Computers and Education: Artificial Intelligence 2 (2021) 100035

Contents lists available at ScienceDirect

Computers and Education: Artificial Intelligence

journal homepage: www.sciencedirect.com/journal/computers-and-education-artificial-intelligence

Decision tree learning through a Predictive Model for Student Academic Performance in Intelligent M-Learning environments

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ARTICLE INFO

Keywords:
Educational data mining
Decision tree learning
Adaptive education
Classification
Predictive model
Evaluation
Intelligent decision environments

ABSTRACT

In the area of machine learning and data science, decision tree learning is considered as one of the most popular classification techniques. Therefore, a decision tree algorithm generates a classification and predictive model, which is simple to understand and interpret, easy to display graphically, and capable to handle both numerical and categorical data. The intelligent m-learning systems, enjoy recently an explosive growth of interest, for more effective education and adaptive learning tailored to each student's learning abilities. The goal of this paper is to further improve personalization in student academic performance, that includes dynamic tests with a predictive model. One major objective of this research is to create adaptive dynamic tests for assessing student academic performance, while constantly comparing the results of the assessment which exhibits the individual student profile, with the results of the decision tree's algorithm which formulates a predictive model for students' knowledge level, according to the weights of the decision tree.

1. Introduction

During the last decade and especially in the last years, during the Covid-19 pandemic, the adaptive learning systems evolved with explosive growth in blended education and in digital learning. This phenomenon indicates the increasing requirements for intelligent m-learning systems dynamically designed for the cognitive level of students, based on personalized characteristics. There is a need for emerging innovative methods, to accurately extract educational information which focuses on the individual student's educational needs, (Virvou & Alepis, 2013).

Taking into account the challenges and problems that are faced by the modern educational community, intelligent systems and algorithms improving the education and teaching levels in educational institutions were employed. Online and blended learning have become common place educational strategy in tertiary education, and hence, instructors need to reconceptualize fundamental issues of teaching, learning and assessment in non traditional spaces, (Virvou, Troussas, Caro, Espinosa). These issues include concepts such as validity and reliability of the assessment in online environments in relation to serving the intended purposes, as well as understanding how adaptive assessment functions within online and blended learning, (Kabassi & Alepis, 2020). Online examination is an increasingly important component of online courses. In most online examination scenarios, face to face supervision is absent. Results point out that a small increase in pass rates could significantly impact the overall success, i.e., decrease of dropout rates, (Lakshmi et al., 2013),(Matzavela & Alepis, 2021).

Educational Data Mining (EDM) is an application of Knowledge Mining Techniques from educational data, and its object is to analyze data, in order to solve research issues in the field of Education. The EDM examines how to guide learners in learning. Its data comes from different sources, such as Databases of Educational Systems, Internet Systems, Trainee Record, etc. The aim is to improve the learning process and to upgrade learning support systems.

Although researchers (see for example (Virvou & Alepis, 2005)) are studying the machine learning process for decades, EDM differs in that it uses experimental results not from theoretical learning situations but from real facts. Research in the EDM area and Learning Analytics from educational data, aim to provide solutions to problems related to educational processes.

EDM researchers respond to questions such as: Which educational sequence is more effective for the student, what actions of the student result in satisfaction and progress in learning, what are the characteristics that lead to the best outcome of a learning process, (Calders & Pechenizkiy, 2012). On the other hand, researchers of Learning Analytics respond to questions such as: What grade is it likely to be obtained

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https://doi.org/10.1016/j.caeai.2021.100035
Received 24 August 2021; Accepted 3 October 2021
Available online 5 October 2021

by a student without supervision, whether students are unable to follow the flow of a course, or whether students are at risk of not completing a course.

Decision tree learning is a method used in data mining, (Topîrceanu & Grosseck, 2017). The goal is to create a model that predicts the value of a target variable, based on several input variables. In data mining, decision trees can be also described as the combination of mathematical and computational techniques in order to help the description, categorization and generalization of a given dataset, (Quinlan, 1986).

The study of (Song & Ying, 2015) applied the intelligent decision technique, in order to chose the best prediction and analysis. The DT-Quest algorithm outputs not only the general decisions, but also the specific decisions in relevant exceptional cases. The effectiveness of DT-Quest is studied by having conducted an experimental process on 213 students. The experiments show that the proposed algorithm is more effective than the traditional machine learning approaches, in predicting the cognitive level of students.

The structure of Decision Tree Learning which is formulated in machine learning, can be implemented in educational predictive models, (Krouska et al., 2020). The weights of the decision trees arose from parameters which consisted of the disclosure of a plethora of results, with pruning or not. The DT-Quest Algorithm was evolved with classification attributes, whereas it was substantiated with its integration with specific data. Among the cases of student performance, important modalities for student knowledge levels and educational student profiles were identified.

Free of ambiguity, a predictive educational model for student academic performance in online tertiary education has been concretized, while an assessment has being intergraded, (Matzavela et al., 2017), with variables that involve and consider the profile of a student. The results of this study followed the path of Decision Tree Learnig with DT-Quest Algorithm, presenting comparisons between various identifying factors, such as student performance and grade, gender, parent education, parent income, if the student is the first child and if he/she is working.

Particularly, a decision tree with weights is defined, in order to create adaptive tests/exercises identifying the students' knowledge levels and in order to dynamically distinguish each individual student's needs.

The challenge for a model predicting student academic performance is increasing due to the huge increase of data in the database, while analysis of students' academic performance constitutes an important factor for the effectiveness of adaptive learning. The above identifying factors determine the variables of students' profile, which in turn affect their academic performance. After evaluating the marks scored by the students in an academic year, the conclusions will assist the instructors to enhance the adaptive learning in tertiary education. The effectiveness of our system in terms of adaptive e-learning interactions was evaluated, using the results obtained through the study of the relations of the student academic performance with the variables of their profile, as mentioned above.

This paper is organized as follows: The second section contains work related to adaptive learning through m-assessment in student academic performance. Furthermore, surveys in the fields of EDM and Learning Analytics are cited. Section 3 revolves around the four stages of the presented method: Data Collection, Classification, Creation of a Predictive Model, and Evaluation. Sections 4 and 5 refer to Data Mining and Decision Tree Learning. The sixth section deals with an experimental process, presenting the data collection, describing the DT-Quest algorithm, studying some use cases, and finally presenting the relevant results. In sections 7 and 8 a discussion and the conclusions are presented, respectively. An appendix, presenting the decision tree related to the algorithm used in our approach, is also available.

2. Related work

The question of the excessive use of technology during teaching has been raised. That issue was addressed by Anshari et al., (Anshari et al., 2017). They conducted research, investigating the fact that the use of portable devices while learning, may cause a distraction to the students. Given that the implementation of m-assessment will extend m-learning, there is a possibility that the problem of interference will be increased. Therefore, corresponding studies should be conducted.

Focusing on the path of m-assessment in student academic performance, it was observed that there is a remarkable lack of studies in that field. Very few researchers, until today, have dealt with m-assessment, which is the evolution of m-learning. On the other hand, the main proportion of the surveys that have been published over the past years makes reference to the evaluation of the m-learning process that it is referring to. In fact, the evaluation is carried out using traditional methods, such as no dynamic questionnaires, or traditional educational tests, (Troussas et al., 2020). Dynamic questionnaires related to artificial neural networks have also been studied, (Matzavela & Alepis, 201 7, August).

Surveys in the fields of EDM and Learning Analytics respond to highly complex questions about what a student is aware of and the extent of his/her engagement. Researchers have experimented with new modeling techniques and with a variety of data types from new education systems, that promise to a good extent the prediction of a student's learning outcomes. The broader application areas of EDM and Learning Analytics are in Online Learning. These areas are distinguished in modeling as follows: Behavior, knowledge, user experience, user profile, sectoral situations, and trend analysis, (Johnson & Adams, 2011, pp. 1–22). One of the most widespread methods of EDM and Data Mining in general for the production of predictive models, is the classification method. The basic concept of Classification in Education is the examination of a subject of interest in the context of a course or class, based on the specific features that govern it, (Bienkowski et al., 2012). Categorization is considered as a key activity of many Learning Support Systems of educational procedures, either directly or indirectly. In online teaching, the population sample is usually large and consequently, the requirements are increased and the implementation of a predictive model (classifier) enables the teacher to form a better image of his/her online class, (Siemens, d Baker). The parameters for extracting a predictive model are the following: The selection of a classification method, a data set whose values are known and the correct division of the dataset into two subsets, the training set and the test set. A learning algorithm is applied to the training set, in order to draw a predictive model. Then, the resulting model is tested for its predictive capacity, by applying it to the test set whose values are hidden, (Desmarais, Lemieux).

Researchers, (Thomas & Galambos, 2004), have dealt with the assessment of students' knowledge through questionnaires, while a decision tree in the background shows that there are paths-options available for the best result. A questionnaire is fully supported by a decision tree, with excellent clarity and visualization of the data, which helps us to draw conclusions and to make the necessary corrections, (Guan et al., 2019). The main limitation of the decision trees is the assumption that all points can be categorized; this results in all possible contradictions being interpreted as errors. One such example is the case where all data represent the performance of students in a lesson where a percentage of snapshots may reveal contradictions. The probabilistic approach to characteristic values is often proposed as a solution. But in this case, the system becomes unstable, since each node has its own chance of appearing. Decision trees are also susceptible to overfitting, especially when the data set is relatively small, (Korte & Vyxen, 2008).

Papamitsiou and Economides, (Papamitsiou & Economides, 2014), utilized TAM in their study, in an effort to investigate whether the students' attitude influences the adoption of m-assessment. They prepared a survey questionnaire that was answered by the students, and the results led to the conclusion that competency, autonomy and relatedness are 3 significant factors that should be taken into consideration when developing the procedure. A more thorough examination of the evaluation of m-assessment is presented in another paper, by Nikou and Economides, (Nikou & Economides, 2017). They proposed a specialized model based on TAM, called Mobile-based Assessment Acceptance Model (MBAAM). When using this model, more factors are taken into account, such as ease of use, usefulness and behavioral intention, leading to increased understanding. The result is a better experience for the students, which promotes learning. Although Ćukušić et al., (Ćukušić et al., 2014), do not employ mobile devices, they propose an assessment based on computer. The importance of this study is that modern assessment is compared to traditional methods, suggesting that there are positive effects on students' performance. Further analysis, with the inclusion of m-assessment in the comparison between traditional and computer-based assessment, shows that both computers and mobile devices have positive effects on learners' motivation and that they could replace old-fashioned ways of assessment, (Nikou & Economides, 2016).

On the basis of the above studies in m-assessment, we have created an algorithm that examines the student's cognitive level and, depending on the level, the classified questions he/she will be asked to answer. Questions, having been categorized into four different difficulty levels, are retrieved from a database. EDM produces extraction of data from real data, which are parameterized and thus the corresponding results are extracted. The following questions will be answered below: What is the shortest route, how to get the best result, what to examine through customization. In the background, there will be a decision tree, which has the advantage of simplicity and versatility. It also presents easily comprehensible data, fast snapshot sorting, and great representational dynamics. By defining the parameters, we begin to construct the decision tree with its weights. Our goal is to find the (weighted) route of minimum length for every individual. We want to construct a Determination Tree with the minimum depth, (ensuring at the same time that the cognitive level of the student is satisfactorily checked), and then construct the categorization rules.

3. Methodology

The method suggested in this paper in order to improve prediction of student academic performance, employs a combination of Data Mining and Decision Tree Learning. There are four main stages in this method: Data Collection, Classification, Creation of a Predictive Model and Evaluation, (see, e.g. (Bienkowski et al., 2012),).

In data collection, the variables of assessment are determined through specific questions for students, the variable types, and the description of variables. Data percentage analysis is achieved by focusing on the student profile. Furthermore, the weights of the decision tree were concretized in order to enable us to define dynamically the student's knowledge level.

In classification, the individual answers of 213 students in tertiary education were integrated, while the variables of the assessment consist of the students' characteristics (gender, grade, parent education, parent income, first child or not, the student is working or not).

In the creation of the predictive model, DT-Quest Algorithm was 'conformed' with the parameters of the experimental process, which employed the weights of the decision tree for the dynamic choice of the exercises, in order to assess the student's academic performance. The decision trees have precedence against alternative predictive models, since they are simple to understand and interpret, easy to display graphically, and capable to handle both numerical and categorical data.

In the evaluation, the results of the assessment were compared to the grades and total scores of the student's performance, and this led to significant conclusions. The comparison between the assessment and the decision tree algorithm is a challenging, yet complicated task, with encouraging results. Accurate predictions of performance could lead to improved learning outcomes and increased goal achievement in adaptive learning. These predictions focus on the enhancement of student cognitive level according to the student's profile, as well as to a more personalized assessment.

The major objective of the proposed methodology is to build the classification and predictive model for student academic performance, that classifies a student's profile through the assessment, and predicts the student knowledge level using the decision tree algorithm.

4. Data Mining

Data mining is the procedure of discovering prototypes in large and complex datasets, (Sarker). There are two aspects to data mining: model building and prototypes detection. Model building in data mining is very similar to statistical modeling, although new problems arise, because of the large sizes of the datasets and of the fact that data mining is often secondary data analysis, (Baker, 2010). We live in a world where vast amounts of data are collected daily. Analyzing such data is an important need, and since necessity is the mother of invention (Plato), data mining can be viewed as a result of the natural evolution in information technology.

A search engine (e.g., Google) receives hundreds of millions of queries every day. Each query can be viewed as a transaction, where the user describes the information needed, (Kotsiantis, 2012). The database and data management industry dramatically improved the development of several critical functionalities. Nowadays, numerous database systems offer query and transaction processing as common practice. Since the 1960's, database and information technology has evolved systematically from primitive file processing systems to sophisticated and powerful database systems. The world is data rich but information poor. Data mining is searching for knowledge in data and for interesting prototypes, (Sarker, 2018).

A database system, also called a database management system (DBMS), consists of a collection of interrelated data, known as a database, and a set of software programs to manage and access the data. A relational database is a collection of tables each of which is assigned a unique name. Each table consists of a set of attributes (columns, or fields) and usually stores a large set of tuples (rows, or records). Data can be accessed by database queries written in a relational query language (SQL), or with the assistance of graphical user interfaces, (Parsazadeh et al., 2018). There are a number of data mining functionalities, used to specify the kinds of prototypes to be found in data mining tasks. In general, such tasks can be classified into two categories, descriptive and predictive. Descriptive mining tasks perform induction on the current data in order to make predictions. Classification is the process of finding a model or function that describes and distinguishes data classes or concepts. The derived model is based on the analysis of a set of training data. The model is used to predict the class label of objects for which the class is still unknown. The derived model may be represented in various forms, such as classification rules, decision trees, mathematical formulas or neural networks, (Rizvi et al., 2019). A decision tree is a flowchart-like tree structure, where the weight of each node denotes a test on an attribute value, each branch represents an outcome of the test, and tree leaves represent classes or class distributions, (Skrbinjek & Dermol, 2019). Unlike classification and regression, which analyze class-labeled and training data sets, clustering analyzes data objects, without consulting class labels. Clustering can be used to generate class labels for a group of data. Each cluster so formed can be viewed as a class of objects, from which rules can be derived. A data set may contain objects that do not comply with the general behavior or model of the data, (Fayyad et al., 1996). These data objects are outliers. Many data mining methods discard outliers as noise, or exceptions. Outliers may be detected by using statistical tests that assume a distribution or probability model for the data, or by using distance measures, where objects that are remote from the 'heart' of a cluster are considered outliers.

Data mining adopts techniques from many domains. Machine learning investigates how computers can learn based on data. A typical machine learning problem is to program a computer so that it can automatically recognize handwritten postal codes on mail, after learning from a set of examples. The classic problems in machine learning that are related to data mining are following: a) Supervised learning, (which is a synonym for classification). b) Unsupervised learning, (which is a synonym for clustering). c) Semi-supervised learning, which is a class of machine learning techniques that make use of both labeled and unlabeled examples when developing a model. d) Active learning, which is an approach that lets users play an active role in the learning process, (Han et al., 2011).

5. Decision tree learning

Decision Tree Learning is a general, predictive modeling tool that has applications spanning a number of different areas, (Qin & Lawry, 2005). In general, decision trees are constructed via an algorithmic approach that identifies ways to split a data set, based on various conditions, (Hamsa et al., 2016). It is one of the most widely used and practical methods for supervised learning. Decision Tree Learning is a non-parametric supervised learning method, used for both classification and regression tasks. The decision rules are generally of the form 'if-then-else' statements. The deeper the tree, the more complex the rules and fitter the model, (Baldwin, Xie).

A decision tree is a tree-like graph with nodes representing the place where we pick an attribute and ask a question, edges represent the answers to the question and the leaves represent the actual class label. They are used in non-linear decision making with simple linear decision form.

Decision trees classify the examples by sorting them down the tree from the root to each leaf, with the leaves providing the classification to the corresponding examples. Each node in the tree acts as a test case for some attribute, and each edge descending from that node corresponds to one of the possible answers to the test case. Decision trees can be easily converted to classification rules.

Decision trees used in data mining, (Ogunde & Ajibade, 2014), are of two main types: a) Classification trees, which are used when the predicted outcome is the discrete class to which it belongs. b) Regression trees, which are used when the predicted outcome is a real number. The term Classification And Regression Tree (CART) analysis is an umbrella term used to refer to both of the above procedures, first introduced be Breiman et al., in 1984. Notable decision tree algorithms include: a) ID3, an algorithm invented by Ross Quintan, which is used to generate a decision tree from a dataset. b) C4.5, which can be used for classification. c) CART. d) CHAID, which is a decision tree technique, based on adjusted significance testing, and was published in 1980 by Gordon V. Kass. e) MARS, which is a form of regression analysis introduced by Jerome H. Friedman in 1991.

Compared to other data mining methods, the decision tree method has various advantages: a) It is simple to understand and interpret. b) It is easy to display graphically. c) It is capable to handle both numerical and categorical data. d) It requires little data preparation. e) It performs well with large datasets.

Trees can be very sparse. Furthermore a small change in the training data can result in a large change in the tree, and consequently in the final predictions, (Sarker et al., 2020).

The decision tree generated by C4.5 can be used for classification. At each node of the tree, C4.5 chooses the attribute of the data that most effectively splits its set of samples into subsets, embedded in one of the discrete classes. The splitting criterion is the normalized information gain. The attribute with the highest normalized information gain is chosen to make the decision. The C4.5 algorithm then recurs on the smaller sub lists. The decision tree is efficient and it is thus suitable for either large or small datasets. It is the most successful exploratory method for uncovering deviant data structures. Trees recursively partition the input data space in order to identify segments where the records are homogeneous, (Wu et al., 2008).

Methods for generating decision trees from data, such as C4.5, allow for a tree-shaped representation of the learning results, (Lin & Fan, 2019). Data mining approaches are proposed to predict students performance.

6. Experimental process

6.1. Data collection/dataset description

The main purpose of using data selection techniques is to minimize redundancy and to maximize the subset of relevant data, while maintaining high accuracy without losing important information. We use data from a course in a university in which attending classes is mandatory.

The student's profile was identified after adjusting for control variables that included gender, grade, parent education, parent income, being the first child or not, working or not, (Guarín et al., 2015). The data set includes 213 students that took the course in Spring 2020. All these students had registered to the course and had declared their actual participation. The classification technique was selected based on its reputation in published data mining literature and its superiority in prediction type problems, (Hand & Adams, 2014, pp. 1–7). The system takes into input several student characteristics that are important for students learning goals attainment. These characteristics have been reported in the literature as significant aspects that influence the educational process, and are the following:

1. Gender: The gender of students is a personal characteristic that can affect the educational process. Male students mainly take into account the learning points of each course, whereas their learning preferences may not be clear, which could be diametrically opposed to the female students.
2. Grade: This variable of an individual cognitive level is also very important for the learning goal attainment. The grade of academic performance could be affected by specific external issues (such as anxiety, tiredness, anger). Using a predictive model through a decision tree algorithm, an e-learning system can have a clearer illustration of his/her knowledge level.
3. Parent education: Parent education is a significant parameter that affects the learning goals of most students. The parent educational level interacts with the student knowledge feedback, and influences the learning pace of each student.
4. Parent income: The acquisition of solid parent income is considered as an important factor for the individualization of students' knowledge needs. The parent income could cause a surprisingly big divergence between students. The e-learning systems incorporated methods that appeal to all students independently of the parent income. Some students may drop out of learning due to low parent income. The learning opportunities given to students in blended education and e-learning systems are parent income independent.
5. First child: A variable incorporated in the questionnaire which was given to the students, concerns whether the student is the first child in his/her family. This variable led to interesting results, as it affected positively the performance of students and negatively their tendency to drop out. Therefore, it has been included as a very important variable that can contribute positively to the quality upgrade of educational process.
6. Working student: After research and percentage analysis, it was found that working students find it difficult to continue their studies and complete them. Also, their performance is negatively affected by lower scores, causing difficulties to the instructors. This variable completes the set of variables that constitute the assessment for students. Whether the student works or not can affect his/her academic performance, so the variable is carefully observed and we note its evolution.

In the table below the variables that influenced the results are listed (see Table 1). These variables were employed in most of the researches (see for example (Ćukušić et al., 2014),(Kotsiantis, 2012)) in adaptive education.

The results of the above assessment identified the profile of students and termed the quality of the course, (Virvou, Kabassi, Alepis, Kameas, Pierrakeas, Theodosiou). The variables related the requirements of the experimental process. After completing the semester, students filled the assessment with variables: Gender, grade, parent education, parent income, being first child, working, leading to the formation of Table 1.

Gender indicates a small precedence (57% vs 43%) for females. On the other hand, the female students obtained high degree at 87% vs 72% of the male students. Most of the students had well-educated parents (83%). Parent income was registered as low at 12%, as medium at 69% and as high at 19%. Students were first children at 52%, while 48% were not. Finally, 33% of the students were working and the rest 67% were not (see Table 2).

6.2. DT-Quest algorithm

In this adaptive educational system a decision tree algorithm was created, aiming to define dynamically the students' knowledge level, while being simple to understand and interpret, as well as easy to be displayed graphically. Exam points were used as an indicator of each student's course performance. Grading is on a scale from 0 to 100, with 50 points required to pass. The goal is to further improve the dynamical personalization in student academic performance. The algorithm that has been created for the purpose of this study has been termed DT-Quest Algorithm and it is represented in the following flow chart. In the beginning, these parameters are set (Table 3):

The rationale for the algorithm is as follows:

6.2.1. Initializing the variables

Variable "i" is used as a counter, in order to show the first 4 questions, one from each level of difficulty.

"Grade" represents the sum of the points collected for each correct answer so far.

"MaxGrade" is the maximum grade that the student could have collected so far, and it is used in order to decide the level of difficulty of the next question, as well as for controlling when the algorithm will end. Of course, the level of difficulty depends on other factors, which will be indicated later on.

6.2.2. First loop

It shows the first 4 questions, one from each level of difficulty, in increasing order.

If the answer is correct, the variable "Grade" is increased by the weight of the corresponding question.

For each question of level i that is being posed, "MaxGrade" is increased by i*5.

The "i" is increased by 1, and if it is less than or equal to 4, the next question is shown.

Table 1
Variables of assessment.

Variable	Variable type	Description
Gender	Nominal	Male, Female
Grade	Numeric	0–100
Parent education[a]	Nominal	Well-educated, Not well-educated
Parent income[b]	Nominal	Low, Medium, High
Being the first child	Nominal	True, False
Working	Nominal	True, False

[a] Well-educated: Secondary or tertiary education degree, Not well-educated: Elementary education degree.

[b] High Income: > 2000€ per month, Medium Income: Between 1000€ and 2000€ per month, Low Income: ≤ 1000€ per month.

Table 2
Percentage analysis of variables.

Gender	Male: 43%		Female: 57%	
Grade	Male 0-45: 28%	Male 50-100: 72%	Female 0-45: 13%	Female 50-100: 87%
Parent education	Well-educated: 83%		Not well-educated: 17%	
Parent income	Low: 12%		Medium: 69%	High: 19%
Being the first child	True: 52%		False: 48%	
Working	True: 33%		False 67%	

Table 3
Initial parameters.

Difficulty levels	i: {1,2,3,4}
Maximum grade	100
Weight of a question	i*5

6.2.3. Second loop

The subroutine "QuestionLevel" is called after the first 4 questions, and it selects the level of the next question. It processes parameters such as:

The number of correct answers; In case of incorrect answers, the highest level among these questions;

At most 3 questions of each level of difficulty can be posed throughout the test;

The weight of the next question must be such that "MaxGrade" will not exceed 100;

If questions of every level of difficulty have already been answered successfully, the next permissible questions are predicted, ensuring at the same time that as few questions as possible will be posed in the remaining steps of the test.

Variable "k" stores the level of the next question that "QuestionLevel" returned.

A question of level k is shown.

If the answer is correct, the variable "Grade" is increased by k*5 and in any case "MaxGrade" is increased by k*5.

If "MaxGrade" is less than 100, the algorithm runs the second loop once more.

6.2.4. Finish

When "MaxGrade" is equal to exactly 100, the final "Grade" is shown and the algorithm ends.

A part of the binary rooted tree T created by the previous algorithm, covering the cases studied in section 6.3 below, is presented in the Appendix.

6.3. Use cases

We will analyze some cases that are useful in drawing conclusions. Through different paths and parameters that we have identified, we recognize the different results. In the academic performance of students, we can identify through the appropriate exercises the well prepared student or the student who needs to study more. Cases with extreme behavior and students with distinct deviations in their performance were selected, in order to obtain interesting results with corresponding study interest. By investigating these specific cases we have analyzed the most important points of the decision tree. The students do not know and cannot see all exercises of academic performance, but only the next exercise that the algorithm will pose. Depending on the individual knowledge level, the predictive model of DT-Quest Algorithm displays a suitable exercise, while, depending on the answer given, the following exercise, not the same for all of students, will be provided. The questions alternate dynamically for the purpose of the optimal result of each student's performance. The decision tree algorithm decides about the number and difficulty level of exercises that are included in the created personalized academic questionnaire. The following 4 cases highlight 4 different student models. In the first case, reference is made to the excellent student who will receive questions according to his level. In the fourth case, we observe a student who ignores a wide range of the curriculum, so customization is suitably tailored. Cases 2 and 3 are referring to students who have done moderate preparation and have attained correspondingly moderate results.

6.3.1. Case 1

In the beginning, the candidate must answer a question from each level (i.e., 4 questions with a sum of 50 points). If all questions are answered correctly, it means that it is very likely that the candidate was well prepared; the next question must be of maximum difficulty (i.e., of the 4th level). If that question is also answered correctly then the next question will be of the 4th level again, which means that the total weight of the questions is by now 90 points ($50 + 20 + 20$). The last topic must inevitably be drawn from the 2nd level, (i.e., with a weight of 10 points), in order for "MaxGrade" to reach exactly 100 points with as few questions as possible. If the student answers correctly this question too, he/she will get a final grade of 100/100. The final grade for this candidate is calculated after only 7 questions, since it is obvious that he/she is very well prepared. This case is displayed by the red path of the tree T (see Figs. 1 and 2 of the Appendix).

6.3.2. Case 2

In case 2, we examine a student who does not answer the 1st and the 3rd level questions, whereas he/she answers correctly the questions of the 2nd and the 4th level. After the first 4 test subjects, he/she has collected 30 points out of 50. Questions from the 1st and the 3rd level have now priority over the other levels and since the candidate must answer as few questions as possible, the next question must be from the highest of those two, that is the 3rd level. Should the candidate answer the 3rd level question, the next subject will be drawn from the 1st level, as he/she has not answered to that level yet. (If the candidate does not answer again a 3rd level question, he/she will be given a 3rd and final chance to do so). If the candidate answers correctly the 1st level question too, he/she will have collected 50 points out of 70. This means that 30 points are still needed in order for "MaxGrade" to reach 100 and finish the examination. Taking into consideration that as few questions as possible must be posed, these remaining 30 points will be separated to 20 and 10. Therefore, the candidate will have to answer a 4th and a 2nd level question respectively. If now, for example, the student fails to answer correctly the 4th level whereas he/she answers correctly the 2nd level question, he/she will get a final grade of 60/100. This case is displayed by the green path of the tree T (see Figs. 1 and 4 of the Appendix).

6.3.3. Case 3

In another instance, after the first 4 questions, the student has not answered the 2nd level question only. So, the next question must be from that level and if he/she does not answer, a third question from that level will be selected. If he/she fails to answers this question too, the student's grade will be 40 out of 70 and 'MaxGrade' needs 30 more in order to reach 100, as in the previous example. However, this time, 30 can not be attained by a 20 and a 10 question, since the student has already answered three 2nd level questions, that have a weight of 10. Therefore, 30 will be attained by 20, 5 and 5, that is a 4th level and two 1st level questions will be posed. If now, for example, the student fails to answers the 4th level question whereas, he/she answers correctly both first level questions he/she will get a final grade of 50/100. This case is displayed by the blue path of the tree T (see Figs. 1 and 3 of the Appendix).

6.3.4. Case 4

Finally, we will deal with the case of a candidate who did not solve any of the first four questions. This means that the candidate was not prepared well enough for the examination; based on the requirement that he/she must face as few questions as possible, he/she will be presented with a question of the highest level. If the candidate fails to answer correctly, another question of that level will be posed. If now, for example, the student fails to answer this question too, the final question will come from the 2nd level, because of the fact that the weight of the previous 6 questions is 90 and he/she needs 10 more to reach 100. So, a 2nd level question will be posed. If the student fails to answer this question too, he/she will get a final grade of 0/100. This case is displayed by the orange path of the tree T (see Figs. 1 and 5 of the Appendix).

7. Results

Considering the grades of students' academic performance, the following 4 tables (Tables 4, 5, 6 and 7) demonstrate the results while taking into account the variables of assessment.

Table 4 presents the findings of case 1, that is for students that had excellent grades, (between 80 and 100 points). 51% of them were female and 49% were male. Almost all students' parents were well-educated, reaching 94%, whereas only 6% were not. Regarding the income of their parents, for 56% of them the income was high, for 40% it was medium, whereas the income was low for only 4%. Finally, 60% of the students were first children in their families, and only 27% of the students were working.

In case 2, the grades of the students varied between 51 and 79 points. Females were 58%, whereas 42% were males. A large proportion of the students had well-educated parents (88%) and only 12% of the students' parents were not well-educated. It is observed that lower parent income is related to decreasing grades, with the income for 37% of them being high, 46% medium and 17% low. Exactly half of the students were first children, and 38% of the students were working (see Table 5).

In case 3, the students got a grade between 31 and 50 points. 52% of them were males, whereas 48% were females. The percentage of students that had well-educated parents was 28%, while 72% of the students' parents were not well-educated. Parent income was high for 13% of the students, medium for 39% and low for 48%. Finally, 31% of the students are first children, and the percentage of students that were working reached 51% (see Table 6).

Case 4 consists of students whose grades varied between 0 and 30 points. Females were 33%, whereas 67% were males. The majority of them (89%) were raised by parents that were not well-educated, while only 11% had well-educated parents. Only 7% of the students' parents had high income, 18% had medium and 75% had low income. Half of the students were first children of their families, whereas 78% of the students were working (see Table 7).

Table 4
Case 1 (Grades 80–100).

	Gender	Parent education	Parent income	First child	Working
Male	49%				
Female	51%				
Well-educated		94%			
Not well-educated		6%			
High			56%		
Medium			40%		
Low			4%		
True				60%	
False				40%	
Yes					27%
No					73%

Table 5
Case 2 (Grades 51–79).

	Gender	Parent education	Parent income	First child	Working
Male	42%				
Female	58%				
Well-educated		88%			
Not well-educated		12%			
High			37%		
Medium			46%		
Low			17%		
True				50%	
False				50%	
Yes					38%
No					62%

Table 6
Case 3 (Grades 31–50).

	Gender	Parent education	Parent income	First child	Working
Male	52%				
Female	48%				
Well-educated		28%			
Not well-educated		72%			
High			13%		
Medium			39%		
Low			48%		
True				31%	
False				69%	
Yes					51%
No					49%

Table 7
Case 4 (Grades 0–30).

	Gender	Parent education	Parent income	First child	Working
Male	67%				
Female	33%				
Well-educated		11%			
Not well-educated		89%			
High			7%		
Medium			18%		
Low			75%		
True				50%	
False				50%	
Yes					78%
No					22%

8. Discussion

The conclusions of this study are very promising and they provide another point of view for the evaluation of students' performance. Using data of student evaluation for the course, it is useful to predict the factors that affect their achievement, (Chrysafiadi et al., 2020). Moreover, this illustrates an original point of view (compared with other papers dealing with adaptive learning, (Nikou & Economides, 2017), (Topîrceanu & Grosseck, 2017)), improving educational quality, which is vital in attracting students.

While studying the results of our work, we realized the following:

In case 1, where students had excellent grades (varying from 80 to 100 points), the percentage of female students was slightly higher than the percentage of male students. The vast majority of them had been raised by parents with high income, (over 2000 euros per month). 60% of them were first children of their families, while most of the students in this case were not working (73%).

Case 2 refers to students with grades varying between 51 and 79 points, with 58% of them being female students. Again, the majority of students (88%) had well-educated parents. The parents of 46% of the students were earning medium income, (between 1000 and 2000 euros per month). Half of the students were first children and 38% of the learners in this case were working. The academic performance dropped and this was related to the parent income, whereas there was no correlation between the grades and the fact that the student was the first child, or was working.

In case 3 (from 31 to 50 points), male learners have small precedence over female students, (52% and 48% respectively). The percentage of the well-educated parents is 28% and the relative majority of the students' parents (48%) had low income. Being the first child applied to 31%, while 51% of the students had a job. The grades were strongly influenced from parent education, parent income, and from the fact that the student was working. On the contrary, there was no correlation between the grades and the fact that the student was the first child or not.

In the 4th case, where students had grades less or equal to 30 points, 67% of them were male. For 89% of the students' parents the education was basic, whereas 75% of the students' parents had low income, (below 1000 euros per month). Half of the students were first children, and 78% were working. The grades, in this case, are the lowest, and this was related to parent income and parent education, as well as to the fact that the student was working. There was no correlation observed between the grades and the fact that the student was the first child or not.

9. Conclusions

As online and blended learning has become a commonplace educational strategy in tertiary education, instructors need to reconceptualize fundamental issues of teaching, learning and assessment in nontraditional environments, (Chrysafiadi & Virvou, 2014).

This paper presented a system that adheres to the general design principles and involves elements related to adaptive e-learning. Finally, it needs to be accentuated that the personalization techniques of our system (Matzavela & Alepis, 2021) impressed the students. This was rather expected, since our system employs classification and a predictive model, for individualized learning and enhancement of student academic performance. The results of the experiment were very promising, provoking a high level of acceptance of our system by the students. Indeed, our system provides an individualized way of adaptive learning, while the proposed predictive model is a novel way of creating dynamic and effective testing of students' knowledge level. Apart from that, the individualization during the learning process impressed the students. This paper presents a classification of students' characteristics and a predictive model using the DT-Quest Algorithm for the enhancement of students' academic performance in intelligent m-learning environments. The students' characteristics employed by this assessment are gender, grade, parent education, parent income, if the student is the first child, if the student is working. Assessment is more effective when it is tailored on students learning abilities. The system creates an intelligent m-learning environment by offering individualization; it was fully evaluated by students and the results showed a high acceptance rate, while retaining a high level of pedagogical affordance. The comparison of the findings obtained from the assessment variables and then from the prediction model that emerged from the algorithm we created, showed that there is a correlation between the performance of students and their specific characteristics. The study of this correlation contributes to the improvement of the evaluation of students' performance in intelligent educational online systems.

Future steps of research may include the enrichment of the domain knowledge with other concepts, through original predictive models and new dynamical features that offer effective m-learning environments in tertiary education. The application that uses effective m-assessment supported by decision tree, is already under development, and it will be presented in a future work. This approach could open new horizons in methods of examining academic performance in intelligent e-learning and m-learning environments. The correlation between data mining and decision tree learning, for classification and prediction of results correspondingly, influences the increase of the effectiveness of adaptive education, according to each student's individualized needs and knowledge level.

Declaration of Competing interest

There is no conflict of interest with any of the suggested reviewers.

APPENDIX

The Binary Rooted Tree T

A part of the binary rooted tree T created by the previous algorithm, covering the cases of the test that have been studied earlier in Cases 1,2,3 and 4, is presented in the following Figs. 1–5; the labels of this tree are determined as follows:

The root is labeled

1a

.

Each internal vertex of T, at level[1] $l \geq 2$, has a label of the form

mn
p/q

, where.

- mε{1,2,3,4} displays the level of difficulty of the corresponding question,
- nε{a,b,c} denotes whether this question is the first, second or third question respectively of level of difficulty m being posed to the student, and where
- p is the "Grade" of the student after his (l-1)st answer, and
- q is the corresponding "MaxGrade".

Finally, the label of each leaf of T displays the total score of the student whose performance has dynamically dictated to the algorithm to follow this particular path (i.e., this particular sequence of difficulty levels) from the root to this leaf.

In Fig. 1, the subtree T′ of the tree T, with all points of level up to 4 is displayed. Due to the very big size of the tree T, its subtrees T_i, i = 1,2,3,4, that correspond to the four cases developed earlier (which are the subtrees rooted at the 1st, 3rd, 6th and 8th leaf of T′ respectively), are displayed in Fig. 2 up to 5.

The star that occurs in each path from the root to a leaf of T, indicates the point where the algorithm decides the level of difficulty and the number of the remaining questions.

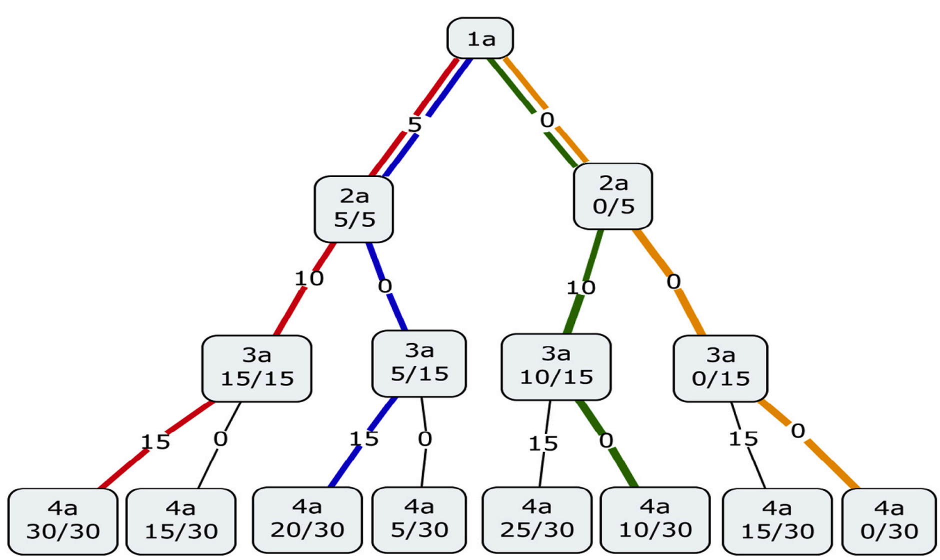

Fig. 1. The subtree T′ of tree T.

[1] The level l(v) of a vertex v of a rooted tree with root r, is defined recursively as follows: l(r) = 1; if u is the (unique) neighbor of v which is nearer to r than v, then l(v) = l(u)+1.

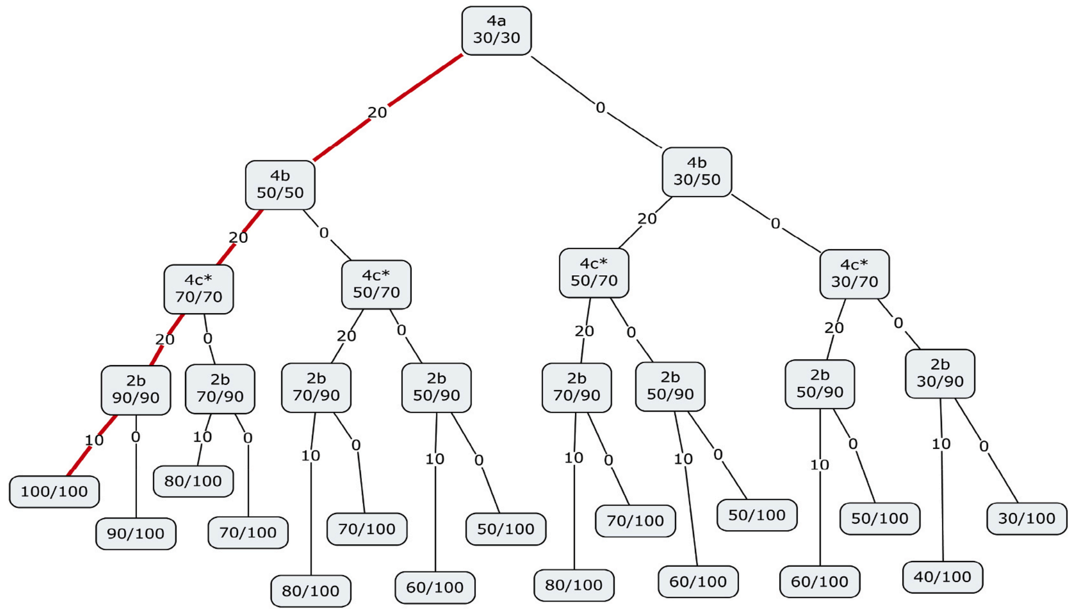

Fig. 2. The subtree T_1 of tree T.

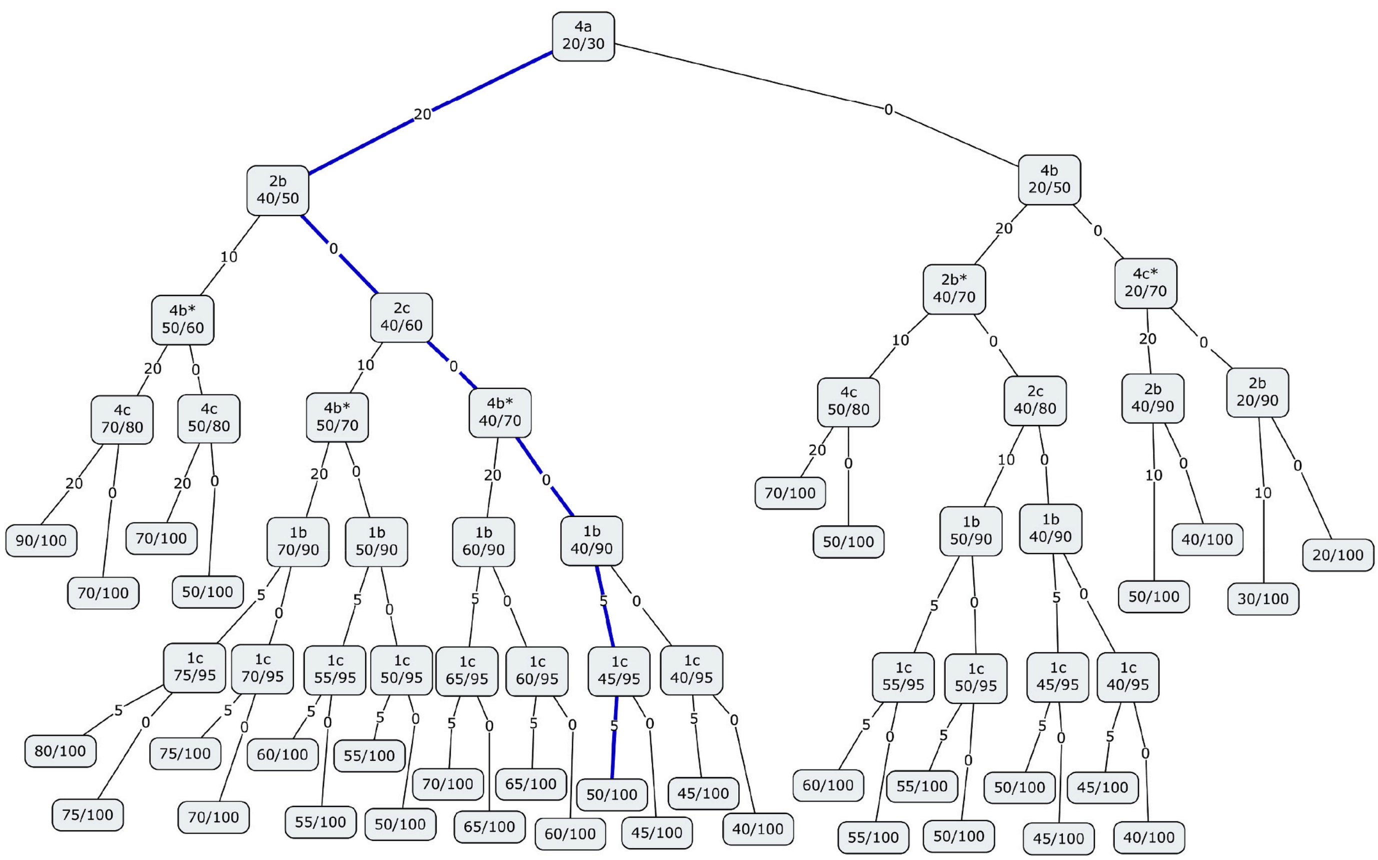

Fig. 3. The subtree T_2 of tree T.

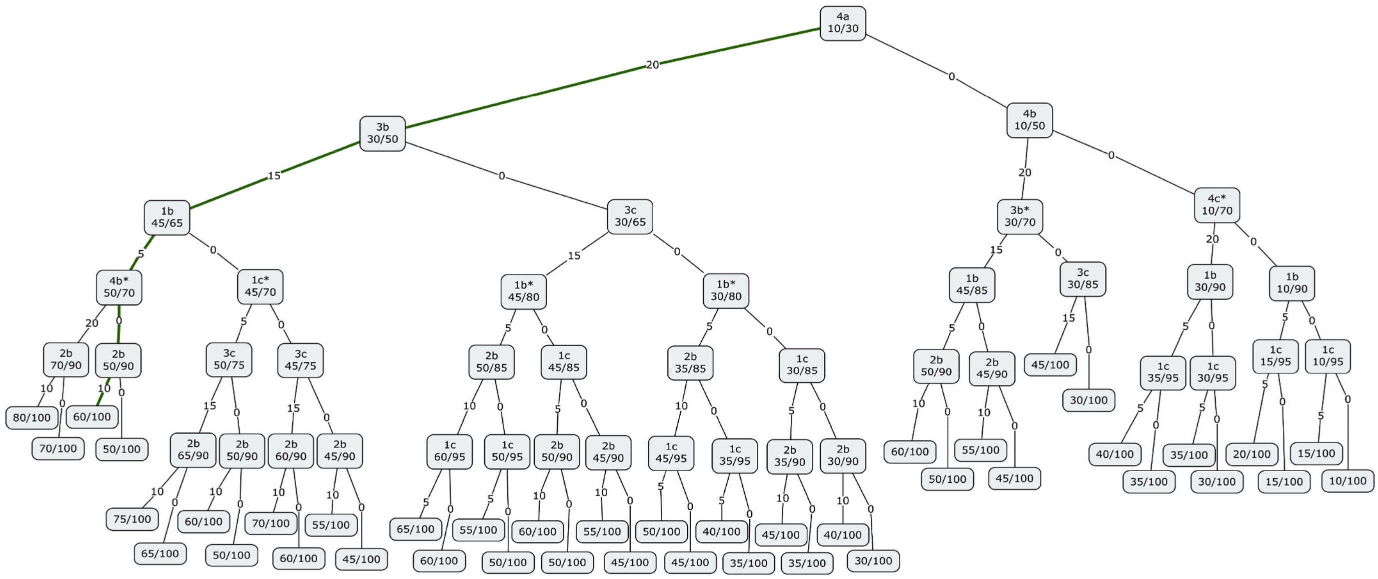

Fig. 4. The subtree T_3 of tree T.

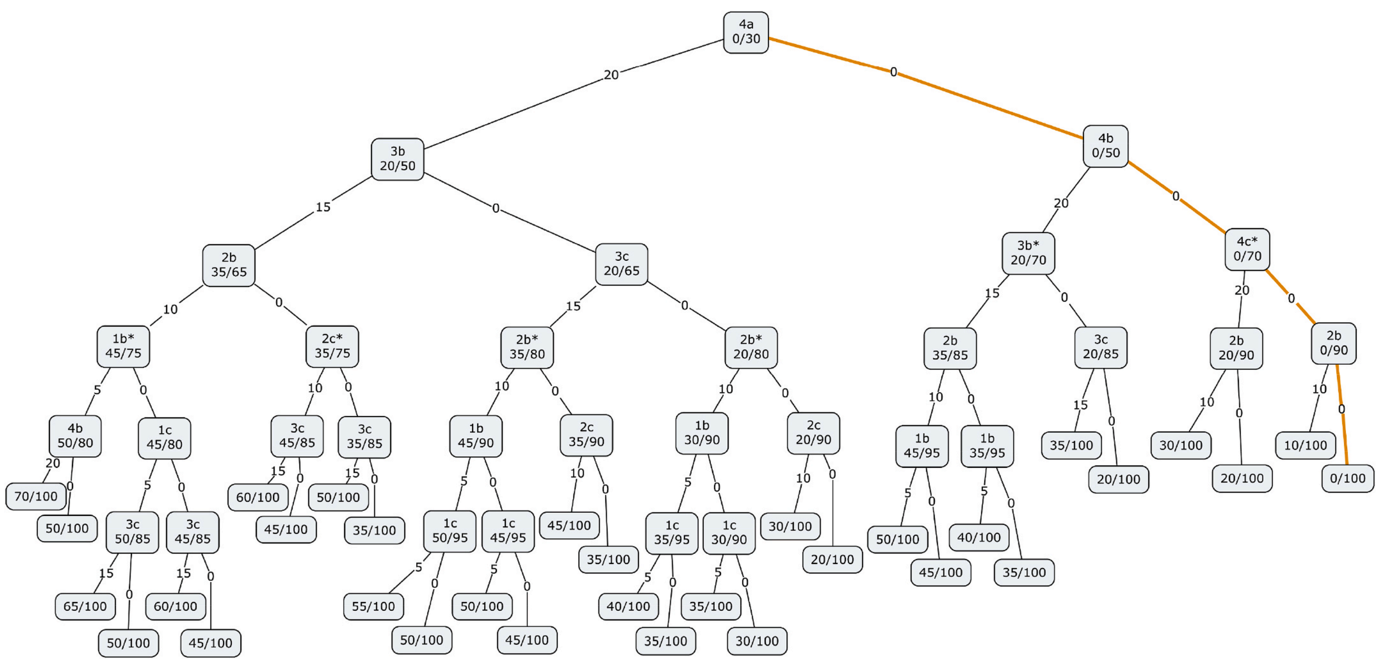

Fig. 5. The subtree T_4 of tree T.

Funding

This study was not funded. Dr. Alepis is the founder of the Greek Company "Software Engineering Innovation Group – SEIG".

Ethics approval

This paper is fully Compliant with Ethical Standards.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and material

All data were stated in the paper.

Code availability

The algorithm is available, but not the custom code.

Authors' contributions

This study was conducted by Matzavela Vasiliki and Alepis Efthimios.

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