Service Business Processes

Figure 1 shows the main activities of after-sales service for home appliances, such as technical field service, spare parts sales, accessories sales, and after-sales service. These activities are important to ensure customer satisfaction and maintain the company's reputation in the market (Durugbo, 2020; Mydyti, 2022).

2.2 Key aspects of data mining approach along the business digital transformation journey

Digital transformation is viewed as the application of new technologies. Digital technologies enable significant operational improvements, such as improving customer experience, mitigating processes, or creating new models. The key drivers of digital transformation are digital capabilities and technologies. Digital technologies are essential to all efforts and provide business opportunities (Morakanyane, 2017; Orfanidis, 2018; Mydyti and Kadriu, 2021c).

Table 1 shows the main aspects of the impact of the data mining approach on the decision-making processes on the way to the digital transformation of the company.

The model for measuring progress-digital maturity-is based on the assessment of digital capabilities primarily within these common business dimensions such as customers, strategies, technologies, operations, organization, and culture (Valdez-de-Leon, 2016; Williams et al., 2019; Felch et al., 2019; Eremina et al., 2019; Deloitte, 2018; Mydyti and Kadriu, 2021a; Rogić et al., 2022).

Big Data analytics is one of the driving forces behind digital business transformation (Ziyadin et al., 2019; Wiesboeck and Hess, 2018; Hausberg et al., 2019; Schwertner, 2017; Telegescu, 2018; Mydyti and Kadriu, 2021a). The key techniques of Big Data and advanced analytics are data mining, machine learning, and natural language processing (Telegescu, 2018; Vivekananth and Baptist, 2015; Sadiku et al., 2018; Galetsi et al., 2020; Rehman et al., 2019; Prabhu et al., 2019; Mydyti and Kadriu, 2021a; Pejic-Bach et al., 2020a).

The most commonly used data mining techniques (Selihu et al., 2020) are clustering, classification, sequential analysis, regression, and association (Kaur and Dhiman, 2016; Mydyti and Kadriu, 2021a; Pejic-Bach et al., 2020b). In addition, Weka (Java), RapidMiner (Java), Orange (C++, Python, C), and R (C, Fortran, R) are considered important data mining tools (Kaur and Dhiman, 2016; Jovic et al., 2014; Dušanka et al., 2017; Mydyti and Kadriu, 2021a). Classification techniques include decision trees, k-nearest neighbors (KNN), random forest, Naïve

Table 1: Key aspects of the data mining approach impact the decision-making process

Key Aspects	Outcomes	References
Dimensions of digital transformation	Customers; Strategies; Technologies; Operations; Organization and culture	Valdez-de-Leon, 2016; Williams et al., 2019; Felch et al., 2019; Eremina et al., 2019; Deloitte, 2018; Mydyti and Kadriu, 2021a;
Digital transformation technologies	Big data analytics; Iot; Cloud; Mobile; Social networks	Ziyadin et al., 2019; Wiesböck and Hess, 2018; Hausberg et al., 2019; Schwertner, 2017; Telegescu, 2018; Mydyti and Kadriu, 2021a;
Advanced and big data analytics	Machine learning; Text mining (NLP); Data mining	Telegescu, 2018; Vivekananth and Baptist, 2015; Sadiku et al., 2018; Galetsi et al., 2020; Rehman et al., 2019; Prabhu et al., 2019; Mydyti and Kadriu, 2021a;
Data mining techniques	Classification; Clustering; Regression; Association; Sequential Analysis	Mydyti and Kadriu, 2021a; Kaur and Dhiman, 2016;
Data mining tools	Weka (Java), RapidMiner (Java), Orange (C++, Python, C) and R (C, Fortran, R)	Kaur and Dhiman, 2016; Jovic et al., 2014; Dušanka et al., 2017; Mydyti and Kadriu, 2021a;
Classification algorithms	Decision trees; Random forest; Naive bayes; Logistic regression; K-nearest neighbour (KNN)	Ragab et al., 2014; Jadhav and Channe, 2016; Mydyti and Kadriu, 2021b;
Benefits of applying data mining	Predictive analytics; Improves decision-making; Increases efficiency and business productivity; Enables Risk Mitigation; Enhances Customer Experience	Saeed, 2020; Mydyti and Kadriu, 2021a;
Challenges of applying data mining	Technology; Skills; Problem of poor data quality; Misuse of information/inaccurate information; Complexity of integration; Security and privacy;	Ikenna, 2014; Sharma et al., 2013; Zain et al., 2017;
Attributes of after-sales service quality	Consistency of service quality, options and variety of services, supply of required spare parts, delivery as promised, reasonable warranty policy, time taken to resolve the complaint, etc.	Murali et al., 2016; Ramya et al., 2019; Parasuraman et al., 1988; Golrizgashti et al., 2020

Source: Authors' work

Bayes, logistic regression, and so on (Ragab et al., 2014; Jadhav and Channe, 2016; Mydyti and Kadriu, 2021b).

Challenges of data mining applications include technology, capabilities, the problem of poor data quality, misuse/inaccurate information, integration complexity, and security and privacy (Ikenna, 2014; Sharma et al., 2013; Zain et al., 2017).

The benefits of data mining applications include predictive analytics, improved decision making, increased efficiency and business productivity, enabled risk mitigation, and improved customer experience, churn, and inventory forecasting (Saeed, 2020; Mydyti and Kadriu, 2021a; Pejić Bach et al., 2021; Selimi et al., 2019).

Service quality attributes, such as consistency of service quality, options and variety of services, delivery of required spare parts, delivery of promised services, adequate warranty policy, response to customer complaints, time taken to resolve the complaint, etc., are considered important in influencing customer satisfaction (Murali et al., 2016; Ramya et al., 2019; Parasuraman et al., 1988; Golrizgashti et al., 2020).

3 Methodology

In the framework of understanding companies in this field, as the case study, studied companies in the Kosovar market. The selected company is the largest in the region, which provides after-sales services for home appliances and electronic repairs for various appliances. In addition, the company provides services for the installation of appliances such as air conditioners, washing machines, dishwashers and so on.

The concept of the recommendation system is guided by several principles, such as a data mining approach and business observation, usability for the end user, and the interacting interface through the implementation of an API design - a system with machine learning concepts. The web-based platform facilitates the process by using data and graphs to present the probabilities for predicting the repair of the product according to their requirements. The Python programming language was chosen for this application. During the development of the recommendation system, numerous meetings were held with the management to integrate the main business components and requirements into the model. The system was developed for the users of the home appliance customer service (decision makers).

The research focuses on the analysis and implementation of the recommendation system as part of the functionality of the data mining system that will be used to predict and digitize the manual data presentation processes for customer service activities.

The studies of the various researchers involved in the conceptual development of our recommendation system differ. For example, they provide a general architecture for collecting and analyzing data and an overview of how to implement an interface (Capozzoli et al., 2016), which then manages the flow of data into the classification algorithm (Lundkvist, 2014; Mydyti and Kadriu, 2021b). In addition, the authors introduce the informative dashboards in the application layer and the last layer in Figure 2, which provide useful information to different users and suggest actions or strategies that can be implemented. The main layers of the system architecture are the application, knowledge, and source layers (Capozzoli et al., 2016 and Mydyti, 2022).

Figure 3 shows the conceptual structure of the implementation and the functions of the proposed model (recommendation system) (Mydyti, 2022), providing an overview of the components of a recommender system, consisting of data preparation, feature extraction, training data, test data, model predictions, and the recommender system itself. Data preparation involves collecting and organizing the data, while feature extraction identifies the most important features for a predictive model. Training data, testing data, and model selection involve choosing the right machine learning algorithm. The prediction block applies the model to new data. the module provides the system user with comprehensive prediction probabilities, capabilities, and permissions. The recommendation system scheme is easy to understand, accessible, helpful and simple to use.

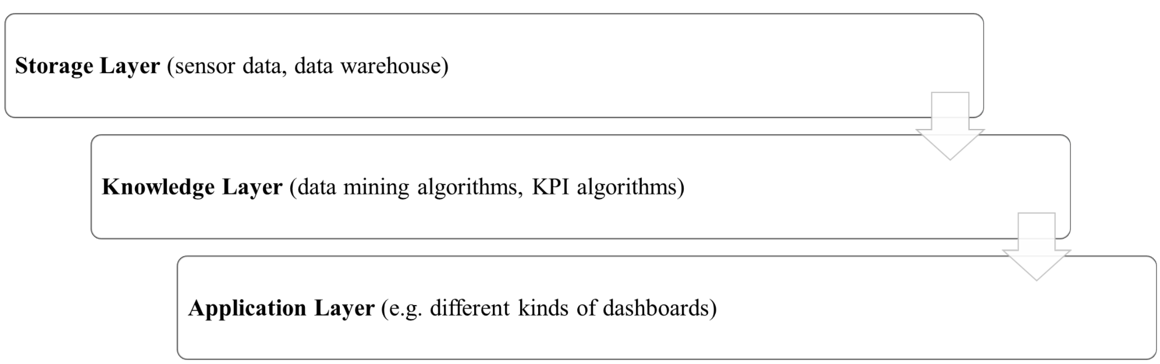


Figure 2: A general architecture to collect, store and analyse data

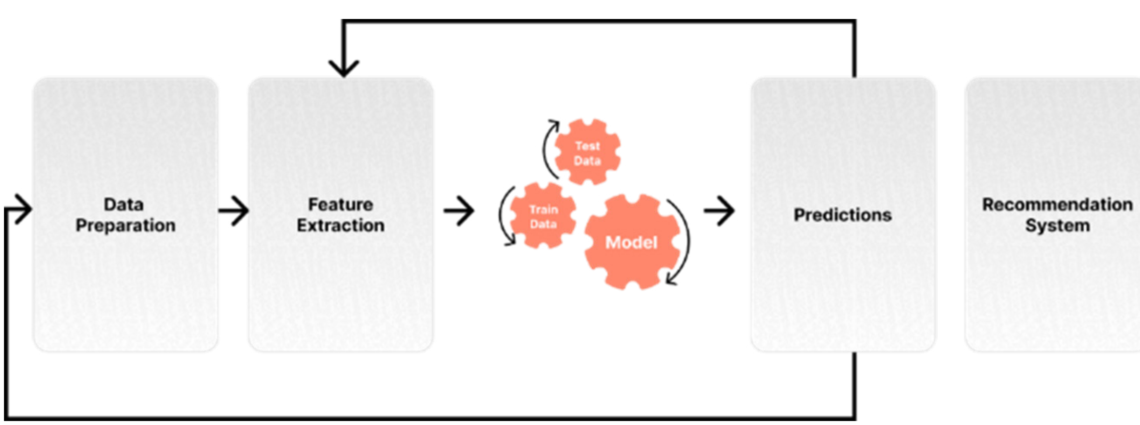


Figure 3: Functionalities of the recommendation system - implementation module

4 Results

4.1 Recommendation System Architecture

A key requirement of home appliance customer service is the digitization of the manual data presentation process, where predictive results are presented in a way that is easy to interpret. This system will help decision makers and managers in the after-sales service business and will have a positive impact by improving efficiency due to predictive business analysis.

Storage layer. The data used in this study come from a database maintained by a company that provides customer service for home appliances. The size of the dataset used is approximately 55,000 cases. The dataset includes three attributes, brand, category, and weeks to repair, as well as a class attribute representing service time in weeks. The brand attribute is nominal and includes six different brands representing the manufacturer of the product, namely Brand One, Brand Two, Brand Three, Brand Four, Brand Five, and Brand Six. The Category attribute is also nominal and includes five different values representing the product category. These values are home appliances (MDA), small home appliances and personal care (SDAP), TV, heating, and air conditioning. The weeks to repair attribute is also nominal and takes four different values, 1, 2, 3, and 4, which correspond to the duration of the service in weeks. The class attribute "weeks to repair" represents the response and is also nominal.

The data cleaning process was performed for the performance of the dataset. Inconsistencies, inaccuracies, missing data, and outliers were identified and addressed. Brand, category, and weeks to repair were the remaining attributes used in the analysis, with weeks to repair being the response variable and class attribute. The dataset contained approximately 55,000 cases and was free of errors, inconsistencies, and outliers after the cleaning process, making it suitable for the recommendation system analysis. The resulting dataset was ready for recommendation system analysis, with the transformed and adjusted variables providing an accurate representation of the basic relationships between attributes

Table 2 outlines the main attributes required in the dataset.

Descriptive statistics were performed for the 'weeks to repair' attribute in the dataset. The mean of 'weeks to repair' is 1.28 weeks, with a standard deviation of 0.65 weeks. The median and mode are both one week, indicating that most services are provided within one week. In addition, the attributes of brand and category were analyzed. From the dataset, Brand One is the leading brand with 82.1% presence. After Brand One, Brand Two is present in 6% of the cases, Brand Three is present in 5.3% of the cases, and the remaining three brands account for 6.6% of the cases. Most of the cases in the dataset belong to the MDA category (83%), followed by SDAP (9%), TV (7.1%), heating (0.3%), and air conditioning (0.6%). These descriptive statistics provide a better understanding of the attribute distribution in the dataset and can be used for recommendation system analysis.

The model is evaluated in terms of its predictive accuracy. The model achieved an accuracy of 80.85 percent.

Knowledge layer. For our predictive research, the decision tree algorithm (J48) has proven to be the one that gives the best results. It can build a predictive model (Mydyti and Kadriu, 2021b). Python was selected as the most suitable programming language for the implementation of the recommender system. Since Python will be implemented shortly, the criterion parameter is used to obtain the best decision tree. The criterion parameter corresponds to the function of the quality of a partition in the selection of the Gini index or entropy.

A decision tree is viewed as a classifier represented as a recursive partitioning of the feature space into subspaces

Table 2: The structure of the dataset of recommendation system implementation

Attributes	Description	Values
Weeks to Repair	The duration of the service is measured in weeks from the time of the initial request.	1, 2, 3 and 4
Brand	A brand encompasses six distinct values and signifies the product's manufacturer.	Brand One, Brand Two, Brand Three, Brand Four, Brand Five, Brand Six
Category	The product category comprises five distinct values: domestic appliances (MDA), small domestic appliances and personal care (SDAP), TV, heating, and air conditioning.	Air Conditioning, Heating, MDA, SDAP, TV

Source: Authors' work

that form a basis for prediction. Decision tree algorithms build a tree based on a given data set and aim to obtain an optimal decision tree by reducing generalization error, nodes, or average depth (Rokach and Maimon, 2005).

Research authors define the Gini index as a contamination factor that calculates the differences between probability distributions above target attribute values (Rokach and Maimon, 2005; Tangirala, 2020). The Gini index is

$$Gini(y,S) = 1 - \sum_{c_j \in dom(y)} \left(\frac{|\delta_{y=c_j} S|}{|S|} \right)^2 \quad (1)$$

defined by the formula shown in Equation Eq. 1, which is expressed as follows:

The training set is represented by S and the target feature is represented by y.

Information gain is a criterion based on impurities, as stated in the equation InformationGain Eq. 2, which im-

$$\text{InformationGain}(a_i, S) = \text{Entropy}(y,S) - \sum_{v_{i,j} \in dom(a_i)} \frac{|\delta_{a_i=v_{i,j}} S|}{|S|} Entropy(y, \delta_{a_i=v_{i,j}} S) \quad (2)$$

plements entropy as a measure of impurity (Rokach and Maimon, 2005).

The input feature set is represented by a_i, and the outcomes of discrete functions are represented by (v1, ..., vn).

$$Entropy(y,S) = \sum_{c_j \in dom(y)} -\left(\frac{|\delta_{y=c_j} S|}{|S|} \right) \log_2 \left(\frac{|\delta_{y=c_j} S|}{|S|} \right) \quad (3)$$

Information gain, as in equation Eq. 3, relies on entropy where:

The empirical result is that the information gain and the Gini index provide similar accuracy in classification. Moreover, the results show no significant differences in model performance using the Gini index and the information gain, regardless of whether the dataset is balanced or unbalanced (Rokach and Maimon, 2005; Tangirala, 2020).

The development of the recommendation system involves a series of clearly defined steps. First of all, the required libraries are imported. The next step is loading the data set. Next, the data is split into features and the target variable is identified. Fourth, the data is prepared for model building by splitting the data. Then, a decision tree classification model is created. Once the model is created, the accuracy of the model is evaluated. Finally, the decision tree is visualized to better understand the internal workings of the model. Following the methodology used in data science projects, the model design is performed by implementing Python code using Jupyter Notebook, following the sequence of steps described in Figure 4 (Mydyti, 2022).

Application Layer. This paper is aimed at business decision makers in customer service. The recommendation system aims to improve the quality of service and thus the customer experience.

The recommendation system will improve service quality and communication between customer service companies and subcontractors, retailers, wholesalers, and manufacturers. Users interact with the recommendation system without having to log in to process the information generated by the classification algorithm - the decision tree. Users have the advantage of receiving the probability prediction - data and charts.

The model created is a classification model that predicts the service quality of home appliance customer service based on the time required to resolve the complaint. Our model solution follows machine learning concepts and applies a decision tree algorithm that can manage categorical predictors and interpret results.

This section consists of one module: the Decision Maker module. The recommender system is built using a Python programming language code for data science projects according to the following steps in Figure 5 to predict the time needed to resolve the complaint (Mydyti, 2022).

The development of a recommender system is based on a series of steps to create an effective system. These steps include the following: (i) collecting the user-entered features and storing them in a data frame, which is the first critical step in building a recommender system; (ii) combining the user-entered features with the customer service record, which helps to create a complete data set; (iii) encoding the ordinal features, which consists of converting the data in such a way that the model (iv) can easily process the data, i. e. i.e., reading a stored classification model, i.e., a model that has already been trained and is used for prediction; (v) applying the model to make predictions, which is an essential step in the process of developing the recommender system. The model makes a prediction and gives a recommendation to the user based on the input features. (vi) finally, the data is visualized in a bar chart using "Plotly Chart" - this step is important for understanding the recommendation made by the model.

This module provides full functionality for users who have full permissions. The relevant forecast data and charts have been appropriately presented. The first part of the system displays the probability of predicting the 'time to resolve the complaint' as a percentage. The second part of the system provides a graphical comparison of prediction results that processes various classification inputs. The user can view the probability of repair prediction by product category and brand and search for predictions for products and product brands.

In addition, the main feature of this system is the probability of predicting the quality of service (time to fix the complaint) demonstrated in the search of an option. The target is 'weeks to repair' as a categorical predictor, and the model predicts service quality based on four response groups, including first week, second week, third week, and fourth week. The target indicates the number of weeks until the repair is completed.

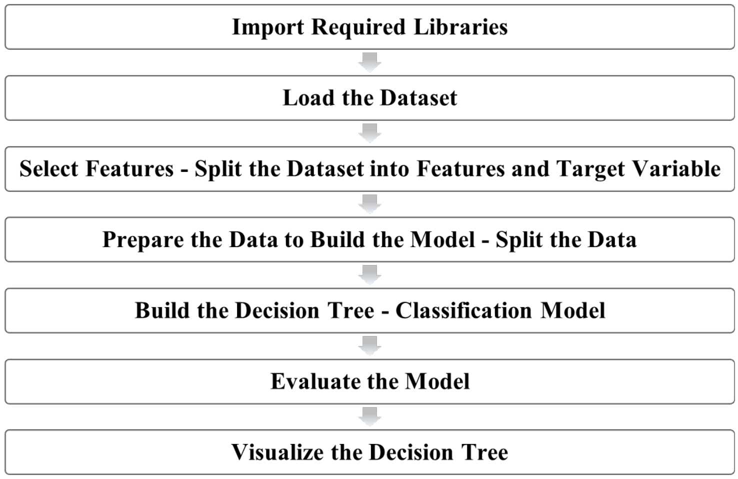


Figure 4: Steps to Build the Model

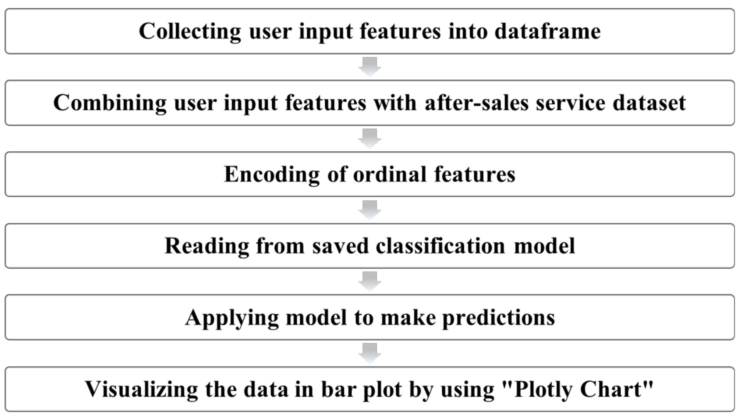


Figure 5: Steps to Build the Recommendation System

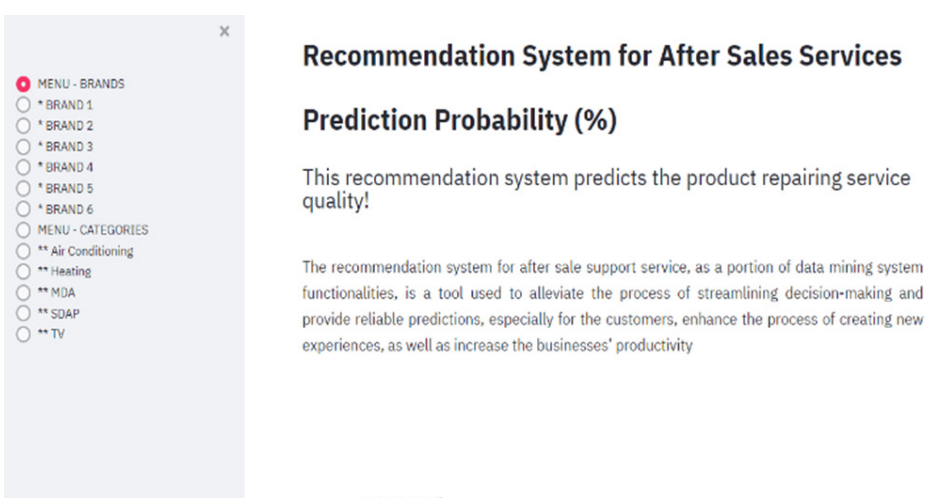


Figure 6: Application - Recommendation System of a decision-maker

In the left sidebar of the module, you can select the brand or category for which you want a prediction of how long the product will take to repair. Figure 6 illustrates the web pages generated by the recommendation system. These illustrations serve as visual aids to demonstrate the functionality of the system and highlight the user interface. Figure 6 shows the options you can select in the left sidebar to get a prediction of the likelihood of a week-long repair, including (i) six leading product brands, including (a) Brand One, (b) Brand Two, (c) Brand Three, (d) Brand Four, (e) Brand Five, and (f) Brand Six, (ii) five leading product categories, including (a) Air Conditioning, (b) Heating, (c) MDA, (d) SDAP, and (e) TV. Figure 6 shows the first part of the recommender system and menu, including the selection of brands and categories.

4.2 Recommender System Usage

This section provides an overview of the two main usage of recommender system: brand prediction, and category prediction.

Brand prediction. The benefits expected and delivered by the recommendation system include security, speed, ease of access, and shorter loading times. The system's brand prediction application has links in the left sidebar to predict product' repair time by brand. For example, selecting the first option - Brand 1 - in the left sidebar displays the predicted results in Figure 7. Figure 7 shows the web pages generated by the recommendation system. These figures serve as visual aids to demonstrate the functionality of the system and highlight the user interface. figure 7 illustrates the prediction of Brand One within the system. Brand prediction within the system provides the probability of service quality prediction (time taken to resolve the complaint) for all five categories. The system indicates the quality of service', specifically the predicted time to complete the repair. The green percentage indicates the predicted probability of completing the repair in the first week for each "Brand 1" category. The percentage in blue indicates the probability of completing the repair within two weeks for each "Brand 1" category. The percentage in red indicates the probability that the repair will be completed within three weeks for each "Brand 1" category. The percentage in orange indicates the predicted probability that the repair will be completed within four weeks for each 'Brand 1' category. The predicted probability for the Heating and TV categories is greater, and therefore better, because the probability of completing the product repair within one week is higher. The predicted probability for the SDAP category is worse, especially because the probability of completing the product repair longer than one week is higher.

The chart in Figure 8 graphically illustrates the comparison of the percent probabilities of how long it will take to resolve the complaint within a week. The comparative demonstrations belong to each "mark 1" category.

The left sidebar includes the same system components for all brands and provides the probability for predicting the time it will take to resolve the complaint for each brand category.

Category prediction. The system's category prediction has links in the left sidebar to predict the product's repair time by category. For example, if you select the first option of Categories - MDA in the left sidebar, the predicted probability results are shown in Figure 9. Figure 9 illustrates the web pages generated by the recommendation system. These figures are intended as visual aids to demonstrate the functionality of the system and highlight the user interface. the system category part indicates the predicted probability of the time required to resolve the complaints

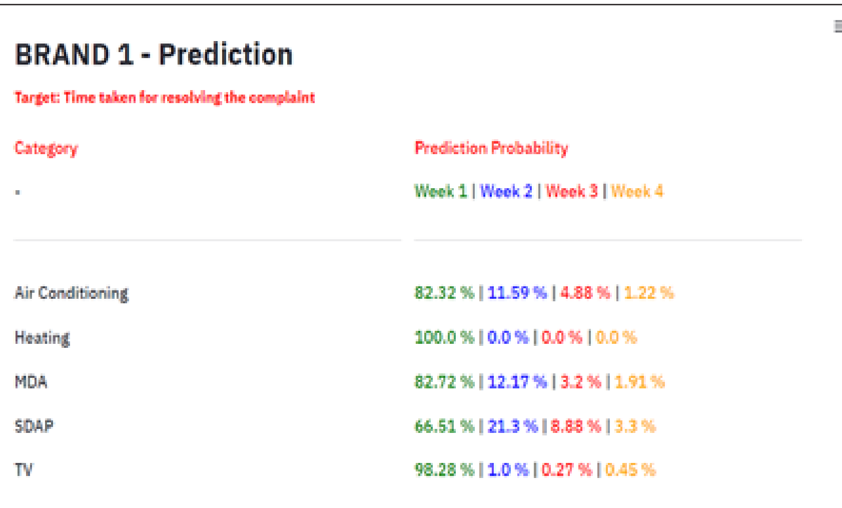


Figure 7: Brand 1 Prediction of the Recommendation System

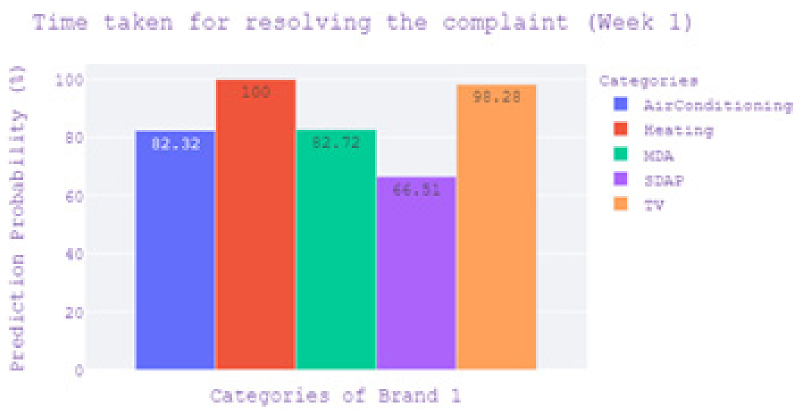
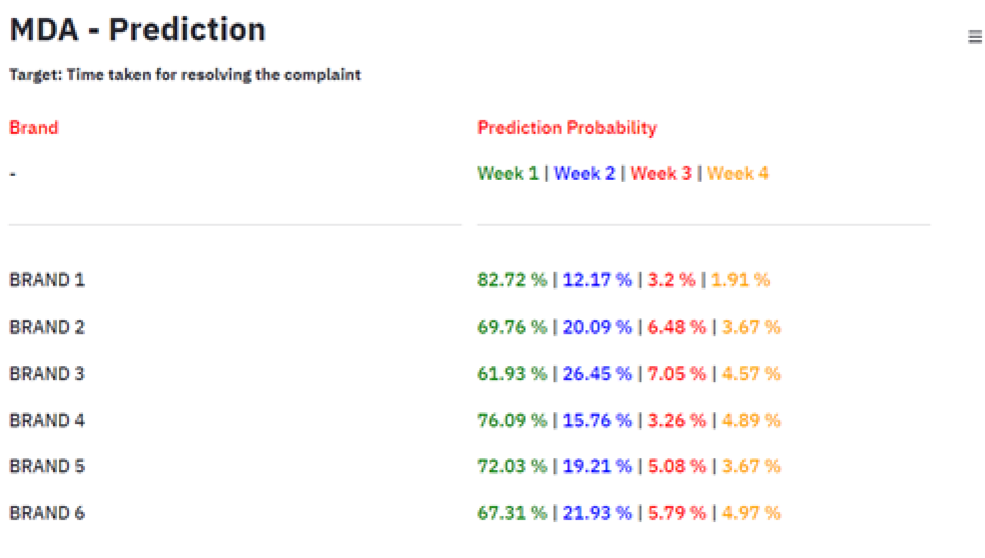


Figure 8: Brand 1 App - Chart of Repair Prediction for One Week



MDA - Prediction

Target: Time taken for resolving the complaint

Brand	Prediction Probability
-	Week 1 | Week 2 | Week 3 | Week 4
BRAND 1	82.72 % | 12.17 % | 3.2 % | 1.91 %
BRAND 2	69.76 % | 20.09 % | 6.48 % | 3.67 %
BRAND 3	61.93 % | 26.45 % | 7.05 % | 4.57 %
BRAND 4	76.09 % | 15.76 % | 3.26 % | 4.89 %
BRAND 5	72.03 % | 19.21 % | 5.08 % | 3.67 %
BRAND 6	67.31 % | 21.93 % | 5.79 % | 4.97 %

Figure 9: MDA Prediction of the Recommendation System

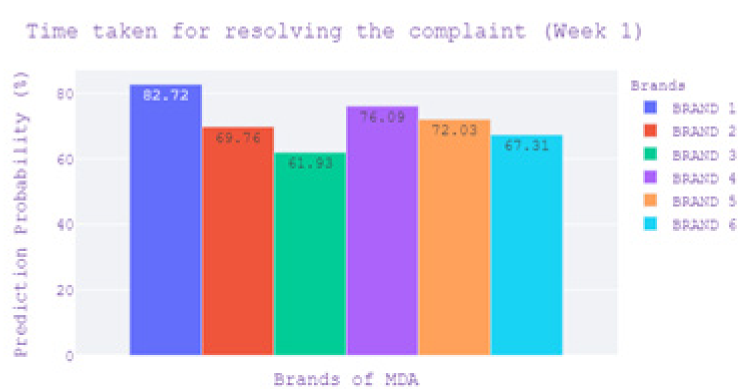


Figure 10: MDA Category App - Chart of Repair Prediction of One Week

of the six brands. The predicted probability for brand 1 is higher and therefore better because the probability of completing the product repair within one week is higher. The predicted probability for brand three is worse, especially because the probability of completing the product repair longer than one week is higher.

The chart in Figure 10 graphically illustrates the comparison of the percent probabilities for the time required to resolve the complaint within one week. The comparative demonstrations focus on each brand in the MDA category.

The left sidebar includes the same system components for the categories, such as air conditioning, heating, SDAP, and TV, and indicates the probability that you can predict how long it will take to resolve the complaint for each brand category.

5 Model evaluation and Discussion of Results

This section presents and evaluates the results, how long it takes to resolve the complaint, and the positive effects of the referral system. The time it takes to resolve a complaint is one of the most important attributes of service quality, which affects customer satisfaction and non-financial performance measures for management decision making.

5.1 Evaluation of the impact of the outcome of the recommendation system

This section presents the results for 2020 and 2021, along with a comparison and positive results. The decrease in the average time to process a complaint in each year shows a positive impact. In 2021, the average time it took to process a complaint decreased by 7.78% (equivalent to 0.54 days) compared to 2020. Figure 11 shows the evaluation of the impact.

Figure 12 shows a year-on-year comparison of results for all brands, revealing a decline in average complaint handling time.

The presentation includes a comparison of brands and positive outcomes for 2020 and 2021. Each year, the reduction in the average time taken to resolve brand complaints is evidence of a positive impact.

In 2021, the average time to resolve complaints for each brand decreased compared to 2020, with a decrease of approximately 0.38 days in the average target time to resolve a complaint for Brand 1. The average target time to resolve a complaint for Brand 2 decreased slightly to approximately 0.05 days. For Brand 3, the average target time for processing a complaint decreased to approximately 0.59 days. For Brand 4, the average target time for processing a complaint increased by approximately 0.65 days. At Brand 5, the average target time for processing a complaint decreased by approximately 3.36 days. For Brand 6, the average target time for processing a complaint decreased by approximately 2.59 days.

5.2 Quality of the Recommendation System

The quality of the recommendation system's predictions depends on the studies conducted to determine the best classification algorithm and the system's speed of response to users.

This ensures that the recommender system can be adapted to the needs of the users, resulting in an effective and efficient system without negative consequences. In

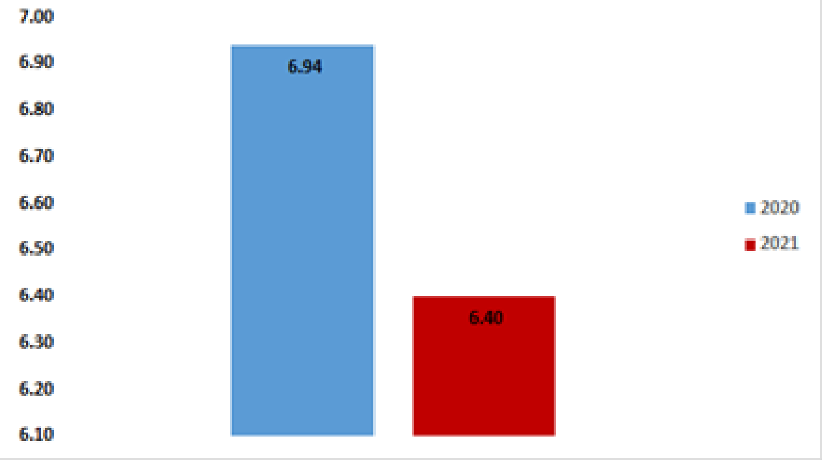


Figure 11: Yearly Comparison - Time Taken for resolving the complaint

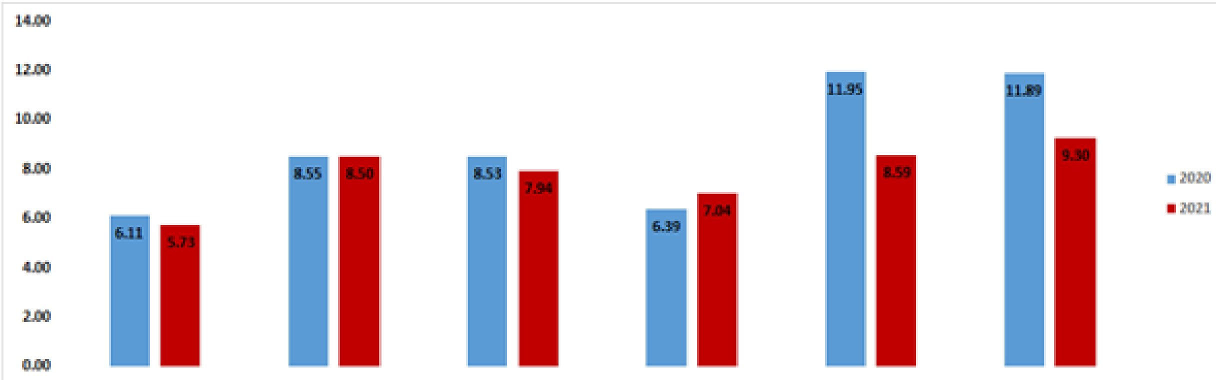


Figure 12: Yearly Comparison, By Brand - Time taken for resolving the complaint

Table 3: Testing Results of the Recommendation System Performance

Steps Taken	Expected Results	Outcome
Flexibility/Responsiveness of the system in different browsers to be tested. Three web browsers such as Chrome, Firefox and IE, were selected.	It is required that all elements of the system load properly without overflowing and remain responsive.	Successfully tested for flexibility and responsiveness, the system encountered no overflow issues.
Accessibility/Easiness to be tested.	We will test the accessibility and ease of use by intentionally refraining from entering credentials and disabling error catching.	Completed testing the ease of accessibility phase.
Incorrect/correct prediction probability percentage to be tested.	The user reported that the predicted probability percentage for the target variable “days to repair” was mostly accurate.	The completion of the testing phase to determine the accuracy of the predicted probability percentage was successful.
User Satisfaction during the testing process.	The testing process was satisfactory to the business.	The system achieved a good performance level.

Source: Authors’ work

addition, the recommender system undergoes testing to identify and fix bugs and errors to ensure a high-quality implementation that meets business and technical requirements. The technique of usability testing, which predicts the quality of service, is beneficial to both decision makers (users) and the customer service business in general.

During the testing process, we received user feedback and ran a simple test with only one user to evaluate the implementation.

We tested the system to identify misclassifications and errors and to test behavior and performance. The features tested included the flexibility and responsiveness of the system in different browsers, accessibility and ease of use, and the accuracy of classification by the decision tree algorithm with prediction probability. The system is responsive to the user’s expectations. The most important aspects of a system include interface, usability, and performance.

Table 3 shows the completed test steps, expected results, and outcomes.

The objective was to develop and apply a recommender system, evaluate its ability to maintain and operate effectively, and achieve this by selecting the most appropriate trends, data mining technologies, and tools.

The most valuable aspect of the research was the impact of the data mining approach on optimizing the strategic goals of the companies and strengthening the links between companies and customers.

In addition, the system implementation section contributes to the detailed elaboration of all phases of the integration of the data mining approach into the system and to the creation of a model for other companies with similar concerns. This case study provides a concrete example of how companies can apply data mining to analyze information and predict processes. Using data mining techniques, we gained insight into how this approach can be applied to the home appliance customer service industry. Following this study, the recommendation system identified Python as the most appropriate implementation trend for system development. The evaluation results show how the implementation of the data mining approach can improve the decision-making process by providing reliable predictions for product repairs that have a positive impact on the company's productivity and efficiency.

6 Conclusions

Our research makes an important contribution to this field by proposing a model that involves the implementation of a recommender system that serves as an outcome. This model aims to promote the digital transformation of home appliance customer service by simplifying decision making. In particular, the recommendation system includes several functions of a data mining system. The implementation of this system can improve decision making, increase operational efficiency, and provide better customer service for enterprises. In particular, the recommendation system uses the decision tree classification algorithm that we implemented to improve the efficiency and accuracy of the system. The recommendation system is designed to streamline processes between business partners involved in customer service. The implemented recommender system provides data that primarily predicts the probability of the time required to resolve the complaint and digitizes the manual data presentation processes.

Evaluating the positive impact of the primary attribute of service quality, time taken to resolve complaints, is critical. Our evaluation proves that data mining improves decision making and increases efficiency by analyzing business forecasts.

The data mining approach empowers managers to make strategic decisions, and the use of data mining technologies is key to improving business performance. By helping companies, managers and researchers to become the main beneficiaries, this paper highlights the positive aspects of data mining, which serves as a contemporary approach to facilitate the digital transformation of companies.

Limitations of the study include the challenges in implementing the proposed model in the Kosovar market for home appliance customer service companies, the lack of previous research in the region for comparative studies, the limited assessment of the impact of data mining only on non-financial performance metrics, and the potential for improving the digitization and automation of the data mining system.

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Uporaba podatkovnega rudarjenja za izboljšanje podločanja: Študija primera razvoja sistema priporočil

Ozadje in namen: Cilj pričujoče študije je prikazati praktičen pogled na to, kako se tehnike podatkovnega rudarjenja uporabljajo v poprodajnih storitvah pri prodaji gospodinjskih aparatov. Študija prikazuje kako lahko sistem priporočil pomaga storitvenemu podjetju, ki načrtuje uporabo podatkovnega rudarjenja za izboljšanje odločanja med postopkom digitalne preobrazbe. Poleg tega študija zagotavlja podroben oris postopka za razvoj in analizo platform za izboljšanje analitike podatkov za tovrstna podjetja.
Metodologija: Za namen raziskave uporabimo pristop študije primera za ocenjevanje uporabnosti sistemov, ki temeljijo na pristopu podatkovnega rudarjenja v kontekstu poprodajnih storitev gospodinjskih aparatov. V raziskavi smo izbrali najnovejše platforme glede na njihovo relevantnost in njihovo uporabnost pri funkcionalnosti sistema podatkovnega rudarjenja kot tudi trende v načrtovanju sistema.
Rezultati: Ocena vpliva uporabe tehnik podatkovnega rudarjenja na odločanje kaže povečanje učinkovitosti organizacij. V članku je predstavljena ocena časa reševanja reklamacije, kot ključne lastnosti kakovosti storitev, ki vpliva na zadovoljstvo strank, in pozitivni rezultati, ki jih dosegamo s pomočjo sistema priporočil.
Zaključek: Raziskava prispeva k razumevanju prednosti pristopa podatkovnega rudarjenja v kontekstu sistemov priporočil. Prednosti podatkovnega rudarjenja, kot pomembnega sestavnega dela napredne analitike, vodijo do povečanja produktivnosti. Za prihodnje raziskave se lahko, za izboljšanje kakovosti rezultatov, vključijo tudi drugi atributi ali dejavniki, ki so koristni za sisteme priporočil.

***Ključne besede:** Digitalna transformacija, Podatkovno rudarjenje, Algoritem odločitvenega drevesa, Odločanje, Poprodajne storitve gospodinjskih aparatov*