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# ANALYSIS OF THE IMPACT OF DIGITISATION OF PUBLIC SERVICES USING THE CART ALGORITHM

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**Abstract:**
The current economic, social, and political context is dynamic and marked by multiple influences. The phenomenon and process of digitisation is affecting all sectors and economies. Digitisation has a cross-cutting impact, contributing to economic growth, innovation, and global connectivity. It is an ongoing process, and adaptability to new technologies is becoming essential for success in the modern world. By digitising services in local public administration, an enabling environment for modern, transparent, and citizen-oriented government is created. In this research approach, we propose the use of the CART algorithm in the analysis of the digitisation of public administration to gain a deeper understanding of the factors influencing the adoption of digital technologies and the possibility to make informed decisions to improve administrative processes and public services.

**Keywords:** digitisation, CART algorithm, public administration

**JEL** D73, H83, M15

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## INTRODUCTION

The digitisation of services in public administration is generally aimed at increasing their efficiency, improving relations with citizens, and adapting to the demands of an increasingly digitally connected society (Zekić-Sušac et al., 2021). Digitisation of services in public administration is of significant importance from several perspectives. Thus, digitisation enables the automation of administrative processes, reducing the time and resources required for managing documents and other repetitive tasks (Sanina, 2023). This leads to increased efficiency in public administration. By providing online services, citizens have easier access to information and can carry out various transactions without having to physically go to the premises of public institutions, which improves the experience of citizens and makes the administration friendlier

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(Lips, 2019). The purpose of digital technologies is not to replace them but to enhance them by making them sources of data and enabling new connections and recombinations (De Nicola, 2023). Digitisation creates possibilities for new interactions and new connections with other components, enabling the digital transformation process.

Digitisation facilitates the transparent publication and distribution of public information, decisions, and policies (Osborne, 2020). Citizens can better track government activities, which contributes to greater trust in public institutions. By eliminating manual processes and paper, significant cost savings can be generated for public administration. Electronic document and information management reduces reliance on physical space and human resources. The adoption of digital technologies paves the way for innovation in public service delivery. The use of tools such as data analytics or artificial intelligence can improve the quality and efficiency of services.

In an era where most activities take place online, digitising public services is essential to remain relevant and meet the expectations of citizens, who are used to solving problems quickly through technology (Torfing et al., 2019). By applying the CART algorithm in this context, a deeper understanding of the perception of digitisation can be gained, and more informed decisions can be made to improve public administration services at national level.

## 1. LITERATURE REVIEW

The CART algorithm is an effective tool for analysing respondents' opinions. The algorithm can identify patterns in large amounts of data, analyse numerical and categorical data and identify relationships between different variables. The algorithm is also used to determine respondent profiles The CART algorithm is an effective tool for analysing respondents' opinions. The algorithm can identify patterns in large amounts of data, analyse numerical and categorical data, and identify relationships between different variables. The algorithm is also used to determine respondent profiles (Hadi et al., 2022). The use of CART (Classification and Regression Trees) algorithm in the study of the perception of digitisation of public administration services at the national level can bring a systematic and structured approach to the data. In order to use the CART algorithm in the analysis of the efficiency of digitisation of public administration services, we follow the following steps (Zanoschi, 2021):

Data collection: First, we collect relevant data about existing services and processes in public administration. This data may include information on the time taken to complete services, the number of interactions with citizens, the costs involved, and other relevant variables.

- Data preparation: In this step, we analyse and prepare the data for use in the CART algorithm. This may include cleaning the data, removing missing values, transforming categorical variables into numeric variables, and splitting the dataset into training and test sets.
- Definition of output variable and characteristics: We define the output variable we want to estimate, i.e. the measure of service digitisation deficiency. We also select relevant characteristics that could influence the efficiency of digitisation, such as the level of technology used, resources employed, and staff capabilities.
- Building the CART model: The CART algorithm helps us to build a decision tree that predicts the efficiency of service digitisation. This will be achieved by partitioning the dataset using the selected characteristics and output variable. While constructing the tree, optimisation criteria such as maximum purity increase or error minimisation will be taken into account.
- Model evaluation: After building the tree, we will evaluate its performance using the test set. It will give us a measure of the accuracy and generalisability of the model to estimate the efficiency of digitising services.

- Interpretation of the results: Based on the constructed decision tree, we can interpret the relationships between the selected characteristics and the efficiency of service digitisation. For example, we can identify which factors have the greatest influence on efficiency and can be improved through investments and technological improvements.

The CART algorithm can be a valuable tool to assess and improve the efficiency of digitisation of services in public administration, allowing one to identify the most important factors influencing the success of the digitisation process. Digitisation of services in public administration is of major importance in the context of today's digital society (Ziółkowska, 2022). Digitisation of services in public administration is considered important because it ensures:

- Higher efficiency: Digitisation of services enables the public administration to provide faster and more efficient services to citizens and businesses. Digital processes can reduce the time and costs associated with interacting and sending documents, facilitating fast and transparent communication between parties.
- Increased accessibility: Digitising services makes it easier for citizens to access public services through online platforms. This is particularly important for people living in remote or resource-constrained areas, as well as for people with reduced mobility or disabilities.
- Transparency and reduction of corruption: Delivering services digitally improves transparency in public administration and reduces the risk of corruption. Through digitisation, processes become clearer and easier to follow, and citizens benefit from more direct and transparent access to administrative information and procedures.
- Savings achieved: Digitisation of services can reduce administrative costs of public administration by eliminating the need for paper, reducing costs for mail and other physical resources needed in traditional processes. Digitisation also facilitates the exchange of information between public institutions and reduces redundancies in activities.
- Innovation and development: The digitisation of services in public administration opens up new opportunities for innovation and development in the public sector. The use of modern technologies, such as artificial intelligence, the internet of things or blockchain, can bring significant benefits, such as personalised services, process automation or improved security in government.

It can be seen that the digitisation of services in public administration has multiple advantages and can significantly contribute to improving performance and the relationship between administration and citizens (El Ammar & Profiroiu, 2020). It is an essential process to respond to the demands of an increasingly digitised society and to promote innovation and development in public administration.

According to the literature, there are numerous studies and research on the digitisation of public administration services. Studies on the digitisation of public administration services play a crucial role in promoting an efficient and sustainable digital transformation in Romania, bringing benefits for citizens, public administration, and society as a whole.

Thus, according to the studies, there are efforts to analyse the benefits and challenges of digitisation in order to provide insight into key aspects of digital transformation in public administration (Fischer et al., 2021).

It also analyses how digital technology is transforming the relationship between citizens and public institutions and discusses the associated challenges and opportunities (Viana, 2021). According to Eom & Lee (2022), by analysing the transformation of digital government in public administration, key trends, patterns, and factors influencing the adoption and effectiveness of digitisation in public services could be identified.

Globally, public sector institutions are in the process of digital transformation, albeit facing regulatory and technological challenges.

In recent years, many governments have developed plans to encourage the adoption of innovative technologies such as work process automation (WPA) and artificial intelligence (AI). Many public administrations have already adopted these technologies, with positive results such as improved productivity, increased employee engagement, and optimised operational costs (Cătană, 2019).

When we refer to digital transformations and the transformative role of digitisation, we are also referring to the changes they bring about. Therefore, we need to look at the technological trends that are causing changes and sometimes even disruptions (disruptive effects) in various areas (Roja, 2019).

It is now important to increase user confidence in public sector digital environments by improving the accessibility, security, and quality of these services. It is also useful to promote the use of digital media and encourage citizen participation in the decision-making and administrative process. The most important factors affecting users' trust in public sector digital environments are transparency of information, but also security of personal data, quality of information and accessibility of digital platforms for effective use, i.e., services and information should be up-to-date, easily accessible, and the platform should be easy to navigate in order to make the time spent on the platform or working time more efficient for public sector employees (Moloiu, 2023).

Studies on the digitisation of services in public administration in Romania play a crucial role in identifying and analysing the challenges and opportunities associated with digital transformation in the public sector. These studies bring to the fore relevant issues such as efficiency of public administration, transparency, easy access of citizens to public services, and reduction of bureaucracy.

## 2. RESEARCH METHODOLOGY

This paper aims to demonstrate the significant influence of three categories of factors (demographics, national government performance and citizens' economic expectations) on citizens' perceptions of the digitisation of public services. The paper proposes three main hypotheses, which it intends to confirm or refute through empirical analysis:

H1: Demographic factors influence citizens' perceptions of the digitisation of public services.

H2: Perception of digitisation tools is influenced by public administration performance

H3: Perception of digitisation tools is influenced by citizens' economic expectations.

Also, by analysing the data it is possible to identify the profiles of people who have a negative opinion in order to identify groups that should be given more attention on this issue.

This work used data collected through a questionnaire administered at national level between April and June 2023, following the principle of representativeness at the level of the regions of Romania. The questionnaire was administered through Google forms, the target population being all citizens interested in providing feedback on the importance of digitisation of services in local public administrations.

Each instance in the sample will be associated with a post-stratification weight, denoted by w1, which is calculated according to the population of the region of origin of the subjects and its socio-demographic structure. In this way, the aim was to correct the importance of the information provided by an instance, taking into account the population size of an administrative region from which the subject comes, as well as the age group, gender, occupation, etc.

The use of these weights is important to obtain more accurate and representative results in the extrapolation process. Since the samples have the same volume, with minor exceptions, they represent populations of different volumes, an instance from a larger population will have a higher weight than an instance from a smaller population, as it is considered that it will be representative of more instances from the source population. The same can be said about population size by gender, age, education, etc.

*Presentation of the CART Algorithm*

The CART algorithm is a non-parametric modelling method that results in classification or regression trees, in which one attempts to classify instances for the dependent, categorical or numerical variable(s) according to a set of explanatory, numerical and/or qualitative variables. CART is an acronym for Classification and regression trees and was first proposed by Breiman in 1996. It works by repeatedly dividing the data into several subspaces so that the results in each final subspace are as homogeneous as possible. This is called a recursive partitioning technique (Berk, 2008).

One aspect that needs to be stressed for this algorithm is that it also provides the importance of the variables that are included in the model. In the CART tree, the importance of a variable is measured by taking into account its contribution to the reduction of variation in the child leaves, relative to the variation specific to the parent node from which they originate. Specifically, the importance of variables is most often quantified using the cumulative Gini index at the tree level according to formula 1 (Tahsildar, 2019).

$$(1) \quad Gini = \sum_{i=1}^{n} p_i^2$$

where *pi* - the probability that an instance is classified in a certain category

*Gini Impurity* is a method of splitting nodes when the target variable is categorical. It is the most popular and simplest way to split a decision tree. This indicator is calculated according to formula 2 (Sharma, 2020).

$$(2) \quad Gini\ Impurity = 1 - \sum_{i=1}^{n} p_i^2$$

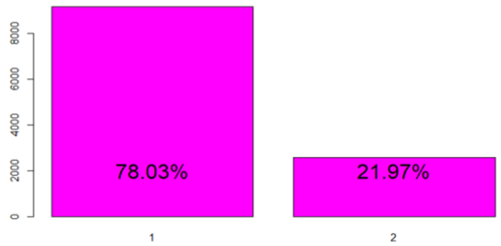
A lower Gini Impurity score indicates that the leaves resulting from splitting the parent node by the predictor variable are purer or more homogeneous. If a split by two variables takes place, the more important variable will produce purer and more homogeneous nodes than the less important variable generating a lower Gini Impurity score.

To calculate the importance of the variables, the algorithm calculates the sum total of the differences between the Gini Impurity scores of a variable and the Gini Impurity score of the tree root. The more a variable contributes to reducing variation and creating cleaner subgroups, the more importance it will have in the resulting tree.

*Balancing methodology*

To ensure the most accurate analysis, "don't know" or "didn't answer" responses were removed from the target variable responses. Since the target variable perce_n (questionnaire q1_1) has the structure shown in Figure 1, the analyses were performed on several balanced samples.

**Figure 1. Initial structure of the target variable percep_n**




*Source: authors' processing based on subjects' answers,2023*

To obtain the validation set, a 30% sample was extracted from the original data, keeping the original structure of the target variable. The training set was divided into three samples, keeping the minority category unchanged and dividing the majority category randomly into three samples. This resulted in a swing percentage of 51% for the majority category and 49% for the minority category. The weighting variable w1 described above was also included in the trees produced. Trees were also produced using the CART algorithm using all three aggregate samples simultaneously, with the minority category replicated three times.

Questions in the questionnaire representing respondents' perceptions of issues related to the digitisation of services in local government at national level were recoded to facilitate interpretation of the results. Thus, answers representing a negative opinion were assigned negative values, answers "don't know" or "neutral" were assigned 0 values and answers representing a positive opinion were assigned positive values.

A PCA analysis identified three constructs related to the different perceptions of the digitisation of services in local government. In order to simplify the models and improve their performance, decision trees were constructed for each construct, with the aim of identifying the most significant variables in each construct. This significance was validated using the Random Forest algorithm. Table 1 shows the importance of the variables as the sum of their importance in all three samples, as well as their relative mean importance. Using the mean importance percentages, weights were created to produce mean scores for each construct at the level of each instance. This was done using formula 3.

$$c_{in} = \sum_{1}^{j} Q_{ji} * p_j \qquad (3)$$

where:
i - is the court order number
n - is the component number
j - is the question number (question code)
Qji - represents the answer of instance i to the question
Pj - represents the weight value obtained by ranking the variables

These variables will be called constructs (C) and represent a weighted aggregation of variables as follows:

- C1 - the construct referring to the reforms needed at the level of each region

- C2 - construct referring to the benefits of digitisation

- C3 - construct referring to the ease of use of digitisation tools by citizens.

Discretisation of the obtained variables was performed in R studio using the discretise() function. From the "rules" package. This function implements several unsupervised methods to transform a continuous variable into a categorical variable (factor) using different interval division strategies. In the discretisation performed, the "cluster" discretisation of this function was used, which uses the k-means algorithm to create the categories of the variable. The purpose of cluster analysis is to identify features in the data and create groups according to these features. Therefore, if two points have similar characteristics, they have the same pattern and therefore belong to the same cluster. By performing a cluster analysis, the resulting intervals have a high homogeneity. The categories of the variables obtained by this function are plotted in Figure 2.

The analysis was performed using the CART algorithm for each of the three resulting samples, and a decision tree was trained. Table 2 shows the relative magnitudes of the explanatory variables retained by the model and their performance. Subsequently, the three samples were merged into a single sample on which the decision tree shown in Figure 3 was trained. The demographic variables were analysed separately, following the above methodology, to see their importance. The results of the three samples for these variables are shown in Table 3 and the tree performed on the three merged samples is shown in Figure 4.

In the final stage of this analysis, trees were created using the CART algorithm for the dataset comprising all three constructs, as well as the important demographic variables mentioned earlier. The analysis methodology is as mentioned above. Thus, trees are created on three samples and then on the three samples combined. Table 4 shows the results for the three samples, Figure 5 shows the tree created for the set where the three samples were merged.

## 3. ANALYSIS OF RESULTS

*Results by dimension*

Table 1 shows the cumulative magnitudes and the mean magnitudes corresponding to the explanatory variables belonging to each construct, valued by the decision trees resulting from the training of the CART algorithm on each of the three samples used.

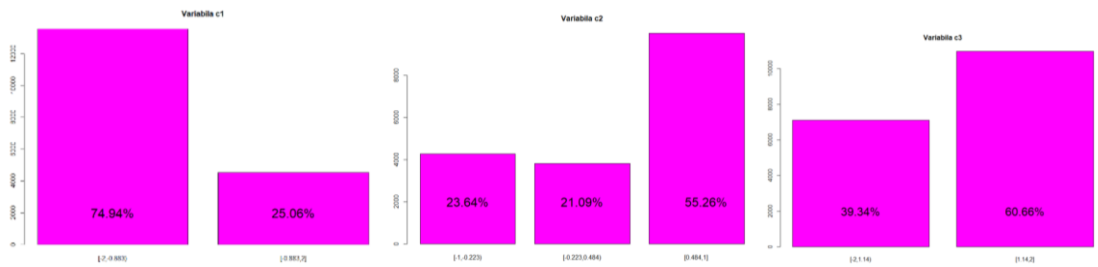
**Table 1. Cumulative importance of variables in the constructs**

| CONSTRUCT | VARIABLE | IMPORTANCE CUMULATED | AVERAGE IMPORTANCE (%) |
|---|---|---|---|
| I. | Tax reforms (Q10.3) | 128 | 31.4% |
| | Significant reforms (Q9.1) | 111 | 27.1% |
| | Digital security reforms (Q10.4) | 52 | 12.7% |
| | Employee motivation system reforms (Q10.2) | 43 | 10.5% |
| | Public service reforms (Q10.5) | 22 | 5.4% |
| | Reforms to the organisational structure of local public administration (Q10.1) | 20 | 4.9% |
| | Reforms of the training system for civil servants (Q10.7) | 19 | 4.6% |
| | Tax system reforms (Q10.6) | 14 | 3.4% |
| II. | Cheaper utilities (Q7.1) | 411 | 58.5% |
| | Online payment facilities (Q7.4) | 121 | 17.3% |
| | Lower taxes (Q7.2) | 110 | 15.6% |
| | Simpler administrative apparatus (Q7.3) | 62 | 8.8% |
| III. | Tax payments (Q3a2) | 305 | 60.8% |
| | Penalty payments (Q3a1) | 197 | 39.2% |
| IV | Number of electronic payment counters (Q4) | 44 | 100% |

*Source: authors' processing based on CART tree applications, 2023*

The mean importance, expressed as percentages, was used to create the aggregation weights of the variables at the construct level. These were denoted as C1, C2, and C3 and were discretised according to the methodology outlined above. Figure 2 shows the distributions of the discretised constructs.

**Figure 2. Breakdowns of discretised constructs**




*Source: authors processing in Rstudio,2023*

Table 2 shows the importance of the constructs and performance indicators resulting from the application of the CART algorithm on each of the three samples.

**Table 2. CART algorithm sample results**

| SAMPLE | IMPORTANT VARIABLES | IMPORTANCE | PERFORMANCE INDICATORS | VALUE INDICATORS |
|---|---|---|---|---|
| I. | C2 | 97% | Accuracy | 71.5% |
| | C3 | 3% | Sensitivity | 76.60% |
| | | | Specificity | 56.07% |
| II. | C2 | 87% | Accuracy | 64.93% |
| | C3 | 11% | Sensitivity | 64.09% |
| | C1 | 2% | Specificity | 67.45% |
| III. | C2 | 87% | Accuracy | 64.93% |
| | C3 | 11% | Sensitivity | 64.09% |
| | C1 | 2% | Specificity | 67.45% |
| AVERAGE VALUES | C2 | 90.33% | Accuracy | 67.12% |
| | C3 | 8.33% | Sensitivity | 68.26% |
| | C1 | 1.33% | Specificity | 63.65% |

*Source: authors' processing based on CART tree applications,2023*

At the level of the tree obtained by applying the CART algorithm on all three aggregate samples, in which the minority category is replicated three times, the C2 construct has a relative importance of 86% , while the C3 construct has a relative importance of only 14%.

At the level of the tree obtained from the application of the CART algorithm on the three aggregate samples, in which the minority category is replicated three times, the variables *Region of origin* and *Age* of completion have a relative importance of 44% and 42% and the variable *Age* has a relative importance of 14%. It is noted that the variable *Profession* was not used, considering that its importance in the description of the rules is negligible, see Table 3. Thus, the variables *Region of origin, Age* on completion of *Studies and Age* will be kept in the rest of the analysis.

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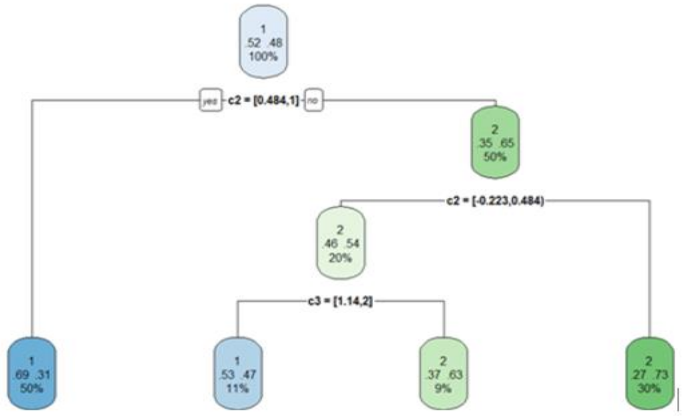
**Figure 3. Decision tree on aggregate variables**




*Source: authors processing in Rstudio,2023*

It can be seen that the C1 construct was not used, as its importance in describing the rules is very small. Thus, citizens' perception of the advantages of digitisation tools (C2) is the most important perception factor. This was also demonstrated by the results of the sample analysis presented in Table 2. The accuracy of the model is 0.715, which means that it correctly classifies about 71.5% of the cases.

The corresponding sensitivity of the model is 0.7660, which means that it correctly detects 76.6% of positive cases. The specificity of the model is 0.5607, which means that it correctly detects 56.07% of negative cases.

*Demographic variables*

The values in Table 3 suggest that the variables Region of origin and Age of completion of studies are important for the decision tree resulting from the application of the CART algorithm built on the three samples, while Age and Profession are less important. It can also be seen that the models have a moderate accuracy, but a slightly higher ability to detect positive cases than negative cases.

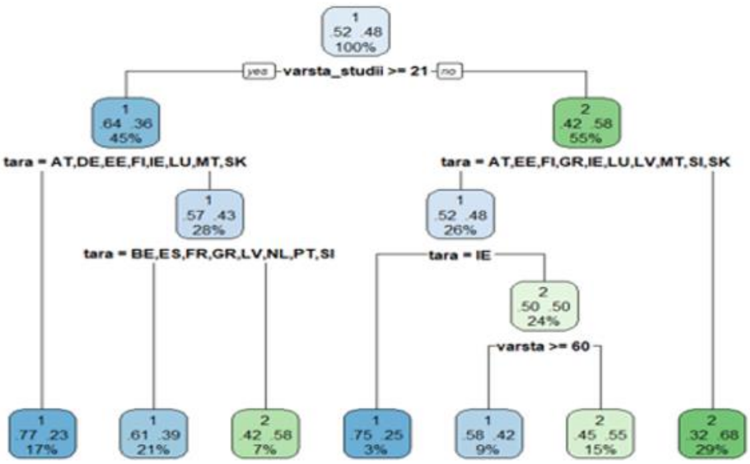
**Table 3. CART algorithm sample results**

| SAMPLE | IMPORTANT VARIABLES | IMPORTANCE | PERFORMANCE INDICATORS | VALUE INDICATORS |
|---|---|---|---|---|
| I. | Region of origin | 42% | Accuracy | 62.99% |
| | Age at end of studies | 36% | Sensitivity | 64.36% |
| | Age | 17% | Specificity | 58.90% |
| | Profession | 5% | | |
| II. | Region of origin | 46% | Accuracy | 64.68% |
| | Age at end of studies | 30% | Sensitivity | 67.71% |
| | Age | 19% | Specificity | 55.55% |
| | Profession | 4% | | |
| III. | Region of origin | 44% | Accuracy | 64.62% |
| | Age at end of studies | 42% | Sensitivity | 67.99% |
| | Age | 9% | Specificity | 54.49% |
| | Profession | 5% | Accuracy | |

*Source: authors' processing based on CART tree applications,2023*

The accuracy of the model is 0.627, which means that it correctly classifies about 62.7% of the cases. The sensitivity of the model is 0.6236, which means that it correctly detects 62.36% of positive cases. The specificity of the model is 0.6373, which means that it correctly detects 63.73% of the negative cases (Figure 4).

**Figure 4. The decision tree on variables**




*Source: author processing in Rstudio,2023*

As can be seen in Table 4, the results of applying the CART-type algorithm to each of the three samples using the previously selected demographic constructs and variables are presented. The table shows the importance of the variables and the performance indicators obtained for each individual sample. In addition, an average value is provided for each of the important variables and performance indicators.

The average importance value for construct C2 is 63.66%, having a high importance in the process of building the model. For the demographic variable *Region of origin*, the moderate importance in the model building process is 21.33%. The variable *Age* at completion of studies has a low importance, of 13.66%, in the process of building the model. The C3 construct has negligible importance in the model building process, the average relative importance being only 1.33%.

The *accuracy* performance indicator has an average value of 71.7%, which shows a good performance of the models in terms of the ability to predict correctly. The *sensitivity* performance indicator has an average value of 76.51%, which means that the models have a good ability to detect positive cases. The specificity performance indicator has an average value of 57.25%, which means that the models have a moderate ability to detect negative cases.

**Table 4. Sample results of the CART algorithm**

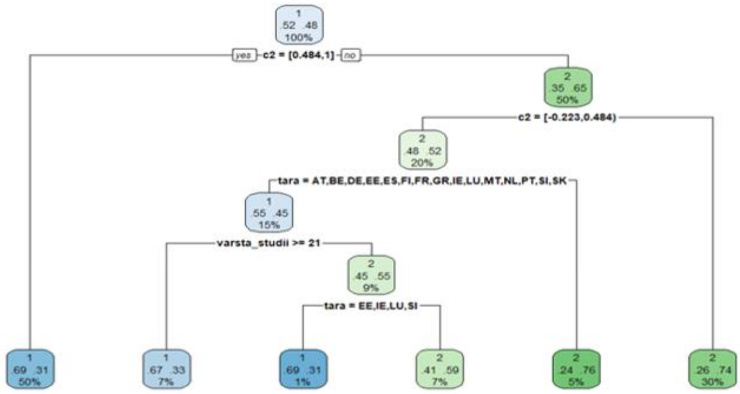
| Sample | Important variables | Importance | Performance indicators | Value indicators |
|---|---|---|---|---|
| I. | C2 | 62% | Accuracy | 71.7% |
| | Region of origin | 23% | Sensitivity | 76.51% |
| | Age at end of studies | 11% | Specificity | 57.25% |
| | C3 | 4% | | |
| II. | C2 | 70% | Accuracy | 67.78% |
| | Age at end of studies | 18% | Sensitivity | 68.78% |
| | Region of origin | 12% | Specificity | 64.75% |
| III. | C2 | 59% | Accuracy | 70.08% |
| | Region of origin | 29% | Sensitivity | 72.30% |
| | Age at end of studies | 12% | Specificity | 63.42% |

| Sample | Important variables | Importance | Performance indicators | Value indicators |
|---|---|---|---|---|
| **Average Values** | C2 | 63.66% | Accuracy | 71.7% |
| | Region of origin | 21.33% | Sensitivity | 76.51% |
| | Age at end of studies | 13.66% | Specificity | 57.25% |
| | C3 | 1.33% | | |

*Source: author processing based on the application of CART type trees,2023*

At the level of the tree obtained after applying the CART algorithm simultaneously on all three aggregated samples, represented in figure 5, construct 2 has the highest relative importance with a percentage of 59%, suggesting that it is the strongest predictor for the output variable (the result of the CART algorithm). Also, the variable *Region of origin* has a relative importance of 29%, which indicates that this variable was also relevant in the process of identifying groups. The lowest value of the relative importance is of the variable *Age at end of studies*, of 12%.

**Figure 5. The decision tree made on the selected variables**




*Source: Rstudio personal processing*

In this case, the accuracy is 71.31%, which means that about 71% of the cases were correctly predicted by the algorithm. The sensitivity is 74.90%, which means that approximately 75% of the positive cases were correctly identified by the algorithm. The specificity is 60.50%, which means that approximately 61% of the negative cases were correctly identified by the algorithm.

## CONCLUSIONS

According to the results, the hypothesis H3- *The perception of digitisation tools is influenced by the economic expectations of citizens* is confirmed. Thus, the advantages generated by the implementation of digital tools in public administration (C2) represent a determining factor on a good perception of it. This hypothesis is also confirmed by the tree made in Figure 5, where the C2 construct is used to make the first branches, having a greater importance.

For the hypothesis H1 - *Demographic factors influence citizens' perception of the digitisation of public administration services*, according to the present data, it is supported by the results obtained separately on the three samples, presented in Table 4. This is also observed in the tree in Figure 5, where *Region of origin* and *Age* at which the person completed full-time education are the only demographic variables used. These variables help to profile the respondents. Therefore, Table 5 summarises the profiles of the respondents by *Age at end of studies* and *Region of origin.*

According to the obtained results, the hypothesis H2 - *The perception of digitisation tools is influenced by the performance of the public administration* cannot be confirmed.

**Table 5. Sample results of the CART algorithm**

| Age at end of studies | Region of origin | | | |
|---|---|---|---|---|
| | **West and North West regions** | **Center and Bucharest regions** | **South and South West regions** | **South East and North East regions** |
| **>=21** | (+) (impurit. 0.33) | | | |
| **<21** | | (+) (impurit. 0.31) | (-) (impurit. 0.41) | |
| It doesn't depend | | | | (-)(impurit. 0.24) |

*Source: author processing based on the application of CART type trees*

The digitisation of local public administration in Romania has the potential to bring significant benefits, but it is important that it is managed responsibly, taking into account aspects such as cyber security, accessibility and inclusiveness to ensure a fair and sustainable transformation. The costs associated with adopting digital technologies can be a challenge. The digitization process requires an adaptation to change on the part of society, authorities and the business environment. This can be a challenge in an initial period. New technologies have significantly transformed the way citizens interact with public services, bringing significant benefits and improvements in several areas. By integrating these technologies, public administration becomes more efficient, transparent and accessible to citizens, contributing to improving the quality of services offered and increasing citizen satisfaction.

## AUTHORS CONTRIBUTIONS

The author/authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

## CONFLICT OF INTEREST STATEMENT

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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