Intelligent Decision System with Predictive Model in smart environments.

Ευφυές Σύστημα Απόφασης με Μοντέλο Πρόβλεψης σε έξυπνα περιβάλλοντα

Ph.D. Thesis of Vasiliki Matzavela

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ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

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Dedicated to

my patient and supportive husband

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Abstract

In this Ph.D. thesis a novel approach of digital education and hybrid education that presents effective individualized learning, adapting all knowledge domains to the learner's needs and path through a predictive model supported by a decision binary tree, is presented. The thesis is based on papers of other researchers that were published in international journals, as well as on the author's papers, that were published in valid journals with a plethora of citations.

The presented approach models the learning path in m-learning environments or how the student's knowledge can be increased. In particular, it performs user modeling by dynamically identifying and updating the student's knowledge level for all the concepts of the domain knowledge. Its operation is based on AI and a predictive model of learners' assessment (Fig. 1).

The presented novel approach was fully implemented and evaluated.

Notably, an original system for digitalized m-learning was developed, based on the programming language JAVA, and the resulting app is called D-Quest. The specific knowledge domain that was chosen, was Mathematics since it has a connection with computer science. Supplementally, informatics and Mathematics have the best knowledge background and embedded implementation combination. Therefore, it is suitable for the implementation and evaluation of the thesis issue. D-Quest incorporates the presented student assessment modeling approach. Thereby, the predictive model of the decision tree visualizes dynamically the path for a new domain concept that is completely unknown to the learner. Furthermore, it recognizes when a previously known domain concept has been completely or partly forgotten by the learner.

The application of this approach is not limited to m-learning environments, but it can also be used in other systems with changeable user states, such as e-shops, and smart cities, where consumers' preferences change over time and

affect one another. Consequently, the approach constitutes a novel predictive model for the evaluation of big data sets, which offers a dynamic adaptation to users' needs and preferences for intelligent systems.

Περίληψη

Σε αυτή τη διδακτορική διατριβή παρουσιάζεται μια νέα προσέγγιση της ψηφιακής εκπαίδευσης και της υβριδικής εκπαίδευσης, προσαρμόζοντας όλους τους γνωστικούς τομείς της εκπαίδευσης στις ανάγκες και την πορεία του μαθητή μέσω ενός μοντέλου πρόβλεψης που υποστηρίζεται από ένα δυαδικό δέντρο αποφάσεων. Η διατριβή βασίζεται σε εργασίες άλλων ερευνητών που έχουν δημοσιευτεί σε διεθνή περιοδικά, καθώς και σε εργασίες της συγγραφέως που δημοσιεύτηκαν σε έγκυρα περιοδικά με πληθώρα παραπομπών.
Η παρουσιαζόμενη προσέγγιση μοντελοποιεί την πορεία μάθησης σε περιβάλλοντα m-learning ή πώς προχωρά η γνώση του μαθητή και πως μπορεί να αυξηθεί. Συγκεκριμένα, υλοποιεί μοντελοποίηση εντοπίζοντας και επικαιροποιώντας δυναμικά τις γνώσεις του μαθητή για όλες τις έννοιες του γνωστικού τομέα. Η λειτουργία του βασίζεται στην τεχνητή νοημοσύνη και σε ένα προγνωστικό μοντέλο αξιολόγησης των μαθητών (Fig. 1).
Η παρουσιαζόμενη νέα προσέγγιση εφαρμόστηκε πλήρως και αξιολογήθηκε. Συγκεκριμένα, αναπτύχθηκε ένα πρωτότυπο ολοκληρωμένο περιβάλλον για ψηφιοποιημένη m-leaning περιβάλλον και τη γλώσσα προγραμματισμού JAVA, η οποία η εφαρμογή ονομάζεται D-Quest. Ο συγκεκριμένος τομέας γνώσης στα Μαθηματικά επιλέχθηκε λόγω του γεγονότος ότι στον τομέα του προγραμματισμού υπολογιστών, υπάρχουν πολλές προκλήσεις σε διαφορετικές περιοχές προγραμματισμού και οι εκπαιδευόμενοι έχουν ποικίλα διαφορετικά υπόβαθρα και χαρακτηριστικά. Συμπληρωματικά, η πληροφορική και τα μαθηματικά έχουν τον καλύτερο συνδυασμό υποβάθρου γνώσης και βασικής εφαρμογής. Ως εκ τούτου, είναι κατάλληλο για την υλοποίηση και αξιολόγηση του θέματος της διπλωματικής εργασίας.

Το D-Quest ενσωματώνει την παρουσιαζόμενη προσέγγιση μοντελοποίησης αξιολόγησης μαθητών. Έτσι, δυναμικά το μοντέλο πρόβλεψης του δέντρου αποφάσεων οπτικοποιεί τη διαδρομή για μια νέα έννοια τομέα που είναι εντελώς άγνωστη στον εκπαιδευόμενο ή όταν είναι εν μέρει γνωστή λόγω του ότι ο εκπαιδευόμενος έχει προηγούμενη σχετική γνώση. Επιπλέον,

αναγνωρίζει πότε μια προηγουμένως γνωστή έννοια τομέα έχει ξεχαστεί εντελώς ή εν μέρει από τον εκπαιδευόμενο.
Η εφαρμογή αυτής της προσέγγισης δεν περιορίζεται σε περιβάλλοντα m-learning, αλλά μπορεί επίσης να χρησιμοποιηθεί σε άλλα συστήματα με μεταβαλλόμενες καταστάσεις χρήστη, όπως ηλεκτρονικά καταστήματα, έξυπνες πόλεις, μετεωρολογικές προβλέψεις, όπου οι προβλέψεις διαφέρουν με την πάροδο του χρόνου και επηρεάζουν η μία την άλλη. Ως εκ τούτου, η συγκεκριμένη προσέγγιση αποτελεί ένα νέο μοντέλο πρόβλεψης για την αξιολόγηση των μεγάλων συνόλων δεδομένων, τα οποία συλλέγουμε καθημερινά και προσφέρει μια δυναμική προσαρμογή στις ανάγκες και τις προτιμήσεις των χρηστών για ευφυή συστήματα.

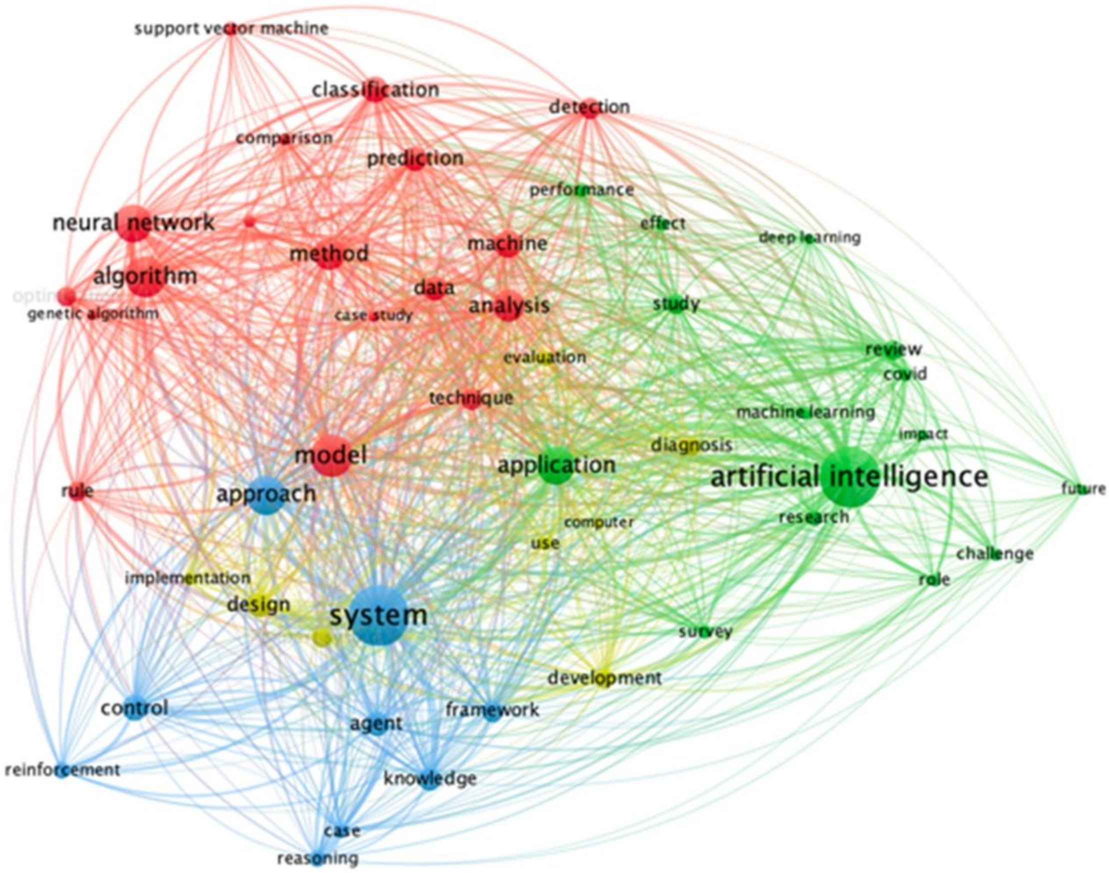

Figure 1: Semantic network of artificial intelligence (Jiang, et al., 2022)

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Introduction

I. Symbiosis between Humans and Artificial Intelligence

Artificial intelligence is already a big part of our daily lives. Whether it's the smartphone or autonomous driving, artificial support is available for almost every area of life. The question arises as to whether humans and artificial intelligence will form more and more symbiotic units in the future.

The symbiosis between humans and artificial intelligence can be said to be a relationship that enhances each other’s abilities. To establish such a relationship, one’s learning needs to have a positive influence on the other’s learning (Nagao, & Nagao, 2019).

Nowadays, the concept of AI has an increasingly profound impact on human life. As the roles of computers in the Age of Information, AI is the antenna of technology in the contemporary era and beyond. AI embodies a heterogeneous set of techniques and algorithms. Various applications and techniques fall under the broad umbrella of AI, ranging from neural networks to speech/pattern recognition, to genetic algorithms, to machine learning (algorithms that enable systems to learn). As AI applications continue to proliferate, organizations are faced with vexing questions about AI’s influence on work.

Marvin Minsky, the founder of MIT's AI Lab, made an even more audacious projection in 1970 about the future of AI: “In from three to eight years we will have a machine with the general intelligence of an average human being… able to read Shakespeare, grease a car, tell a joke, and have a fight. At that point, the machine will begin to educate itself with fantastic speed. In a few months, it will be at genius level and a few months after that its powers will be invaluable.” However, it is a discussion of how the unique strengths of humans and AI can be synergized (McCarthy, Minsky, Rochester, Shannon, 1995).

Enormous amounts of data are available for model training. The quality and the scale of the datasets are the determinants of the robust performance of prediction/classification. In this context, people devote efforts to designing and carrying out exhaustive experiments to collect real-world data, representing typical working conditions. In this process, the types of variables and how the data are measured constitute a part of the intellectual inputs by humans. Publicly available datasets function as a baseline for defining AI challenges and for fair comparison of novel AI algorithms.

II. Machine Learning and AI

Machine Learning (ML) shows superiority in the following aspects. First, ML is good at learning from huge amounts of structured data while humans are not, due to limited memory and brain capacity. Second, having “seen” an adequate number of training samples, the ML solutions obtained show good generalization capability. Apart from supervised learning, there are also practical requirements for unsupervised learning. However, for estimation and prediction tasks, proper encoding/decoding procedures are needed. A similar idea applies to reinforcement learning. (Kotsiantis, 2012).

The current AI boom is accompanied by constant calls for applied ethics, which are meant to harness the “disruptive” potentials of new AI technologies. As a result, a whole body of ethical guidelines has been developed in recent years collecting principles, to which technology developers should adhere as far as possible. However, the critical question arises: Do those ethical guidelines have an actual impact on human decision-making in the field of AI and machine learning?

AI is just a collective term for a wide range of technologies or an abstract large-scale phenomenon. The fact that no ethical guideline goes into greater technical detail shows how deep the gap is between specific contexts of research, development, and application on the one side, and ethical thinking on the other. A transformation from ethics to technology ethics, to machine ethics, to computer ethics, to information ethics, to data ethics must take place.

Collaborative intelligence leverages the strengths of both humans and AI systems to achieve collective goals. Humans excel in creativity, intuition, and empathy, while AI excels in data processing and pattern recognition. By combining these strengths, humans and AI can work together to solve complex problems, generate innovative ideas, and develop solutions that would be challenging for either party alone.

AI can assist humans in making better-informed decisions by providing real-time data analysis and predictive insights. In fields such as finance and investment, AI algorithms can analyze vast amounts of financial data, identify patterns, and make recommendations. This enables humans to make more accurate and strategic decisions, mitigating risks and maximizing opportunities.

As the integration of AI into society progresses, it is crucial to address the challenges and concerns associated with its implementation.

While AI systems can process data and make decisions autonomously, human oversight is necessary to ensure ethical and responsible use. Humans should retain the ability to intervene, interpret AI-generated results, and make judgments based on contextual understanding and ethical considerations. This human oversight helps prevent the potential negative consequences of relying solely on AI-generated outcomes. As AI continues to advance, the future of the human-AI relationship holds both exciting possibilities and critical considerations. The most productive and beneficial approach is one that embraces collaboration between humans and AI. By leveraging the unique strengths of each, we can tackle complex challenges, drive innovation, and create a future where AI works in harmony with human values and aspirations.

The Artificial Intelligence in Education (AIED) has been focusing on the creating systems that are as effective, adaptive in digital education as traditional education (VanLehn, 2011) (Kochmar, 2021). Over the past 25 years, there have been posted many significant papers towards that goal. Further, the ethical implications of AIED referenced in the paper of Schiff, (2021).

The Next Generation Science Standards (NGSS) have highlighted the importance of more general learning skills (Trilling & Fadel, 2009) and competencies such as metacognition, critical thinking, and collaboration. The field of AIED correlation follow to these changes. (Roll, & Wylie, 2016).

Machine learning is one of the initial and base drives. Since the late 1980s, a series of important ML theories and techniques have been proposed. Typical ones include decision trees, proposed by J. R. Quinlan in 1986; support vector machine, proposed by Vapnik and Cortes in 1995; Adaboost, proposed by Freund and Schapire in 1997; random forests, proposed by Breiman in 2001.

Society and technology continue to evolve given the ever-increasing access to data and information with impact across industries and even education. New approaches to teaching and learning prepare the graduates for demanding jobs. The purpose of instructors is to showcase the potential of learning through technology. The way of achieving the aforementioned is by integrating the fundamental structure of current educational systems with new technologies which require a pedagogical shift to the digital world. Many education institutions are engaging with the idea of disruptive education where traditional approaches are more student-centered. New education support models and new content creation methods can lead to enhanced student support.

Nowadays more emphasis has been paid to modern instructional technologies, such as online learning, blended learning, artificial intelligence, virtual reality, which have become increasingly important for educational settings.

The challenges posed by the pandemic of 2020 are reinforced with the growing digitization, personalization, and internationalization of education. The design of immersive virtual educational worlds opened up the opportunity for a learning experience well beyond the traditional classroom. New technological developments for education have been on the rise and the personalization factor influences the technology and data-based systems, leading to further support of the individual's educational profile. The Covid-19 pandemic forced educational institutions to use digital technologies and to organize lessons exclusively online. Many experiences have been gained; many infrastructures have been established for online teaching. Researchers distinguish different designs between blended, hybrid, or adaptive learning.

Machine learning is becoming more widespread and has been used for predicting students' grades, modeling student behavior, and improving curriculum design in all levels of education. Recent developments in machine learning relate to a deep learning approach that refers to a subset of machine learning (i.e., a component of artificial intelligence) and describes algorithms that analyze data with a logic structure.

Historically, changes in learning have been made due to various factors: striking events such as wars or natural disasters, or the emergence of new resources and concepts, etc. Currently, the crisis caused by the Covid-19 pandemic has challenged educators from all over the world, in all areas of knowledge, and educational levels to a rapid transition in their approach to learning and teaching, leading to forced virtualization of education. In this context, evaluations of the decisions, class interactions, and technological resources are needed, together with their impact on students’ competencies, such as the ability to adapt to new situations, oral and written communication, autonomy, teamwork, creativity, critical thinking, etc.

Predicting student performance in advance can help students and their teachers track their performance. Currently, an educational model is created which aims to reduce the dropout of studies. Identifying underperformers at the beginning of the semester/year and increasing the attention allotted for them will aid the educational process as well as improve students’ grades. This process enables the original algorithm to solve discrete optimization problems without altering or hybridizing the original algorithmic framework.

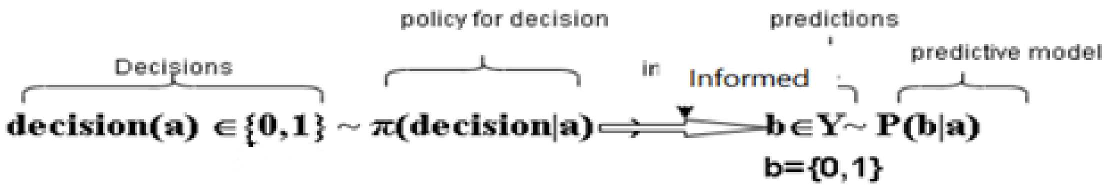


Figure 2: Decision-making process with a predictive model using historical data (Mahmud, B. U., Hong, G. Y., & Fong, B., 2022)

The above expression in Figure 2 describes the general setup for decision making with decision rules that are informed by a machine learning predictive model. Here, decision(a), a ~ P(a), where a is a feature. b is the feature from historical data and Y= {0,1} is the prediction. P(b|a) denotes the prediction model. So, the decision depends on the set of rules and historical data combined, (Mahmud, Hong, & Fong, 2022).

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, recently enjoy an explosive growth of interest, for more effective education and adaptive learning tailored to each student's learning abilities.

Emerging technologies, such as the development of the Internet of Things and the transition to smart cities, and innovative handheld devices have led to big changes in many aspects of our lives, while more changes were imminent. Education is also a sector that has undergone huge changes due to the spreading of those devices. Even at the era of feature phones, it started to become clear that portable devices with access to the internet can be used for learning. The process of learning with the use of mobile phones was then in an early stage, due to the limitations of feature phones. Whereas, with the introduction of smartphones, education is expected to be drastically altered in the future, in most parts of the world. New, radical, and controversial in some cases, approaches have been developed, over the past years, in an effort to implement a mobile learning process in real life conditions. Intelligent systems have had rapid growth, especially in the COVID-19 era, while a significant increase in online courses via social networks has also been noted.

An eruptive increase in the demand for intelligent m-learning environments was observed because instructors in the online academic procedures need to ensure reliability. The research for decision systems was inevitable for flexible and effective learning in all levels of education. The intelligent decision system can predict, with an algorithmic approach, the behavior of students during their academic performance, while leads to better individual educational results, focused on the integration of studies all students.

The prediction of the performance of students during their final exams is considered a difficult task for various reasons. However, an accurate prediction would assist educators and learning experts in the extraction of useful knowledge for designing learning interventions with enhanced outcomes. The main objective of the current paper is to explore and propose a predictive model, which is supported by a structure of a decision tree algorithm, creating an application for student self-assessment and performance at all levels of education.

In recent years, distance learning has evolved rapidly with the help of technology. As a result, mobile learning has also emerged, where learners use electronic devices to access the teaching process. However, there are several aspects of this process that need to be more systematically studied, such as how to make distance learning more adaptive and which devices the learner should prefer. Studies that analyze the factors that allow learning to be adaptive are referred to in this work, as well as the issues that arise by the use of modern mobile electronic devices.

Therefore, the issue of personalized education that adapts to the needs and the particularities of each trainee, emerges.

In education, questionnaires are used for many reasons and problems, such as for quantifying motivation, satisfaction, and reflection. They are also used in the procedure of examining, influencing, knowledge management, and for cognition. As for the basis for the construction of a questionnaire, research was conducted by Koulaidis and Ogborn (2007), analyzing whether the use of systemic networks has potential value.

Questionnaires also became useful tools for universities with low budgets, helping them correctly plan the next semesters without excessive spending.

As well as in e-learning, it was very valuable to predict the next course that each student would choose, and it could be achieved by using questionnaires.

In that direction the contribution of Artificial Neural Networks (ANN) was remarkable. ANNs are directed graphs with weights, and they are used, apart from education, in weather forecasting, predicting earthquakes, calculating the financial risk of a loan, in automatic pilots, in the stock exchange.

The disadvantage of questionnaires is that they are not dynamically adapted to each student. Thus, when someone takes an examination, he must answer all questions, whether he is well prepared or not. The capabilities of ANN can allow us to implement them in complicated problems and eliminate that disadvantage, minimizing time and cost. This Ph.D. thesis presents an assessment of learners that has been supported by dynamic and random questions.

Adaptivity is a characteristic of questionnaires helping researchers extract data about the different aspects of courses. In that direction, a questionnaire was created and validated by Flores, del-Arco & Silva (2016) to provide evidence of the efficacy of collective online learning at the university. Also, a study demonstrated that peer feedback is an effective strategy to reach deep learning which was proved with the use of feedback units and questionnaires (Ion, Barrera-Corominas & Tomas-Folch, 2016). Furthermore, Houston, Mather, Wood, et al (2010) made an investigation on university students about their conceptions of mathematics, using open-ended questions and found that for many students modeling is fundamental and that a small number of students have a broader conception of mathematics. Questionnaires can be used to examine a) Cognitive, as it is indicated in the paper by Watson, McSorley, Foxcroft & Watson (2010), explore the cognitive and non-cognitive predictors related to identifying learners who will succeed academically. b) Learning styles, to give the appropriate syllabus to each student, according to the profile (Tzouveli, Mylonas & Kollias,2008). c) Affective state, as in the paper of Alepis, Virvou and Kabassi (2008), where a system for portable devices that is not impersonal, is introduced. d) Motivation, which was studied by Pintrich (1991) for the first time, conducted a questionnaire to assess the motivation of students for learning. e) Satisfaction of the students, modeling their behavior while selecting courses (Kardan, Sadeghi, Ghidary & Sani, 2013). f) Curriculum, for which an evaluation tool is made, to collect data (Lewthwaite, 2001).

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).

Considering 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 nontraditional spaces, (Virvou, Troussas, Caro, & Espinosa, 2012, September). 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, Martin, Begum, & Venkatesan, 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, 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 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 to assistant the description, categorization and generalization of a given dataset, (Quinlan, 1986).

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 proposed 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.

The thesis is organized as follows:

In Part A various techniques in learning are referenced. That includes a theoretical approach to concepts such as Artificial Intelligence, Artificial Neural Networks, Decision Tree Learning, and Data Mining. These concepts may be useful in developing m-learning and m-assessment systems.

In Part B, the parameters of a digital classroom are analyzed. Through the empirical study, the attributes of a learning system emerge.

In Part C an introduction to the novel implementation of learning, which is called DT-Quest, is presented.

Finally, Part D includes four use cases and an analysis of the application derived from the algorithm that was described in Part C.

Part A: The theoretical approach of the various techniques in learning

1. The philosophy of AI

For much of the last 25 years, the Artificial Intelligence in Education (AIED) community has been focusing, to a large degree, on solving the two-sigma problem by creating systems that are as effective as human one-on-one tutoring (VanLehn, 2011). According to the father of Artificial Intelligence, John McCarthy, it is “The science and engineering of making intelligent machines, especially intelligent computer programs”. Artificial Intelligence is a way of making a computer, a computer-controlled robot, or a software think intelligently, in the similar manner the intelligent humans think.

AI is accomplished by studying how human brain thinks, and how humans learn, decide, and work while trying to solve a problem, and then using the outcomes of this study as a basis of developing intelligent software and systems. Various technologies have been developed to make it easier for learners to learn and to create an environment where teachers can more easily teach. An example of this is called e-learning or intelligent tutoring systems (ITS). The e-Learning is an educational system using online media and has developed together with web technology. ITS was developed using a rule-based system which is an initial result of artificial intelligence. In the process, user models for learners called learner models and educational contents have been improved. As an application of data science, technology called learning analytics was developed. This is a technique for statistically analyzing learner’s historical data obtained by e-learning, etc. and discovering the characteristics of the learner. This will contribute to personalized learning that adapts the educational system to the learner’s characteristics.

Furthermore, the development of learning analytics will clarify the concept of evidence-based education. As with medical care, a feedback loop should be constructed that educates in accordance with data-based analysis and the learning strategies obtained from it and improves if there are problems. Machine learning, which is an important achievement of recent artificial intelligence, is used for data analysis currently.

Symbiosis between humans and artificial intelligence can be said to be a relationship that enhances each other's abilities. In order to establish such a relationship, one's learning needs to have a positive influence on the other's learning. The current mainstream is to advance artificial intelligence by machine learning based on human-made data. However, if artificial intelligence can properly support human learning and human beings can generate useful data for artificial intelligence as a byproduct of humans' main activities, positive circulation will be established between human and artificial intelligence learning. If a universal pattern is found in human behavior (happen at the same time every day at the same time, sleep at the same time every day, when we wake up in the morning, first check the weather, etc.), artificial intelligence could also prefetch human demands and provide information. It begins with a leak of privacy, which in turn involves human control and management. To ensure that artificial intelligence does not become a disadvantage to humans, a symbiotic relationship with artificial intelligence as soon as possible should be established. (Nagao, & Nagao, 2019).

The intelligence is intangible. It is composed of reasoning, learning, problem solving, perception and linguistic intelligence, as it is shown in Fig. 3.

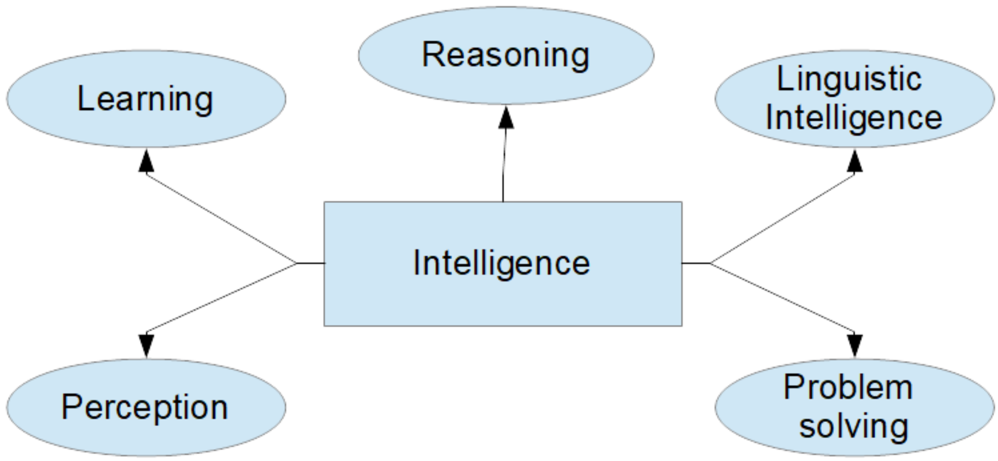


Figure 3: The components of intelligence.

Reasoning: It is the set of processes that enables us to provide the basis for judgment, making decisions, and prediction. There are broadly two types: Inductive Reasoning and Deductive Reasoning.

Learning: It is the activity of gaining knowledge. Learning enhances the awareness of the subjects of the study.

Perception: It is the process of acquiring, interpreting, selecting, and organizing sensory information. Perception presumes to sense. In humans, perception is aided by sensory organs. In the domain of AI, the perception mechanism compares the data acquired by the sensors together.

Problem Solving: It is the process that perceives the problem and focused on a solution from a present situation by taking some path, which is blocked by known or unknown hurdles.
Problem solving also includes decision making, which is the process of selecting the best suitable alternative to reach the desired goal are available.

Linguistic Intelligence: It is the ability to use, comprehend, speak, and write verbal and written language. It is important in interpersonal communication.

The domain of artificial intelligence is huge, and it is divided into different sectors (Fig. 4), while proceeding, the broadly common research areas in the domain of AI will be referred to.

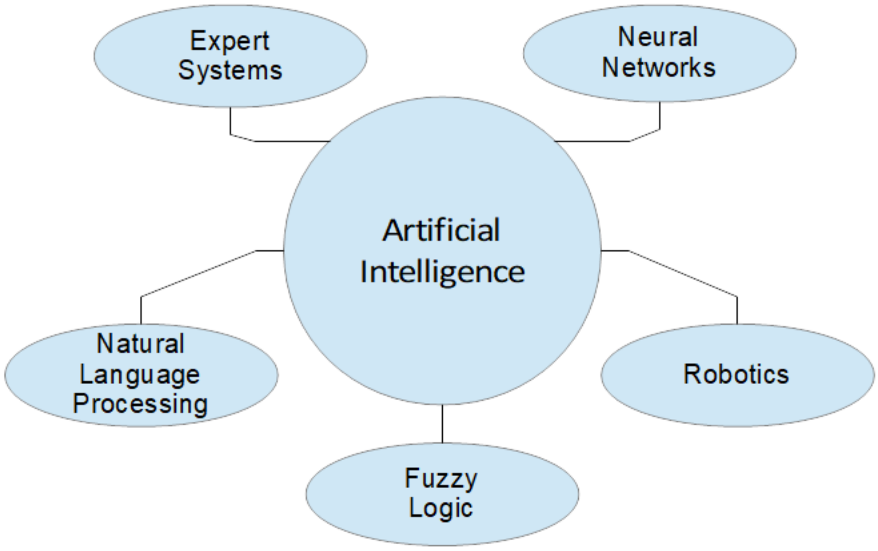


Figure 4: The domains of AI.

The philosophy of AI, while exploiting the power of the computer systems and the curiosity of human, lead him to wonder, “Can a machine think and behave like humans do?” Thus, the development of AI started with the intention of creating similar intelligence in machines that we find and regard high in humans. The goals of AI are: To Create Expert Systems (Fig. 5) that exhibit intelligent behavior, learn, demonstrate, explain, and advise their users. To implement Human Intelligence into Machines which will lead to the creation of systems that understand, think, learn, and behave like humans.

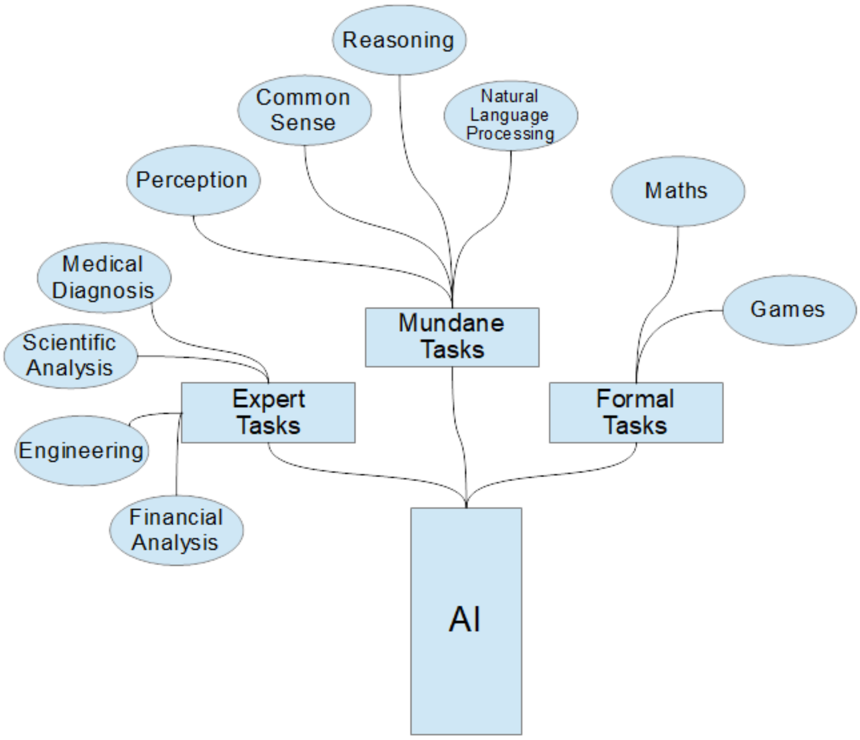


Figure 5: The tasks of AI

2. Artificial Neural Networks

Artificial Neural Networks (ANN) belong to a scientific area which has developed in recent decades and overlaps almost all science fields. The object of ANN is to develop appropriate training algorithms and recall information they contain to simulate intelligent processes. The teaching of neural networks offers huge potential to both cognitive science and computer science students (Fulcher, 2006), nevertheless the aim is to implement them in the procedure of teaching itself.

Cognitive functions, such as learning, as well as general linear and nonlinear regression, can be simulated using ANN (Watters, 2010). The use of cognitive attribute task-based assessments based on ANN, contributes to increasing focus on the cognitive aspects of learning (Lamb, Annetta, Vallett & Sadler, 2014). Simulating student cognition is feasible by creating a computational model in the form of an ANN, has been described by Lamb, Vallett, Akmal & Baldwin (2014). Cognitive diagnostics and Item Response Theory analyze student response patterns, providing inputs for the ANN. Then the cognitive attributes are processed and finally it was shown that the results of the students improved.

Therefore, personalizing learning content according to the needs of a student, renders teaching very efficient and that can be achieved by utilizing neural networks. In order to individualize e-Learning systems for each student, questionnaires are used. However, questionnaires are time-consuming and not so reliable and thus, an approach based upon feed-forward neural networks is preferred (Villaverde, Godoy & Amandi, 2006). Using a multi-layer feed-forward neural network, it is possible to process imprecise data derived from students' behavior and present recommended content to them, based on their cognitive style. (Lo, Chan & Yeh, 2012). According to de Melo, et al (2014), the personalization of didactic content is possible by means of an artificial neural network that classifies the student's profile and assigns it a proximal learning pattern. In addition, expert rules are used to refine the contents reactively. Being able to adapt to some student characteristics, is also necessary when combining the three sectors of educational software, basic pedagogical, computing and domain areas (Curilem, Barbosa & de

Azevedo, 2007).
The great advantage of neural networks is that they can be used to make predictions in several aspects in education. For example, it is very important for the professors of a university to be able to predict the number of registrations of a course. In many cases, because of insufficient resources, a university must know the students' desires, before the start of semester, so it would make optimal scheduling. Using neural networks and analyzing parameters such as student satisfaction, can lead to high prediction accuracy (Kardan, Sadeghi, Ghidary & Sani, 2013).
Along with neural networks and specifically feedforward neural networks, there are other techniques that can be combined all together to increase prediction accuracy. If one technique is not successful, it will be overlapped by the others, as it was proposed by Lykourentzou, Giannoukos, Nikolopoulos, Mpardis and Loumos (2009), who studied a dropout prediction method for e-learning courses.
Another field where neural networks can be implemented is for predicting students' mood. The recognition of a learner's affective state is one of the main aims in education and to address this issue neural networks were also combined with conventional algorithmic techniques. The resulting system improves tutoring methods (Moridis & Economides, 2009).
Moreover, ANN can be used to investigate the performance of students and predict their achievement in mathematics. A system with acceptable prediction accuracy, can form an essential tool for schools with low achievements (Luft, Gomes, Priori & Takase, 2013).
Closing the reference to predictions, it is equally significant to be able to predict quality in education. In fact, neural network models based on back-propagation algorithm were employed to improve satisfaction (Mahapatra & Khan, 2007).
There are additional indications that neural networks should be complemented with other methods, such as expert systems. Those two methods were applied to recognize pupils as mathematically gifted and they were more effective than their teachers (Pavlekovic, ZekicSusac & Djurdjevic, 2009).
By exploiting the functions of ANN we can implement them to achieve flexible

dynamic questionnaires, easily customizable and with correct classification. Also, the potential of ANN allows us to use them in complex problems, minimizing the time and cost. The questionnaires that should arise will stir the interest of students, since they will be dynamically altered, improving the students' performance, thus remaining alert.

Artificial Neural Networks (ANNs) are a scientific area that has developed over the last few decades and overlaps almost all the positive sciences.

The object of ANNs is to develop appropriate training algorithms and retrieve the information they contain to simulate intelligent processes.

The first Neural Network model was introduced in 1943 by McCulloch and Pitts. In 1949 D. Hebb with the book "The organization of behavior", introduces the learning rule of Hebb. The Hebb model says that each time the network uses neural connections, those connections are amplified, and the network comes closer to learning the pattern being presented. The sensor model (Perceptron) was introduced in 1957 by F. Rosenblatt. It is a simple model with 2 levels, the input, and the output, where the signal proceeds one way from the input to the output.

In 1982 Hopfield gave impetus to the development of Neural Networks. In one of his works he proved, with strictly mathematical proof, that a Neural Network can be used as a storage space and can retrieve all the information of a system even if it is given only a few parts and not the whole system.

The next step was the error correction rule. The error activates a control mechanism to bring about a series of corrective changes in the weights w of the neurons. In 1986, McClelland and Rumelhart introduced the idea of how a Neural Network could be used as a parallel processor. They proposed the method of back-propagation which is today the most useful network training technique.

The first conferences on Neural Networks by the American Physical Society and the IEEE began in 1985. At the same time, special professional Neural Network companies are created with thousands of members. (Thomas J. Anastasio, Tutorial on Neural Systems Modeling, March 2013)

Examining the Neural Networks, we see that one of the basic properties of the Neural Networks is their ability in education. This training is achieved through the exchange of values and burdens, which aims at the gradual capture of

information.
The general model of a neuron:

$$S_i = \sum_j \alpha_j w_{j,i}$$

where αi, αj are the outputs of the various neurons, i, j are the inputs to other neurons.
The various signals αj that are the input of a neuron i, are multiplied by coefficients of gravity wj,i.
Learning in TNDs involves changing the weights of connections between neurons.
Coupling algorithms are a family of algorithms, which at each step perform a local search trying to find the optimal value and the optimal direction of weight change.
Recursive Networks are called when there is even one connection from a level i neuron to a level j neuron, where $j \leq i$.
Elman network is the network consisting of 2 levels of neurons. The hidden level and the output level. The hidden plane usually has many neurons.
Dynamic Networks are those networks that have either latency elements, or backlinks, or both. In dynamic networks the data need special preparation, so that initial values are given to all the delay elements. The weight of an error can be a function of time, sample number, etc.
Bayesian Networks the Bayesian classification is based on
Bayesian statistical theory of categorization. The goal is to categorize an X sample into one of the given categories Ci, C2, ..., Cn using a probability model defined according to Bayes theory. Each category is characterized by a prior probability of observing the Ci class. We also assume that the given sample X belongs to a class Ci, with the conditional probability density function: $p(X/C_i) \in [0,10]$. Then, using the above definitions and based on Bayes theory, the posterior probability p (Ci / X) is determined as follows:

$$p(c_i | X) = \frac{p(X | c_i)\, p(c_i)}{p(X)}$$

Decision Trees take as input a value vector with some properties and return an answer. Input values can be continuous or discrete. The output can also be

continuous or discrete. If the output is discrete, there is a classification problem. If the output is continuous, there is a regression problem.
In graded learning the output is characterized as good or bad based on a numerical scale and the weights are adjusted based on this characterization. The Neural Network rewards right behaviors and punishes wrong ones. This is based on Thornlike law which is interpreted as follows: “If an action of a learning system is followed by a satisfactory state or behavior, then the tendency of the system to produce that energy is enhanced. Otherwise the tendency of the system to produce this energy weakens ".
Pattern Mode is a way of learning that multi-level Perceptron weight adjustments are performed one by one. This process continues until a training cycle is completed.
The generalized delta conductor is a variation of the basic back-propagation algorithm that uses the momentum parameter μ (momentum). The back-propagation algorithm gives an approximation of the descending cost curve to the minimum, in the field of weights using the method of steepest descent. In Dynamic Neural Networks (Dynamic Networks) we have:

$$u(K)=u(K-1)+\sum_{i=1}^{u+1} w_i x_i(K)$$

where K is the discrete time required to store u (K-1) which is the previous input value.
IMFs are distinguished in that:

- They have no feedforward dynamics
- They have output feedback
- They have state feedback

(Simon Haykin, Neural Networks and Machine Learning, Papasotiriou Publications, 2009)

A neural network is a directed graph consisting of nodes with activation interfaces.
Defining the learning process implies the following series of steps:
1. The neural network is "stimulated" by an environment.
2. The neural network undergoes changes because of this stimulation.

3. The neural network "responds" in a new way to the environment, due to changes that have occurred in the internal structure.

(NK Bose and P. Liang, Neural Networks Fundamentals with Graphs, Algorithms and Applications, McGraw-Hill, New York, 1996)
Neural Networks have the advantage that they can give results in a very short time. The disadvantage is that the construction and training of a Neural Network is done using real input data, from a specific existing problem. Therefore, Neural Networks are not a general model and cannot solve all problems, because each problem is a special case.

3. Decision Tree Learning

Decision Tree Learning is a general, predictive modeling tool that has applications spanning several 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, Indiradevi, & Kizhakkethottam, 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, 2004, October).

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.

Educational institutions are promoting the incorporation of blended learning in school activities to improve the assimilation of knowledge and development of skills through technology, (Boelens, Voet, & De Wever, 2018), (Harrison, & West, 2014). In particular, universities are increasing the use of blended learning because this type of learning offers the flexibility of time and space to students.

The paper of Wang, Q., Quek, C. L., & Hu, X., (2017) implemented blended synchronous learning through video conferences to improve teaching-learning conditions and offer space flexibility. On the other hand, researchers Cavanaugh, C., Hargis, J., & Mayberry, J. (2016) proposed the use of a Learning Management System such as Sakai and Moodle to perform online evaluations and consultation of audiovisual content at any time and place.

Educational institutions can improve the organization of school activities through blended learning, (Blaine, 2019), (Prasad, Maag, Redestowicz, & Hoe, 2018). In fact, this type of learning allows the planning of various tasks inside and outside the classroom through technology to improve academic performance and develop students' skills, (Van Niekerk, & Webb, 2016), (Yamagata-Lynch, 2014).

Manuscripts are published on such diverse areas as artificial intelligence, fuzzy techniques, genetic algorithms, intelligent agents, multi-agent systems, cognitive science, mathematical modeling, neural systems/neural networks, computer-supported cooperative work, geographic information systems, user interface management systems, informatics, knowledge representation, applications of intelligent systems and others, presenting methods of modeling systems, which develop and evolve the educational process according to the needs of students.

Intelligent decision technologies are interdisciplinary in nature, bridging computer science with the development of artificial intelligence, information systems with the development of decision systems, and engineering with the development of systems.

Researchers, Thomas, E. H., & Galambos, N. (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, Song, & Liao, 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, (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, (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., (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).
Decision Tree Learning is a general, predictive modeling tool that has applications spanning several 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, Indiradevi, & Kizhakkethottam, 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, 2004, October).
The question of the excessive use of technology during teaching has been raised. That issue was addressed by 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 refers 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, Krouska, & Virvou, 2020). Dynamic questionnaires related to artificial neural networks have also been studied, (Matzavela, Chrysafiadi, & Alepis, 2017, April).

4. M-Learning

M-learning has gained an increasing interest around the globe by academic disciplines, while in the days of COVID-19, the need to enrich this way of education has appeared. The latest technological advances are used to create interactive educational environments where students can learn, collaborate with peers, and communicate with tutors while benefiting from a social and pedagogical structure similar to a real class, (Chrysafiadi & Virvou, 2015). The diversity of the methods that are employed by researchers while using intelligent tutoring systems contribute to enhance adaptive learning, (Virvou & Alepis, 2005). Among all the papers that fall within the specified time period (2010-20), it was discovered that a large proportion of them was dealing with the question of whether there are differences based on gender, which led to the relevant categorization. Features that were encountered among the papers of our sample, such as attitude, (Hwang & Chang, 2011), usefulness, (Garaj, 2010), ease of use (Park et al., 2012), behavioral intention, (Lan et al., 2012), etc. were addressed and evaluated. Statistics indicate that 78% of users are using their smartphones more than they did a year ago, while the corresponding growth for laptops/desktops is limited to 42%, (Kontogianni & Alepis, 2020). The new generation of portable devices, namely smartphones and tablets, has become popular very fast, to such an extent that people in developing countries prefer those kinds of devices, even without having used laptops or computers priorly, (Ally & Tsinakos, 2014). Using such devices, that are easy to carry, helps people to stay connected to the internet almost continuously, allowing them to communicate, entertain themselves, and be informed. Apart from communication, entertainment, and information, smartphones and tablets can and should be used for educational reasons too, consisting of the basis of a new model of learning, m-learning, (Alepis & Troussas, 2017). M-learning can be based on the use of handheld computers within the classroom during regular lessons, but also outside the classroom, (Motiwalla, 2007) any hour of the day. Regardless of whether it is called “anywhere, anytime”, (Liaw et al., 2010), or “Here and now”, (Martin & Ertzberger, 2013), while other researchers call it “ubiquitous”, (Shanmugapriya & Tamilarasi, 2011), distance learning and m-learning have a huge variety of ways that can be implemented. During the last decade, there are many research studies published that refer to the vast potential of m-learning, (Matzavela & Alepis, 2017). On the contrary, there are very few studies that refer to mobile assessment (m-assessment), (Nikou & Economides, 2017a). Provided that students are familiar with the use of portable devices in general and specifically while learning, the obvious next step is to use such devices to assess their progress. After thorough research in the related scientific literature, it was found out that there is a shortage of papers in that field, thus, the need for more research emerges. This paper discusses in detail the current trend of m-learning, a notion that has come up before the revolution of smartphones took place, (Gikas & Grant, 2013). As Motiwalla analyzed in his study, m-learning could be facilitated with the use of feature phones, that is phones with a keyboard and a small screen, but capable of accessing the internet, (Motiwalla, 2007). Both electronic devices and internet connection protocols of that era may seem primitive compared to the respective technologies a few years later, nevertheless, students had already expressed a positive attitude towards m-learning, (Tsihrintzis, & Virvou, 2021).

4.1 Investigating the Acceptance of M-Learning

In an effort to explore the parameters that contribute to accepting an m-learning procedure, it is found out that generally there is a positive attitude towards it. It is crucial to define whether a process of m-learning will be accepted and for that purpose several tools have been used, such as TAM and the theory of planned behavior, among others. TAM is one of the most frequently used tools, which extracts the tendency of adopting m-learning, in comparison to other theories and models that have been developed. It can be used to find the variable (Mobile Readiness, Interaction, Ease of Use, Usefulness, Attitude to Use) that is more effective, (Almasri, 2014) in the decision of adopting m-learning. According to Sek, et al. (2010), TAM is a practical tool and it was evaluated in their study. They concluded that the perceptions and attitudes of the user have a major impact on the intention and use of smartphones. The attitude was also denoted as the most important factor in accepting m-learning, followed by relevance and subjective norm, as it was presented by Park et al. (2012). On the other hand, Liu et al. in their paper (2010), claimed that the most significant parameter in adopting an m-learning procedure is the long-term usefulness. Another field where TAM is utilized is for investigating whether there are differences based on gender. Padilla-Meléndez et al., (2013) provided evidence that differences do exist, with females being influenced by the contribution of playfulness on attitude, whereas males are influenced by perceived usefulness. On the contrary, according to Bao et al., there are no significant differences in perceived usefulness and computer self-efficacy (CSE), but there are gender differences in perceptions of general CSE, perceived ease of use, and behavioral intention to use, (Bao et al., 2013). TAM is not only used for investigating the adoption of new technologies in an educational environment. It could be extended to study the intentions of employees to participate in an e-learning process, also. Lee et al. (2011) used it, combined with the innovation diffusion theory, to define the attitude of employees towards learning with the assist of modern devices. Another type of learning, where TAM can be employed in order to extract conclusions about the acceptance, is called procedural learning. Although procedural learning is not based on m-learning, nevertheless, it could be exercised using YouTube, which is available on various types of electronic devices, including of course portable ones, (Lee & Lehto, 2013). Sánchez-Prieto et al., (2017), established a system based on the TAM which was used while studying the adoption of mobile devices by students of a university of primary education teachers. On the other hand, the research to determine the learner's acceptance towards m-learning can be conducted without necessarily using the TAM. For example, Cheon et al., (2012) used a model based on the theory of planned behavior to investigate whether the acceptance of m-learning is influenced by the students' beliefs. In their paper, they presented the factors that contribute to adopting m-learning which are attitude, subjective norm, and behavioral control, (Torres et al., 2019). Other factors that increase acceptance can arise based on the activity theory approach, such as enhancing learners' satisfaction, encouraging learners' autonomy, empowering system functions, and enriching interaction and communication, (Liaw et al., 2010). The variety and the diversity of the m-learning procedures give room for experimenting with different aspects of technology. For instance, a Virtual Reality Learning Environment is an interactive and innovative system based on 3D technologies, that stimulates the imagination of the learner, (Huang et al., 2010). Together with the expansion of mobile devices that include Virtual Reality (VR) capabilities, new opportunities for acceptance emerge. In addition, a greater level of acceptance can be achieved by using tools with social interaction. Therefore, using web-video conferencing systems can have a positive effect on the learner's engagement and his/her motivation, (Giesbers et al., 2013).

4.2 Mixed Methods of Studying Through Mobile Computing Devices.

There are literally countless ways to implement new technologies in learning. The use of modern electronic devices with access to the internet, (Suanpang, 2012), combined with other teaching techniques, can lead to different models of m-learning, that can be equally effective, (Sha et al., 2012). In some cases, social media are used to enhance the learning procedure, whereas in other cases, not only portable devices but also common computers are used, (Sharples et al., 2009). Social media sites have emerged almost simultaneously with smartphones, while both are very attractive to young people. Thus, it makes perfect sense to use a combination of those two technologies in learning in order to enrich the procedure and make it more engaging for young learners. In the paper of Jin Mao, it is indicated that students have a positive attitude towards the use of these technologies in learning, but there are important issues that need to be taken into consideration, such as the complexity of the designing and how students will interact, (Mao, 2014). Furthermore, the usage of a specific micro-blogging site (Twitter), combined with traditional assignments can lead to a positive result. By posting tweets publicly, students interact with each other, while at the same time, a better perspective towards the technologies was observed, (Hsu & Ching, 2012). The different options for implementing mobile learning solutions are numerous, allowing the creation of many versions. Mobile devices could be used for online surveys, while at the same time teachers can develop activities in the classroom to obtain better observations, (Kissinger, 2013). For instance, students in an elementary school may have the opportunity of using different devices for different tasks, such as searching for information or listening to podcasts, on one hand. On the other hand, they can select plain paper for traditional activities such as drawing, (Crichton et al., 2012). Mobile devices can pose a temptation for students, that is because there are various applications other than educational. That's why teachers must be careful to avoid improper use and to ensure an effective learning procedure, (Henderson & Yeow, 2012). The vast advantage of mobile devices is the fact that they are portable. That means, learning does not have to be restrained in the classroom, especially when the purpose is to discover an area. It is impossible for people to get familiar with their surroundings without getting out of the classroom, (Pérez-Sanagustín et al., 2012a). Consequently, students can use portable devices as well as computers while they are in the classroom, at home, and around the city, (Pérez-Sanagustín et al., 2012b), thus combining technologies. An example of a system that allows learning in and out of the classroom is the Student Response System, (Stav et al., 2010). They relied on XML technologies and web services, with the usage of modern mobile devices, in order to create a flexible service. There are parts of the world where it is a necessity to turn to mobile learning, due to lack or unreliability of infrastructures. For example at the paper of Han et al., (2016), students suffer from power losses, so the use of portable devices and not having to depend on computers with short battery life can be crucial for their academic progress. Thus, mobile learning was added to the existing learning process, augmenting the overall procedure, (Jan et al., 2016).

4.3 User Modeling

In the following subsections, parameters that concern personalized learning and are part of the field of user modeling are analyzed. Specifically, those parameters consist of gender differences, individual knowledge of learners, active learning methods, and user behavior.

4.3.1 Gender Differences and Individual Knowledge Management

Each person has its own preferences about every aspect of life. All people are different from each other, and everybody wants to be able to regulate his/her time according to his/her approach. Learning is not an exception to that fundamental principle. Therefore, it is of great interest for researchers to study whether there are differences among learners based on their gender and how learners will be able to adjust their learning process according to their needs, (Panadero et al., 2017). According to Diemer et al., (2013), there were no differences due to gender, during classroom activities using iPads. But, analyzing the acceptance of m-learning in separate parameters, can lead to better insight. With the structural equation user modeling approach, conclusions about the computer self-efficacy (CSE) regarding the gender of university students can be drawn. For instance, at a university in the Arab Gulf region, students who participate in an m-learning procedure answered a questionnaire about their attitude towards it. Several factors were taken into consideration, but no differences were found based on gender, while on the contrary, there were significant differences in other factors, like country and age, (Al-Emran et al., 2016). Similarly, the study of Sabah on students' awareness and perceptions led to the conclusion that there are no major differences, considering gender, (Sabah, 2016). The results of the research of Bao et al. were to some extent contradictory because in some cases it was shown that there were no differences and that in other differences do exist, (Bao et al., 2013). Specifically, there are differences in general CSE, perceived ease of use, and behavioral intention to use, whereas there are no differences in specific CSE and perceived usefulness. On the other hand, significant differences were found based on gender, during research on the impact of podcasting on student motivation in online courses, (Bolliger et al., 2010). Furthermore, in the paper of Padilla-Meléndez et al. it is considered that gender differences do exist, (Padilla-Meléndez et al., 2013). More specifically, males are not influenced by playfulness in order to accept a modern learning system but by perceived usefulness, whereas females are keen on accepting the system due to playfulness. The hypothesis that gender differences exist was also confirmed by the research of Han and Shin, who studied the adoption of mobile learning management system by students of an online university, (Han & Shin, 2016). Obviously, a huge advantage of m-learning is that it allows learners to regulate their learning process according to their wishes. The notion of self-regulation was investigated by Liaw and Huang (2013), while Simonova and Poulova dealt with cloud and m-learning and specifically with teaching based on the learner's preferences, (2015). To enhance the potentiality of individual knowledge management, there are several systems that have been introduced. Systems like that include features such as the delivery of learning content, reporting student progress, the interaction between students and teachers, etc., (Saračević et al., 2011). There have been developed several variations of the system that helps students manage their knowledge. Some approaches may be referred to as Personal Knowledge Management, while usually it is called Learning Management System or LMS. The prospective evolution of LMS is called mobile LMS and it was studied by Joo et al., (2016), who focused on the actual usage of the system, in an online university. In the effort of implementing such a system, some problems emerge that should be taken into account, according to Zhuang et al., (2011). The integration of knowledge management can be achieved with different models and different criteria, according to each instance, (Judrups, 2015) and even the color is a significant parameter when designing the interface of a relevant application, (Pelet & Uden, 2014).

4.3.2 Active Learning Methods and User Behavior

In most cases, students are of young age and in the majority, they are fond of playing video games. While playing, people tend to be more concentrated and have a better attitude and behavior towards learning online, (Faiola et al., 2013). During the engagement with a video game, the player is very immersed and focused, a status called “flow”, which leads to improved learning. Thus, playing games can be utilized as an active learning method combined with the capability of adapting to a student's learning style, (Soflano et al., 2015). The notion of learning by playing games is referred to as game-based learning (GBL), but it has not been studied to a great extent yet. Furthermore, in order to create learning systems that will adapt, there are several factors considering the user behavior that should be taken into account, (Seufert, 2018). One of the most important factors is attitude, (Cheon et al., 2012; Park et al., 2012), while perceived usefulness and ease of use, behavioral intention (Park et al., 2012) and control, beliefs, (Cheon et al., 2012), personalization (Wang & Wu, 2011), performance and effort expectancy, personal innovativeness, (Abu-AlAish & Love, 2013) could be accounted as important too, among other factors. To enhance the experience of a student during a teaching procedure, different approaches have been proposed. Receiving rapid feedback with rich content about the curriculum on handheld devices is the key concept according to Chen et al., (2010). On a similar basis, the process of learning via mobile phones could take advantage of the short messaging system. By sending messages frequently, the connection between the tutors and the students is increased, leading to increased interaction and more motivated students, (Van Rooyen & Wessels, 2015). Another efficient model of active learning is the flipped classroom, which is a combination of using a smartphone app and the traditional tutoring in the class. The study of Chen et al., (2017) shown that the flipped classroom leads to increasing the students' motivation and improving their knowledge acquisition. The Student Response System, which is based on web services and mobile devices, also supports active learning, providing intuitive control interfaces and flexible response services, in the classroom or from distance, (Stav et al., 2010). One of the oldest learning methods is the “Socrative method”, which is based on the collaboration of students, where they ask each other questions, resulting in better acquiring knowledge. Entering the modern era, the aforementioned method could be combined with the use of smartphones, allowing teachers to interact with their students and also students with their peers. Thus, collaboration is increased, leading to improved academic performance, (Awedh et al., 2015). Probably the most radical approach, but not a very efficient one, is based on the concept that the students should participate more actively in the procedure of m-learning. Specifically, instead of just using portable devices with existing applications installed, students taking part in the study of Garaj (2010) expressed their ideas of how m-learning should be, leading eventually to the development of ad hoc smartphone apps. The problems that arise with that approach, are two: a) not all students are capable of programming and b) developing applications could be time-consuming.

5. M-Assessment

Turning our attention to m-assessment, it was observed that there is a remarkable shortage of studies in that field. Very few researchers until today have dealt with m-assessment, which is the evolution of m-learning, (Nikou & Economides, 2017b). On the other hand, the main portion of the surveys that have been published over the past years refers 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 a static questionnaire, (Parsazadeh et al., 2018). Combining learning and assessment has resulted in the Fully Online Learning Community, which addresses the demands of all entities that are involved in the educational system. A unified system for learning with embedded assessment can lead to beneficial results for everybody, constituting a democratized model, (Blayone et al., 2017). In order to develop an effective m-assessment procedure, this new approach of evaluation should also be assessed. Some of the factors that have been studied already are whether the achievement and the attitude of the student are affected while using m-assessment, (Sahin, 2015). Nikou and Economides utilized TAM in their study, in an effort to explain if the 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 three significant factors that should be taken into consideration when developing the procedure, (Nikou & Economides, 2014). A more thorough examination of the evaluation of m-assessment is presented in the paper of Nikou and Economides (2017a). The authors proposed a specialized model based on TAM, called the Mobile-based Assessment Acceptance Model (MBAAM). When using this model, more factors are taken into accounts, such as ease of use, usefulness, and behavioral intention, leading to increased understanding. The result is a better experience for the students, that promotes learning. Although it is not based on assessment via mobile devices, in the paper of Ćukušić et al., (2014), the assessment is based on a 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 assessment and computer-based, 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). While investigating the field of m-assessment, it was observed that until today questionnaires have been employed to measure the effectiveness of m-learning to students, whether they prefer learning without a physical presence or not. In addition, questionnaires are being employed, in order to evaluate the performance of university students, the educational staff, as well as the facilities. Also, questionnaires based on static content have spread widely throughout the educational sector, allowing the assessment of the curriculum, (de-Marcos et al., 2010). M-assessment with the use of dynamic questionnaires can form an interesting and useful expansion of m-learning, (Matzavela et al., 2017). Students consistently show a positive attitude towards mobile devices and smartphones, which they wish they could use for reasons that may vary from gaming to learning. In this survey, the significance of learning with portable devices was studied. Education is making progress, from a technological scope, while class lessons are taking new dimensions. Focusing on dynamic questionnaires for education is an essential move, because they are innovative and flexible. The aforementioned characteristics are attractive to young users, who are willing to make changes in the learning procedure. Most questionnaires that are used in education do not focus on examining students. As traditional learning is leaving space for m-learning, (Chrysafiadi & Virvou, 2015), similarly, dynamically changing questionnaires should be developed. The tendency is to move from exams with static questionnaires, to dynamic questionnaires, through m-assessment.

6. Data Mining

Educational Data Mining (EDM), and data analytics are included in the field of Data Mining, which is the procedure of discovering prototypes in large and complex datasets, (Sarker, 2018, March). 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, Ali, & Rezaei, 2018).

There are several 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, Rienties, & Khoja, 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, Piatetsky-Shapiro, & Smyth, 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, Pei, & Kamber, 2011).

Surveys in the fields of EDM (Educational Data Mining) 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).

One of the most widespread methods of EDM and Data Mining in general to produce 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, Feng, Means: Mining, T. E. D., 2012, October). 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, 2012, April). 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, 2013, July).

7. Intelligent Decision Systems

The traditional educational process is losing ground in relation to distance learning. Modern technology, with mobile devices, allows more and more people to be trained without having to visit the classroom on regular days and hours. However, in order to make the e-learning process even more effective, it is advisable to make it adaptive, that is, to be customized and personalized appropriately. In order to achieve adaptivity, a number of factors referring to the learners must be taken into account, such as learning styles (Dorça et al.,2013), habits, whether they are extrovert or not, cultural perspectives, emotional status (Ortigosa, Martin and Carro, 2014) and others. While these factors automatically affect the process, it is advisable for the user to be able to intervene.

Moreover, emphasis should be placed on the medium used for learning, namely the kind of electronic device. There are differences between using the computer and the smartphone or tablet. On the one hand, it is considered whether one kind of devices should be preferred over another, while on the other hand we see how it is possible to use different devices and to switch from one to the other, according to their needs (Nedungadi and Raman, 2012). Finally, a reference is made to the effort to support the students in order to reduce the number of students who discontinue e-learning programs.

7.1 E-Learning Environment

Learning outside of the traditional classroom, using wireless network and portable devices, is an innovative teaching approach that can enhance the pupils' learning intention (Chen & Huang, 2012). E-learning is a huge area of interest, growing and spreading worldwide because of the expansion of technology. Teachers turn to e-learning techniques, enhancing the procedure of learning and making it more exciting for students, who are obviously familiar with new technologies.

Tutors can base their methodology to several instruments, such as performance tests, blog contents, (Mohamad, Tasir, Harun & Shukor, 2013), online course (Han, Chang & Duan, 2010), online assessments (Wang, Li, Feng, Jiang & Liu, 2012), e-questionnaires (Tzouveli, Mylonas & Kollias, 2008) and of course, in each case, questionnaires provide encouraging results of the effectiveness. Specifically, tutors used performance test and blog contents, as well as questionnaires, in order to demonstrate the positive effect of writing and reading blogs, to students (Mohamad, Tasir, Harun & Shukor, 2013). Moreover, an online assessment system was developed by Wang, Li, Feng, Jiang & Liu (2012), forming a novel approach to assess the learning of computer programming languages. The system was called EduPCR and it allowed students to achieve collaborative and interactive learning, which was confirmed by two questionnaire surveys.

Traditional teaching methods can be combined with new methods through hybrid learning, which consists of daily classroom teaching, as well as online course. The teaching pattern can be improved, as it was shown by Han, Chang & Duan (2010), with the help of questionnaires. As teaching evolves, so do questionnaires, thus e-questionnaires were developed. They were designed by a group of experts and through the responses, all learners are assigned to different learner profiles.

According to the profiles, each student is supplied with learning material that matches his educational needs (Tzouveli, Mylonas & Kollias, 2008). Questionnaires are usually based on multiple choice questions (MCQ), but that limits students in giving strict answers. To surpass that restriction, an application (Evidential MCQ) was proposed by Diaz et al (2008) for the management of the uncertainty and imprecision of answers to Multiple Choice Questions (MCQ) in Mathematics. Through that application, the knowledge of a student is assessed in a better way, without to restrain the student to express a precise answer.

E-learning procedures could be improved due to the amplitude and diversity of data acquired by such type of questionnaires. Moreover, in the context of e-learning, motivation, attention, and interactivity are precious characteristics, as it was confirmed with the use of questionnaires. Also, with the characteristics, students achieved an adequate level of thinking skills (Al-

Samarraie, Teo and Abbas 2013).

E-learning has adapted to the new generation of devices, thus creating mobile learning, which is encountered increasingly nowadays. Modern portable devices have many capabilities; therefore, it is of great interest to measure how much time students spend for learning. Online Self-Regulated Learning Questionnaire and Validity and Reliability of Time Management Questionnaire are tools that contribute to that purpose. The results of those tools reveal that monitoring time has positive impact on students (Tabuenca, Kalz, Drachsler & Specht, 2015).

7.2 Adaptivity in E-Learning and M-Learning

By exploring e-learning and m-learning, it is obvious that there is growing interest from researchers to properly target and collect useful data for analysis. Scholars have dealt with learning styles of students and their background knowledge to achieve maximum personalization. There are papers referring to user intervention and cultural perspectives, that offer in the evolution of e-learning. Also, the emotional state of the student plays a huge role in m-learning, since according to the student's mood, the appropriate information is sent to him / her. As for the user environment, it is of utmost importance that the administrator, who is constantly receiving the user's location, knows the appropriate time to send the appropriate program.

7.2.1 Analysis of Adaptive E-Learning Factors

Adaptive e-learning can be divided into several sectors, based on factors such as learning styles, cultural perspectives, emotional state, user environment and user intervention. Those factors are demonstrated in Fig. 6 and will be analyzed below.

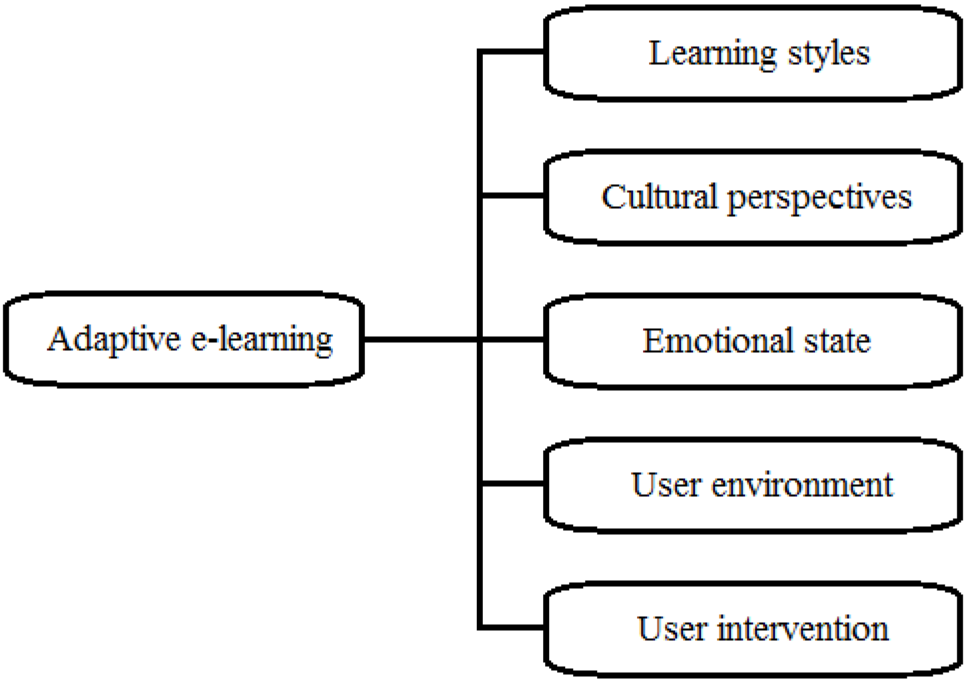


Figure 6: The factors of e-learning

7.2.1.1 Learning Styles

The learning process can be optimized if it is adapting to the learning styles of the students. The approach proposed by F.A. Dorça et al. (2013), automatically and dynamically detects the students' learning styles and adjusts accordingly. Their study was based on three different strategies, a) the probabilistic learning styles are incremented if the student has good performance, b) the probabilistic learning styles are incremented or decremented if the student has good or bad performance respectively and c) the probabilistic learning styles are decremented if the student has bad performance.

As it was shown, the third strategy was more effective in adjusting the student model and therefore was primarily used. Namely, their approach continuously updated the student model according to the student's performance, in order to approximate his/hers real learning styles. In their approach, Yang, Hwang and Yang (2013) suggested that it is equally important with the aforementioned factors, to take into consideration the preferences and habits of the individuals. Thus, they conducted an experiment, where one group of students attended the traditional learning process and another group their proposed adaptive learning system. It was shown that the second group had better results than the first.

7.2.1.2 Cultural Perspectives

While it is out of the question that an e-learning procedure must be adaptive, it is a difficult task to fulfill, due to the diversity of the students' characteristics. Learners have different backgrounds, skills, preferences and learning styles, so the learning procedure should be customized and adjusted accordingly. The proposed system by Gasparini et al (2012) is structured in a way that it draws data from the student's cultural and technological perspectives and adapts to his/hers context. That system is called AdaptSUR and it is implemented in two e-learning environments, with positive results in providing personalized assistance to students.

7.2.1.3 Emotional State

E-learning is based on the fact that the learners do not have to be present in classroom, during a lesson. Thus, the educator might never meet the students, so he or she cannot realize the emotional state of them. It would be very useful for a teacher to know the sentiment of a learner, in order to adapt and personalize the learning procedure and also to recommend the most suitable activities. One way to do that, is by giving questionnaires to the students, to answer. But that method is considered time-consuming, and it is not very discrete.

This issue was addressed in the research of C. Troussas et al (2013), where they analysed the sentimental state of internet users, by using Naive Bayes classifier. Their analysis was based on Facebook statuses and provided useful data, thus assessing the language learning process.

Taking it one step further, A. Ortigosa, J.M. Martin and R.Carro (2014) used a Facebook application, in which they embedded the capability of extracting a user's mood. The purpose was to understand the sentiment and the emotional transitions of a user by the messages he or she is posting on the social network. In that approach, they combined two techniques, first a lexical-based technique and second a machine-learning technique, as it is shown in Fig. 2. The results indicated that it is possible to conclude a user's emotions, by analyzing what he or she is writing on Facebook.

In addition, the emotions of the learner can also be extracted by other means, in order to optimize the procedure of e-learning and thus, adapting the system to the individual, providing a personalized experience in education. Namely, the system will suggest suitable content and activities according to the student's sentimental state. In their paper, Rodriguez, Ortigosa and Carro (2012) presented a case study, where 12 essays of a student were examined, instead of the posts on Facebook, and conclusions about the student's emotions where extracted discreetly. Of course, it would be preferable for the conclusions to be drawn from the student's work, which he or she delivers to the teachers anyway and not to examine his/hers writings on Facebook.

Moreover, the fact that the students do not have to be present in a classroom, is dealt by E. Alepis and M. Virvou (2011), who described an authoring tool in their study. That tool is modeling emotional states of students, thus helping tutors such as medical instructors to interact with their students affectively. Finally, the idea that keyboard-stroke pattern can provide additional help in extracting the sentiment, was studied in the paper of I.O.Stathopoulou, E.Alepis, G.A.Tsihrintzis and M.Virvou (2010). That, combined with a facial expression recognition system, leads to better results in implementing a multimodal affect recognition system.

7.2.1.4 User Environment

Furthermore, Kim, Lee and Ryu (2013) studied the difference in learning performance between extrovert and introvert learners. Based on this, they suggested that the curriculum and the educational process should be customized according to the participant's personality, achieving optimized results. However, by implementing personality traits in the e-Learning system can result in it being costly, while the purpose is to establish a cost-effective solution. This, of course, should not be an obstacle and discourage the creation of even more efficient systems but a trigger for better use of personality traits.

7.2.1.5 User Intervention

Adaptive applications must be able to predict the user's wish and respond accordingly. Such applications take into consideration various parameters like the data provided from sensors and change their state in real time. In order to create an application that efficiently adapts to the context, several implementations were made, such as the MAPE-K (Monitoring, Analysing, Planning and Executing – Knowledge, Fig. 3) feedback loop. Because of the fact that in this approach the user is excluded, and decisions are made by the system, the challenge is to embed the capability to allow the user to interfere in the decision making. Users prefer to personalize an application to a certain degree, rather than let it operate autonomously.

In their study, C. Evers, R. Kniewel, K. Geihs and L. Schmidt have defined the requirements for the interaction between human and machine and suggested a way to include the user's decisions in the feedback loop. Thus, the user will be able to affect the behavior of the application, increasing the controllability, while considering his focus. They also provide implicit mechanisms for ad-hoc interaction and explicit mechanisms that allow the user to parameterize the behavior in advance.

7.2.2 E-Learning and M-Learning Process

The procedure of studying a specific subject can be transferred outside the classroom and take place at any time, using portable devices. Thus, a new approach is being shaped, in which teachers can deliver knowledge through tablets and smartphones. According to F. Martin and J. Ertzberger (2013) that novel approach is called “here and now” and it is described as “learning that occurs when learners have access to information anytime and anywhere via mobile technologies to perform authentic activities in the context of their learning”. That makes “Here and now” engaging, authentic and informal, as it is indicated in Fig. 4. “Here and now” is based on five properties: a) the need to learn, b) giving information to learners whenever, c) including the learning process in everyday activities, d) adapting the context depending on user location, time, activity etc and e) the freedom of students to regulate their learning process. The specific learning technique is a subset of ubiquitous learning, because it is not based on other characteristics such as interaction, personalization, adaptive learning and learning community.

The results of the study of Martin and Ertzberger revealed that the group of students who used portable devices did not have better achievement. That was mainly because the group of students that used computers were not distracted as much as the others. On the other hand, the students who used tablets had the highest attitudes, meaning that mobile devices were engaging them, in comparison to those who used computers. Although, the device that the learner is using to access the learning system is a significant parameter of that procedure, the choice should not be exclusive. Many people nowadays are using both desktop computers and portable devices and it is useful if the learner can switch from one device to another. Thus, Nedungadi and Raman (2012) suggested an e-learning system that can be transformed into an m-learning system when the student is using his/her mobile phone. The challenge is to deliver content that is adapted to the user's device without any obstacles, regardless of the device. Also, the proposed system is based on a scalable and extendable architectural framework, and it provides teachers with real-time feedback.

A rather radical approach in e-learning is the MemReflex system which is based on flashcards. According to that system, instead of testing the students on knowledge they have been acquainted with a few days earlier, it is a more dynamic, everyday procedure. The learner is tested throughout the day on new knowledge, with adaptive flashcards. Thus, the student is motivated by being fed with new items, even while walking and being distracted by other activities (Edge, Fitchett, Whitney & Landay, 2012).

As e-learning becomes more and more widespread and accepted, there is also a problem with the great number of withdrawals that occurs. To cope with that problem, SookYoung Choi and Jang-Mook Kang suggested a system in which learners can connect with each other. The purpose is to give to the learners the opportunity to exchange knowledge (Fig. 7), in the context of a social network. Within that network, it is easier to create communities, in order to advice learners/users, making it feasible for anyone to get help. There is also the ability to place online meetings, where learners can communicate with each other, increasing interaction, which is an essential feature. Thus, the gratification of the learners will be improved, and the drop-out rate will be decreased.

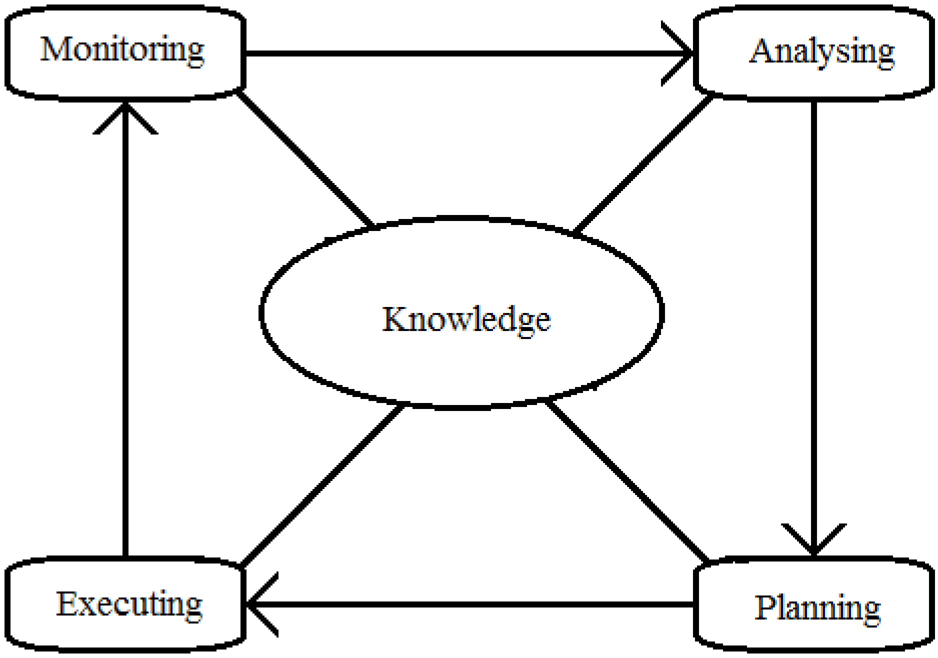


Figure 7: The route of knowledge

Society and technology continue to evolve given the ever-increasing access to data and information with impact across industries and even education. New approaches to teaching and learning prepare the graduates for demanding jobs. The purpose of instructors is to showcase the potential of learning through technology. The way of achieving the aforementioned is by integrating the fundamental structure of current educational systems with new technologies which require a pedagogical shift to the digital world. Many education institutions are engaging with the idea of disruptive education where traditional approaches are more student-centered. New education support models and new content creation methods can lead to enhanced student support.

Nowadays more emphasis has been paid to modern instructional technologies, such as online learning, blended learning, artificial intelligence, virtual reality, which have become increasingly important for educational settings.

The challenges posed by the pandemic of 2020 are reinforced with the growing digitization, personalization, and internationalization of education. The design of immersive virtual educational worlds opened up the opportunity for a learning experience well beyond the traditional classroom. New technological developments for education have been on the rise and the personalization factor influences the technology and data-based systems, leading to further support of the individual's educational profile. The Covid-19 pandemic forced educational institutions to use digital technologies and to organize lessons exclusively online. Many experiences have been gained; many infrastructures have been established for online teaching. Researchers distinguish different designs between blended, hybrid, or adaptive learning.

Machine learning is becoming more widespread and has been used for predicting students' grades, modeling student behavior, and improving curriculum design in all levels of education. Recent developments in machine learning relate to a deep learning approach that refers to a subset of machine learning (i.e., a component of artificial intelligence) and describes algorithms that analyze data with a logic structure.

Historically, changes in learning have been made due to various factors: striking events such as wars or natural disasters, or the emergence of new resources and concepts, etc. Currently, the crisis caused by the Covid-19 pandemic has challenged educators from all over the world, in all areas of knowledge, and educational levels to a rapid transition in their approach to learning and teaching, leading to forced virtualization of education. In this context, evaluations of the decisions, class interactions, and technological resources are needed, together with their impact on students’ competencies, such as the ability to adapt to new situations, oral and written communication, autonomy, teamwork, creativity, critical thinking, etc.

Predicting student performance in advance can help students and their teachers track their performance. Currently, an educational model is created which aims to reduce the dropout of studies. Identifying underperformers at the beginning of the semester/year and increasing the attention allotted for them will aid the educational process as well as improve students' grades. This process enables the original algorithm to solve discrete optimization problems without altering or hybridizing the original algorithmic framework.

Part B: Analyzing the parameters of the digital classroom

1. Empirical Study

This specific empirical study was based on real data that were extracted from students and adult learners during the pandemic of COVID-19 from a Greek university and a lifelong learning institute. The lessons stopped for all in the physical classroom and continued in digital classrooms with educational adaptive platforms. In subsection 1.1 the most popular parameters of m-learning are employed, in 1.2 the composition of the questionnaire is described and in subsection 1.3 the results of the empirical study that were noted, are analyzed.

1.1 Parameters of The Study

Based on the data collected from the reviewed papers, it was notable that there are some characteristics of m-learning that concerned many researchers. The most important of them, which were referred to in many papers, were used to form the parameters of the questionnaire. These parameters are demonstrated in Figure 8, where each one of them is represented with a column. Gender differences were studied in 8 papers, and it was concluded that there are differentiated preferences according to gender. Many researchers, (Pedaste, et al., 2015), have pointed out that it is important to consider the usefulness of the system while implementing an m-learning process. This parameter, which was highlighted in 15 papers, can be the key factor in order to create a flexible and attractive to students' process.

Based on 14 studies that were concentrated majorly on the acceptance of m-learning, it is concluded that the acceptance is increasing over the past years and that people are becoming more and more familiar with the idea of learning without being physically present in a classroom. The perceptions of the students have been altered in a positive direction lately, which has been the subject of 10 studies. Concerning the use of mixed methods of learning, that is by combining a modern technique like m-learning with a traditional one, optimum results can be achieved. The number of papers that referred to mixed methods was 10. Social media, e.g., Facebook, Instagram, offer more capabilities that would not have been possible with traditional methods. 6

papers explored the communication between students and teachers via social media. One of the most significant parameters is the interaction between the students and the teachers, which was encountered in 18 papers. The ease of use in the m-learning environment and friendly to learners was surveyed in 14 papers. Finally, the students' behavior has also been analyzed and measured by researchers in 14 studies.

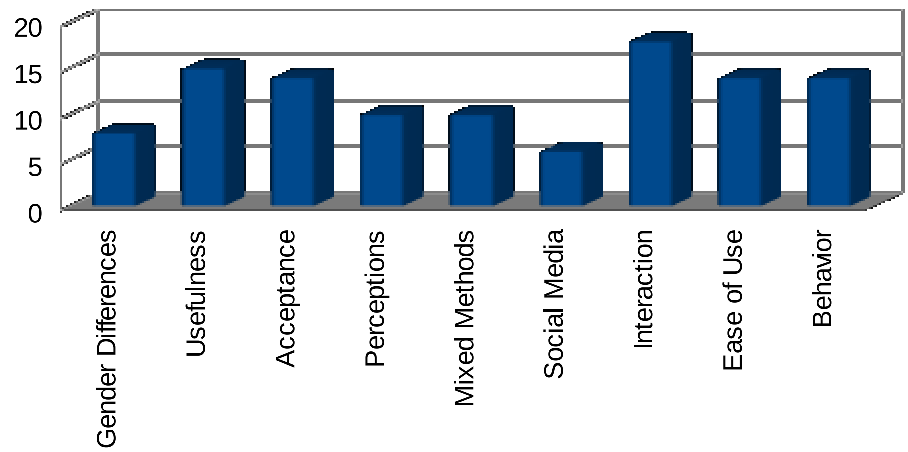


Figure 8: Number of papers referring to each characteristic

1.2 Settings of The Empirical Study

During the general lockdown due to COVID-19 pandemic (March 2020) in Greece, m-learning was a one-way solution. Schools and universities were closed, while lessons continued normally in all educational levels, forcing learners to utilize their mobile devices in order to attend courses. M-learning supported all students through various platforms, covering all educational needs. Students were connected by mobile devices and the interaction of m-learning can be analyzed with specific data derived from their feedback. The criteria for the composition of the questionnaire were the parameters that emerged from the analysis of the literature.

By classifying the most frequently displayed parameters in papers, a set of the following parameters was extracted: gender, usefulness, acceptance, perception, methods, social media, interaction, ease of use, and behavior.

The questionnaire was created based on this set of parameters, which was sent to the students via social networks or e-mail, during the COVID-19 pandemic.

Educational level	Delivery of questionnaire via	Participants
High school students	Social media	29
University students	e-mail	11
Long-life learners	e-mail	12

Table 1: Number of participants per age group

The people that answered the questionnaire were divided into 3 age groups, the first group consists of 29 students at high school, the second group includes 11 students at a University and the composition of the third group is 12 adults that were participating in life-long learning, reaching a total of 52 people. The following figure (Fig. 9) illustrates the number of participants in each paper that was surveyed. The number varies from 9 to 2732 participants.

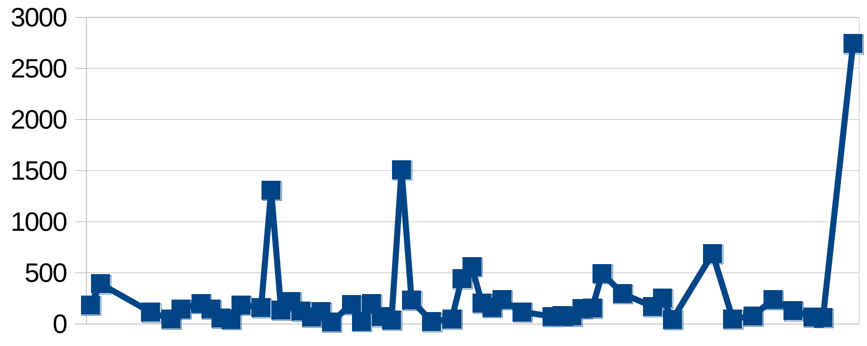


Figure 9: Number of participants per study

The first question concerned the gender of students and there is a suitable column with the preferences of an individual participating in distance learning. Question number 2 concerned the usefulness of m-learning with a proportional column of options. The 3rd and 4th questions concerned the acceptance of m-learning which is a parameter of high importance in m-learning, hence 2 questions were applied. Question number 5 was a reference to the perceptions of participants. Question number 6 was related to the mixed methods which are the combination of traditional and digital class or not. The seventh question concerned the social networks and the increasing use from year to year. Question 8 was based on the interaction between students and teachers. Question 9 referred to the ease of use of mobile devices or laptops for connection. The tenth question concerned the behavior of the learners.

Q	Attributes/Parameters	Questions
Q1	Gender differences	Gender
Q2	Usefulness	How useful did the m-learning procedure seem to you?
Q3	Acceptance of completed courses	Did you like the learning through your computer or mobile phone?
Q4	Acceptance of future m-learning courses	Will you prefer m-learning in upcoming courses?
Q5	Perception	How easy was it to understand the lesson?
Q6	Mixed methods	Which teaching method do you prefer?
Q7	Social media	Did you find it easy to send/receive content via social media?
Q8	Interaction	Did you like the interaction with the teachers via the screen?
Q9	Ease of use	How user friendly was the access to the online platform?
Q10	Behavior	Were you enthusiastic about m-learning?

Table 2: The questionnaire

Apart from these parameters that were found to be the most important of m-learning and which were matched with a question, there was another one taken into consideration, the attitude of learners. The attitude of learners provides a novel framework that moves further away from traditional classes, while incorporating a wide range of recent advances to provide personalized solutions to future challenges, (Alepis, Kabassi, & Virvou, 2017, November). These parameters can improve and assist the learning process with individual results and utilization of them, from authors and researchers.

1.3 Results of The Empirical Study

The classification method assisted to extract results and the categorization was achieved indirectly or directly. In view of them, the questionnaire was created, with specific parameters and shared in 3 target groups learners. The answers ware collected via social networks or mails. The first target group was students at high school, the second target group was students of a university and the third target group was adults of long-life learning. Each question was matched with a parameter of the aforementioned and the answers were demonstrated in figures and tables with percentage ratios. The attitude of learners was evaluated by the teachers during the distance learning and after the conclusion of each lesson when the connection was interrupted. The results of the aforementioned parameter will be demonstrated in the following table.

	Very	Moderate	Little
High school students	77.30%	18.40%	4.30%
University students	58.60%	29.30%	12.10%
Long-life learners	65.70%	30.50%	3.80%

Table 3: The percentages of the level of attitude of the participants

The most widespread method to produce predictive models is the Classification method utilized in this approach. The classification method in education based on specific features for supporting the learning process. The categorization is applied to the parameters in order to draw a predictive model. In the first question of the questionnaire, the participants determined their gender, with approximately 69% of the participants being female and 31% male. As for the gender differences, after analyzing the data, the acceptance, and the preference of the participants towards m-learning are depicted in Figure 10.

In order to distinguish whether there are gender differences among the participants, their answers on whether they prefer distance learning and on acceptance were taken into consideration. There was no significant difference in the percentages that reflect the preference towards m-learning of the male

(25%) and female participants (22%). On the contrary, there was a notable difference between the two genders, with 55.56% of women accepting m-learning, whereas only 37.5% of men are accepting it, as it is demonstrated in Figure 10.

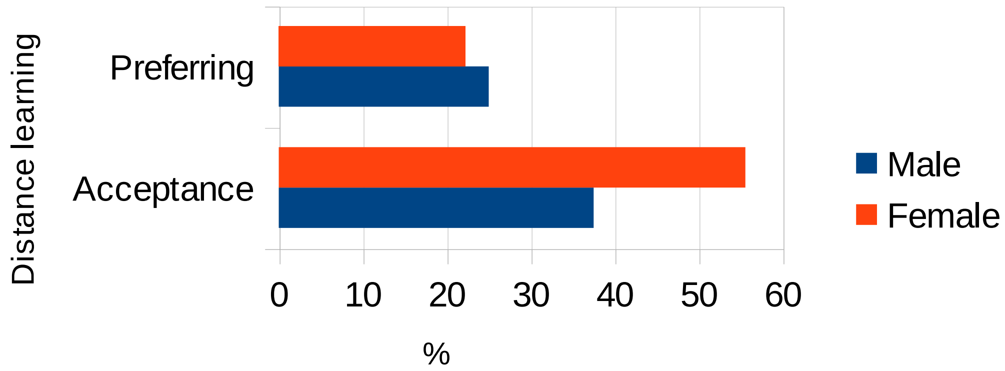


Figure 10: The preference of the participants

In the question for the usefulness (Fig. 11), 48.08% of the people, almost half of them, found it very useful, 44.23% answered moderate and 7.69% answered that distance learning was a little useful. Almost half of the learners believe that the lessons were very useful. If the percentage of the learners who answered "Moderate" is added with the previous, the combined percentage reaches an impressive 92%, leaving a small minority who believe that m-learning was not useful.

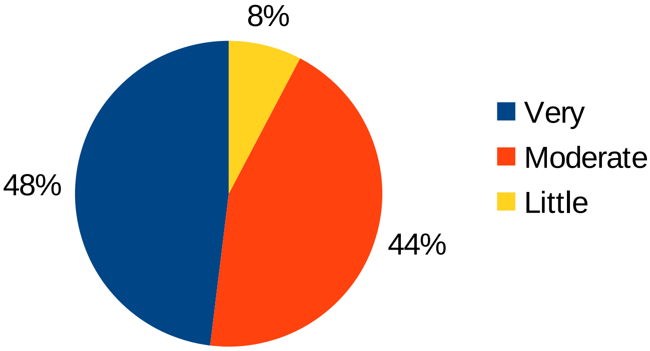


Figure 11: Usefulness

The parameter of acceptance was investigated with two questions, in the one question participants were asked directly if they liked m-learning and 40.38% answered very much, but the majority, 44.23% answered moderate and 15.38% showed little acceptance towards m-learning (Fig. 12). The other question regarding acceptance was indirect, with participants being asked whether they would like to attend again a course via m-learning, where the opinions of the participants were divided equally, i.e., 50% in favor and 50% against (Fig. 13). One possible explanation might be the fact that none of the participants had attended m-learning courses in the past, which means that there should be an adaptation period until everybody gets familiarized with it.

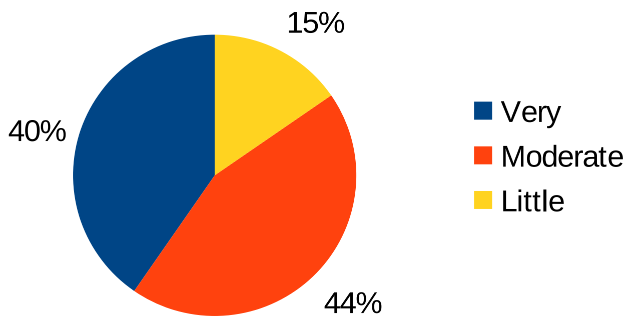


Figure 12: Acceptance of completed courses

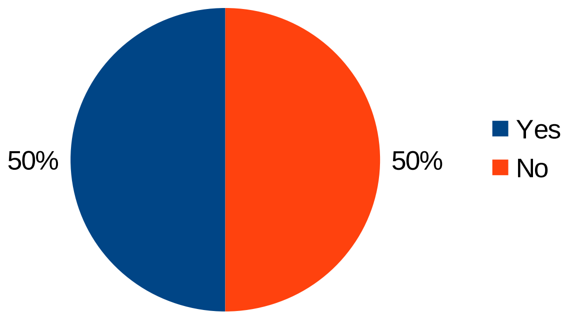


Figure 13: Acceptance of future m-learning courses

More than half of the participants, which is 51.92%, answered they have a very good perception towards m-learning. A large part of the participating learners had a moderate perception in m-learning, specifically 42.31%, and only 5.77% answered they had low perception (Fig. 14). On the contrary, the method which is preferred by 76.92% of the participants is the traditional class (Fig. 15). To get a better insight into this aspect, Table 4 was created, which enumerates the learners and the percentages per age group.

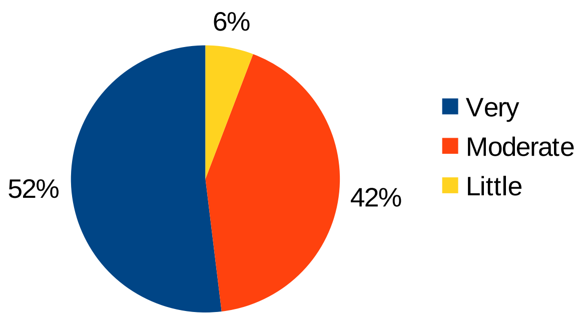


Figure 14: Perception

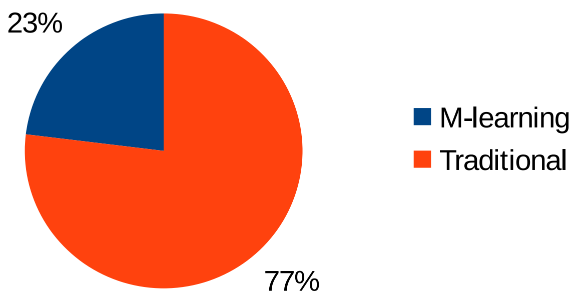


Figure 15: Methods

	M-learning		Traditional	
High school students	5	17.24%	24	82.76%
University students	5	45.45%	6	54.55%
Long-life learners	2	16,67%	10	83.33%

Table 4: Comparison of the preferred method between age groups

The remarkable fact is that the vast majority of teenagers students prefer the traditional class and the physical presence over m-learning. Their percentages are like those of adults attending long-life learning courses, who are expected to be inexperienced and not familiarized with mobile devices. On the other hand, the University students who are young adults and very keen on using mobile devices, are divided between digital and traditional class.

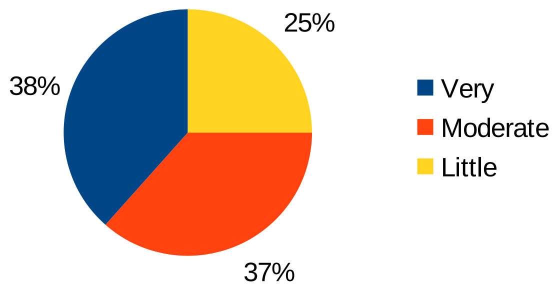


Figure 16: Social Media

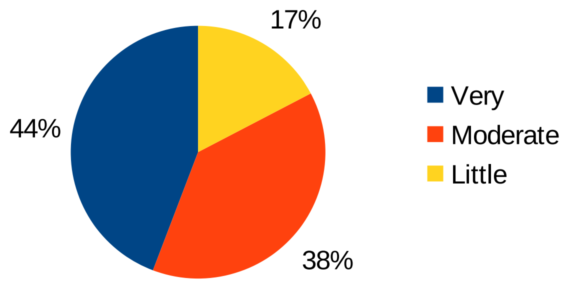


Figure 17: Interaction

Social media is a widespread way of communication nowadays, with which almost everybody is familiarized. During the lockdown and the online courses, social media were used to post exercises for all students, instead of sending them via email, in order to achieve high engagement. In the question for utilization of social networks, 38.46% liked using social media very much, 36.54% answered moderate and 25% found little utilization (Fig. 16). Despite the usefulness of social networks, students' views about them were almost equally divided into the 3 available answers, with approximately one-third of the students (38.46%) being very positive in using them.

The overall satisfaction of the students about the capability of interacting with each other and with their tutors was surveyed. In that question, 44.23% answered very much, 38.46% answered moderate and 17.31% believed there was little interaction in m-learning (Fig. 17). The conclusion is that almost half of the participants were very satisfied and 38% were moderately satisfied, leaving a small percentage of 17% who were a little satisfied.

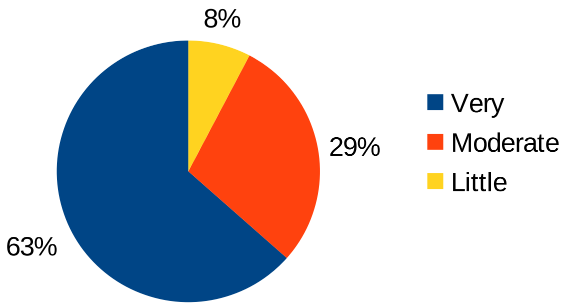


Figure 18: Easy to use

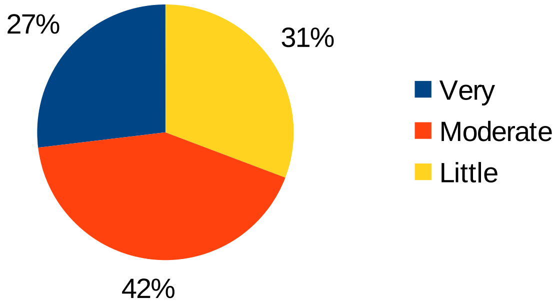


Figure 19: Behavior

Concerning the ease of use, 63.46% answered m-learning was very easy, 28.85% answered moderate ease, and 7.69% believed ease of use was low (Fig. 18). It is observed that most of the learners (63.46%) found high ease of use while using mobile devices, namely smartphones and tablets, and relative apps. The last question concerned the behavior of learners and 26.92% felt very enthusiastic, whereas 42.31% answered that their behavior was moderate (Fig. 19). In addition, a large part of the learners, 30,77%, was not fond of the idea of online lessons, which were mandatory.

2. Discussion

This Ph.D. thesis aims to analyze the parameters of m-learning with published papers in quality journals or significant international conferences (Virvou, Alepis, Tsihrintzis, & Jain, 2020; Virvou, Troussas, & Alepis, 2012, June) and the second step was the creation of a questionnaire for 3 different educational groups, that continued their lessons in the COVID-19 era, and the results are useful for tutoring systems which based in adaptive learning, providing important information to researchers, educators for e-learning and m-learning systems, (Alepis, & Virvou, 2011). Also, this Ph.D. thesis can be used as a guide for making decisions about the techniques of student models. The similarities or differences between learning in digital or physical classrooms and the reflections of learners were analyzed while was employed specific data from popular parameters referring to m-learning. Moreover, learning analytics enabled the increase of understanding of the students' learning needs.

The presented system provides an adaptation of the instructional material, considering the individuality of learners in terms of background, skills, and pace of learning. The innovation of the presented approach is the student model. It is a mixed student model that combines 3 different student groups: high school students, university students and long-life learners. In particular, the student model is based on focusing on the parameters of m-learning, while the learning analytics are incorporated into the student model. Also, the student model includes a mechanism of rules over the questionnaire which is triggered after any change of the value of the parameters. The presented novel approach shows the benefits of m-learning, whereas the student preferences were influenced the learning in the physical classroom.

The student model of the particular system has 3 layers. The first layer includes the educational data, which was extracted from the students with specific parameters. The second layer includes the learning analytics, where the answers of the learners were utilized. The third layer includes the categorization of the results and evaluation of them. Consequently, the presented educational model contributes significantly to adaptive learning in m-learning environments, while an educational effective process in a traditional classroom is promoted. The ability of the presented educational system to recognize the attitude and behavior of learners renders the particular approach a novel useful tool for instructors and institutes. The encouraging results could be evaluated and utilized for the effectiveness of individual learning in a digital or physical class.

Part C: Assessment Support Intelligent Decision System

Problem Settings

During the pandemic, there was an eruptive demand for online courses. Instructors in secondary and tertiary education have adapted the course to the requirements and needs of each student. The academic performance of the students or final exams then had to be digitally adapted and to be completed using m-learning environments. Subsequently, there was a large increase in the average of the student's grades in all courses, in favor of due. All educational institutes researched ways to solve the problem, which was presented, with digital tools and methods aimed at sound examinations in a digital class.

Intelligent decision systems have been employed in a plethora of sectors in our community and blended learning has utilized full advantage of predictive models in digital classes. One of the learning problems is for the instructors to predict the academic performance of students, aiming at the optimal individualized learning of the students. In this approach, an algorithm was created with an intelligent decision system and a predictive model for self-assessment of students before their academic performance, focusing on their best preparation for all courses. Self-assessment, as an important stage of the “how to learn” process, has been identified by much research, as a key factor of learning success, (Maldonado-Mahauad, et al., 2018; Bannert, & Reimann, 2012). Assessment tasks play an important role in the selection and implementation of learning strategies, (Scouller, 1998; Struyven, et. al., 2006).

1. Experimental Study

1.1 Data collection/dataset description

The method suggested in this experimental study 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, Feng, Means: Mining, T. E. D., 2012, October).

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 performances, 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.

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. Data from a course in a university in which attending classes is mandatory were used.

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, Guzmán, & González, 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). 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 its evolution was noted.

In the table below the variables that influenced the results are listed. These variables were employed in most of the researchers (see for example Ćukušić, Garača, & Jadrić, 2014; Kotsiantis, 2012) in adaptive education.

Variable	Variable type	Description
Gender	Nominal	Male, Female
Grade	Numeric	0 – 100
Parent education[1]	Nominal	Well-educated, not well-educated
Parent income[2]	Nominal	Low, Medium, High
Being the first child	Nominal	True, False
Working	Nominal	True, False

Table 5: Variables of assessment

The results of the above assessment identified the profile of students and termed the quality of the course, (Virvou, et al., 2015, July). 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 the following table:

<table>
<tr><td>Gender</td><td colspan="2">Male:
43%</td><td colspan="2">Female:
57%</td></tr>
<tr><td>Grade</td><td>Male
0-45:
28%</td><td>Male
50-100:
72%</td><td>Female
0-45:
13%</td><td>Female
50-100:
87%</td></tr>
<tr><td>Parent education</td><td colspan="2">Well-educated:
83%</td><td colspan="2">Not well-educated:
17%</td></tr>
<tr><td>Parent income</td><td colspan="2">Low:
12%</td><td>Medium:
69%</td><td>High:
19%</td></tr>
<tr><td>Being the first child</td><td colspan="2">True:
52%</td><td colspan="2">False:
48%</td></tr>
<tr><td>Working</td><td colspan="2">True:
33%</td><td colspan="2">False
67%</td></tr>
</table>

Table 6: Percentage analysis of variables

1 Well-educated: Secondary or tertiary education degree, not well-educated: Elementary education degree.

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

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.

2. 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 figures 20-28; the labels of this tree are determined as follows:

The root is labelled $\boxed{1a}$.

Each internal vertex of T, at level[3] l ≥2, has a label of the form $\boxed{\begin{matrix} mn \\ p/q \end{matrix}}$, where

- m϶{1,2,3,4} displays the level of difficulty of the corresponding question,
- n϶{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. Due to the very big size of the tree T, it is divided into 9 subtrees which are shown in Figures 20 to 28.

In Figure 20, the subtree T' of the tree T is displayed, with all points of level up to 4. Each leaf of the subtree T' continues to a different subtree. For instance, the remaining path of the leaf indicated as $\begin{bmatrix} 4a \\ 5/30 \end{bmatrix}$ in Figure 20, is displayed in

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

Figure 24, where the root of that subtree has the same indication.

Some paths of subtree T’ are colorized and correspond to the four cases analyzed in section 3.2. The red path of T’ is continued in Figure 21, where the subtree T1 is displayed, and which corresponds to Case 1. Case 2 is highlighted in green in Figures 20 and 26. The blue line that begins in Figure 20 and ends in Figure 23 consists of the 3rd case. In subtree T4 (Fig. 28) the orange path represents the last case.

The rest of the subtrees, which are demonstrated in Figures 22, 24, 25, and 27, show various instances of the dynamic questionnaire.

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 (predictive model).

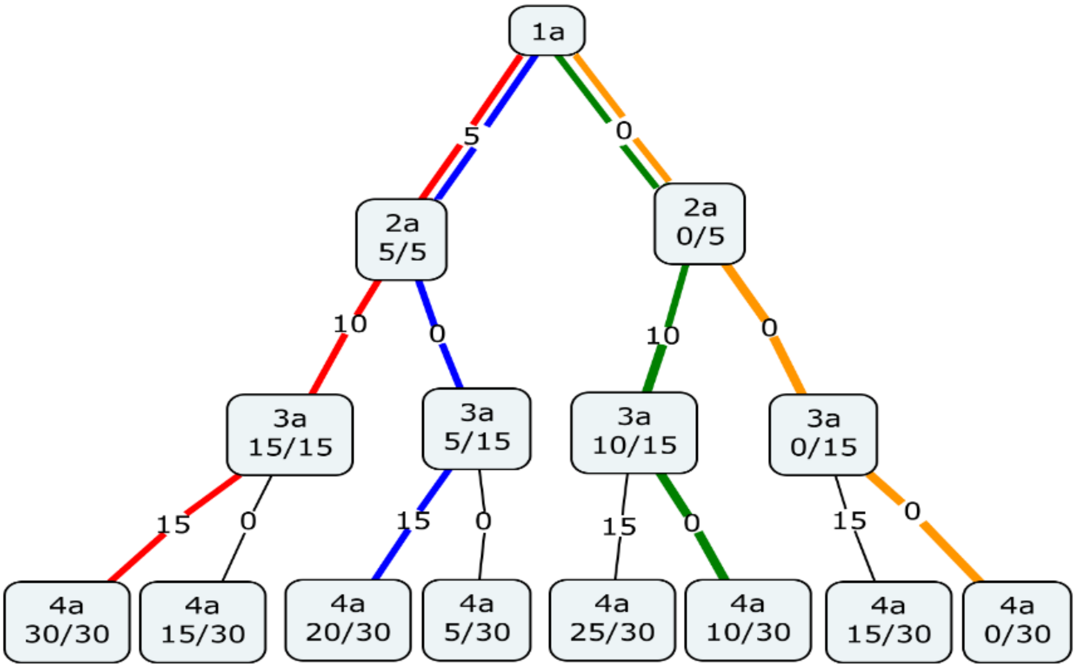


Figure 20: Subtree T'

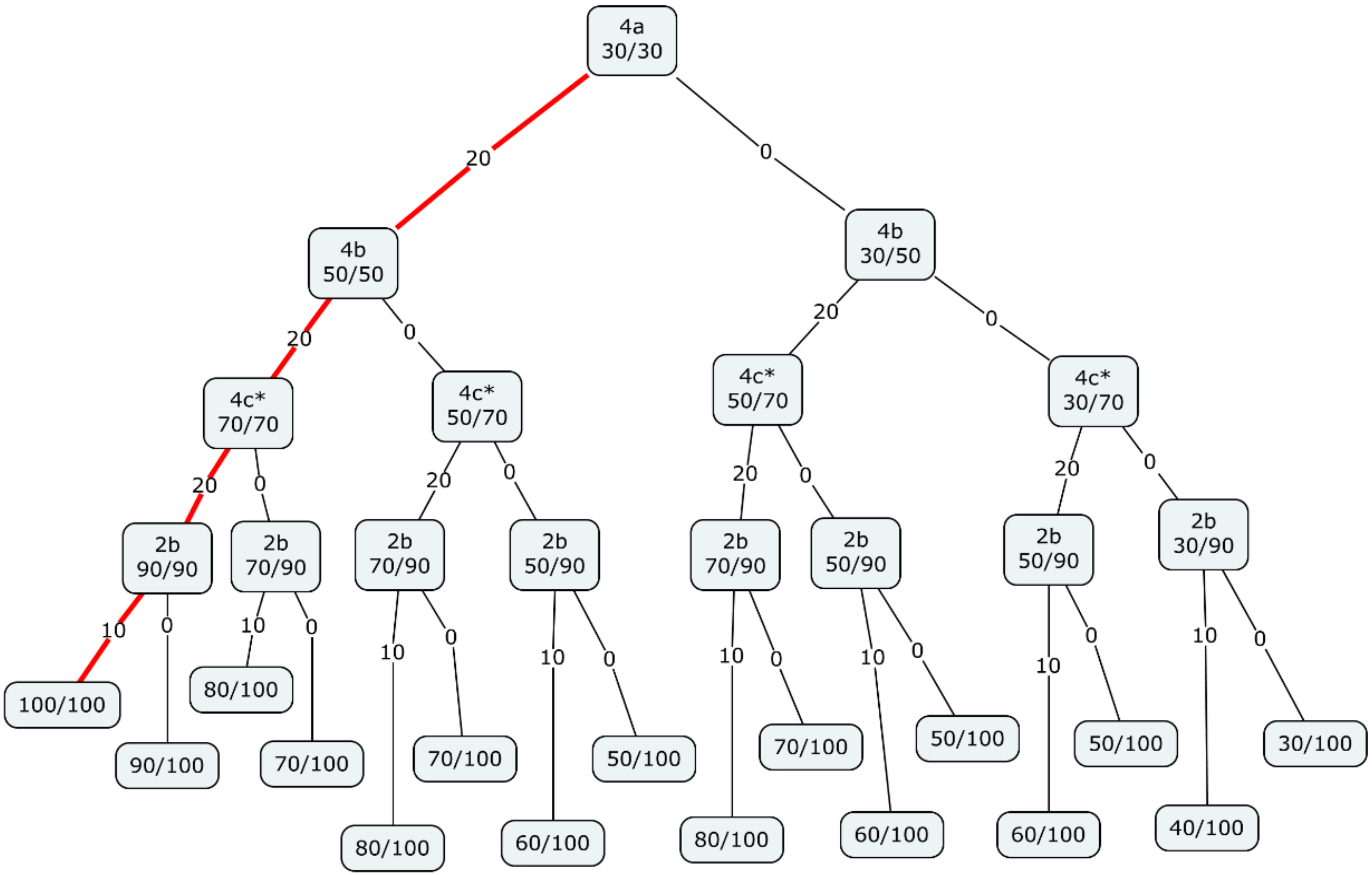


Figure 21: Subtree T_1

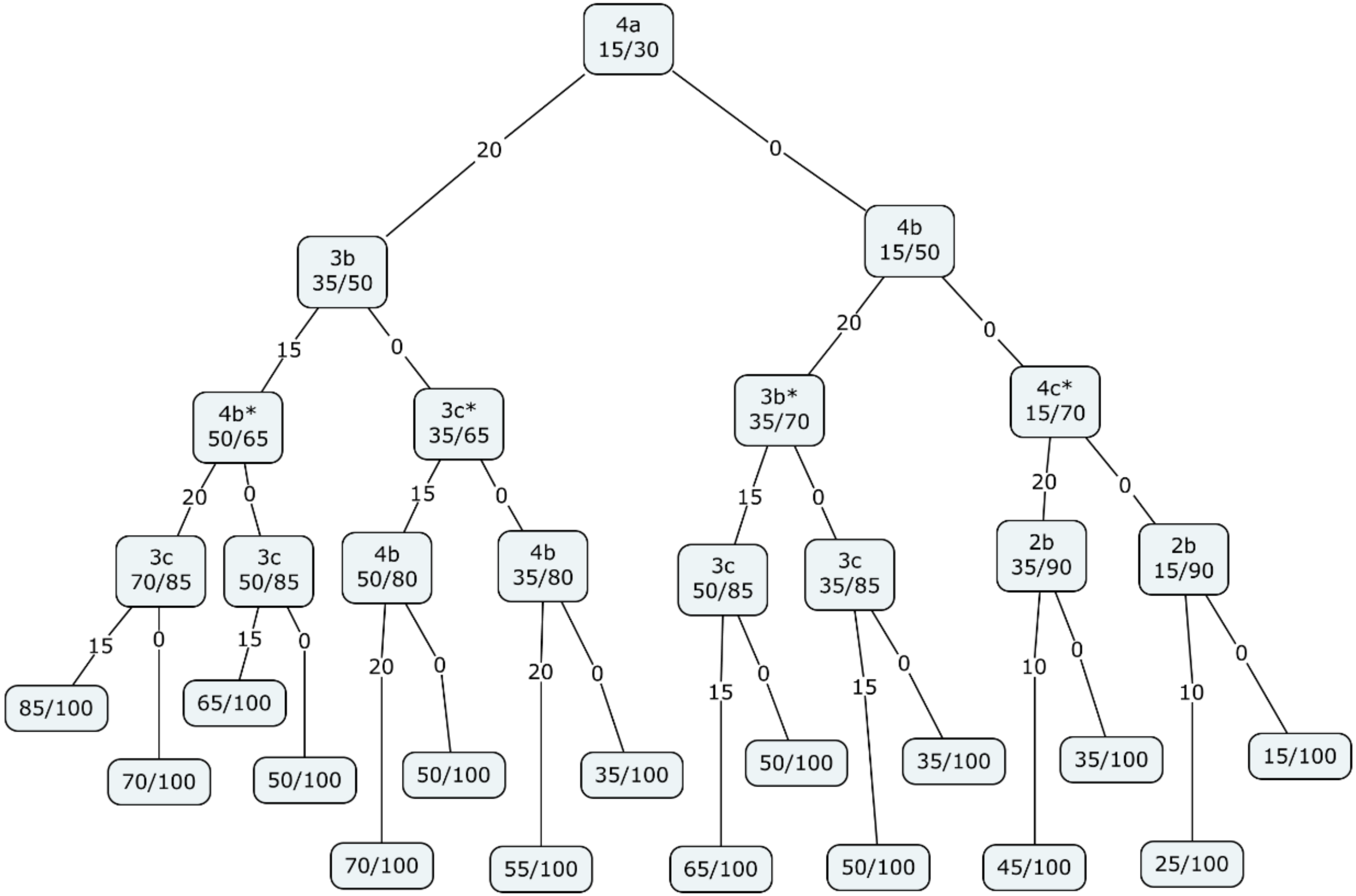


Figure 22: The subtree of the 2nd leaf of T'

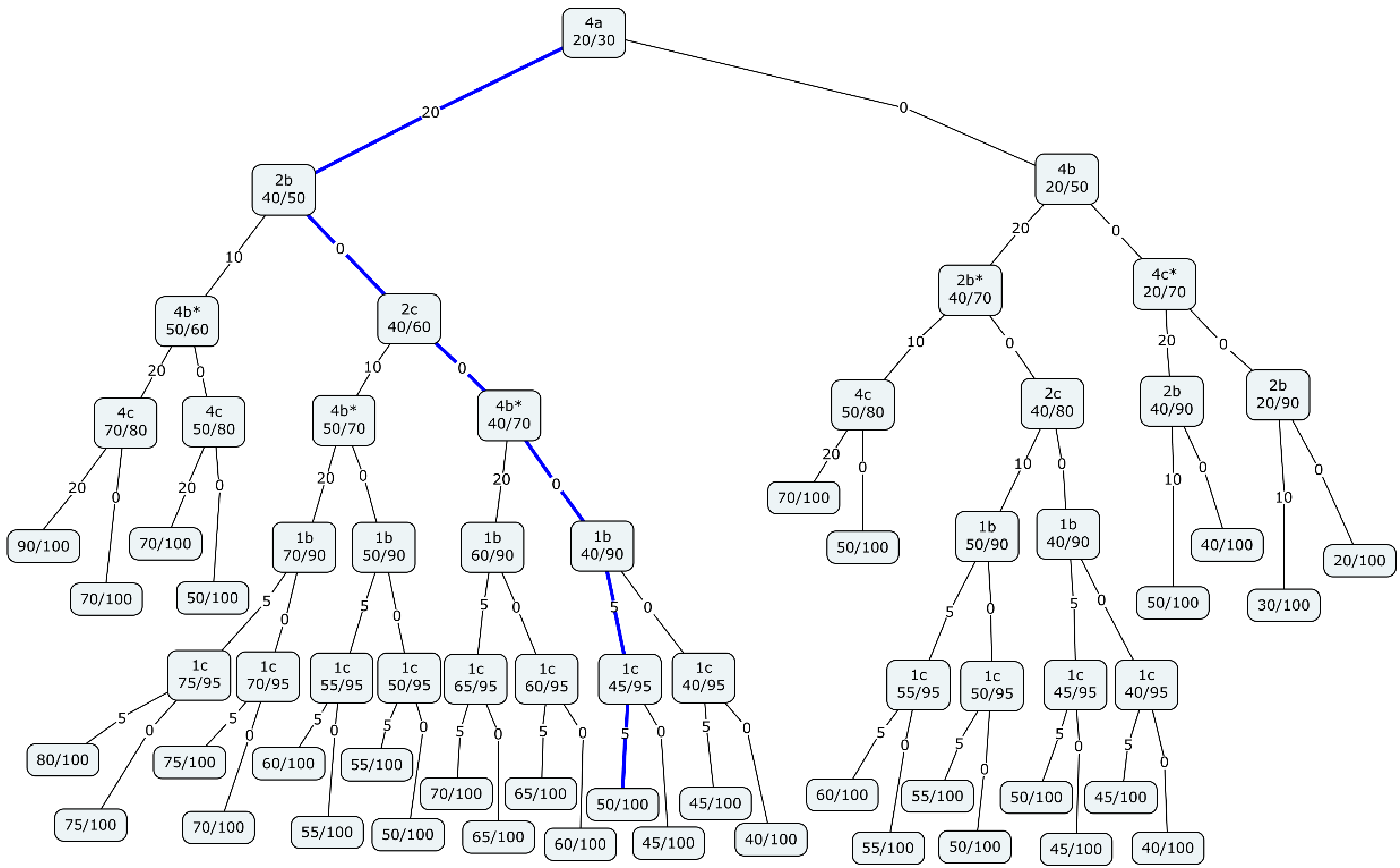


Figure 23: Subtree T_2

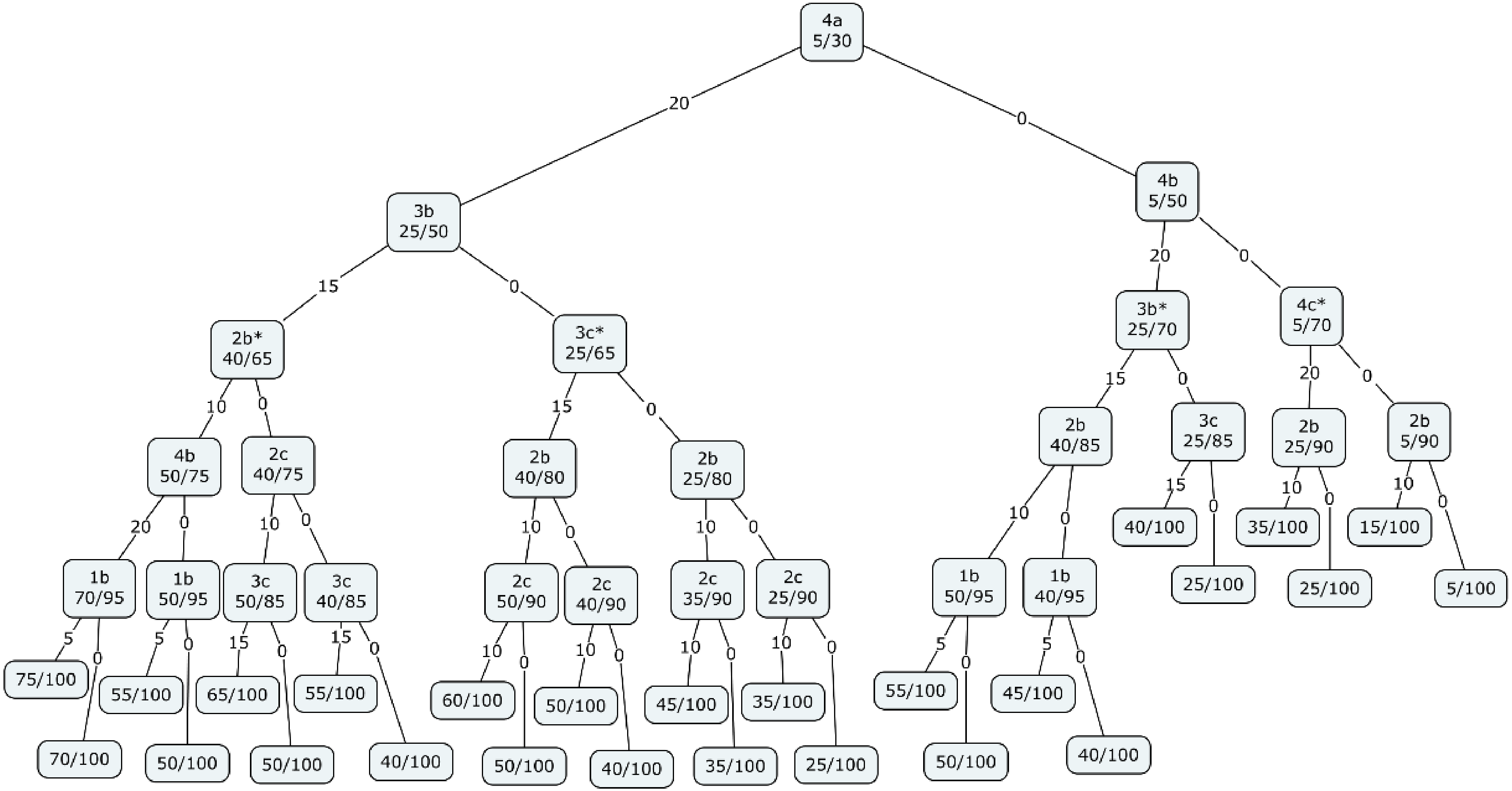


Figure 24: The subtree of the 4th leaf of T'

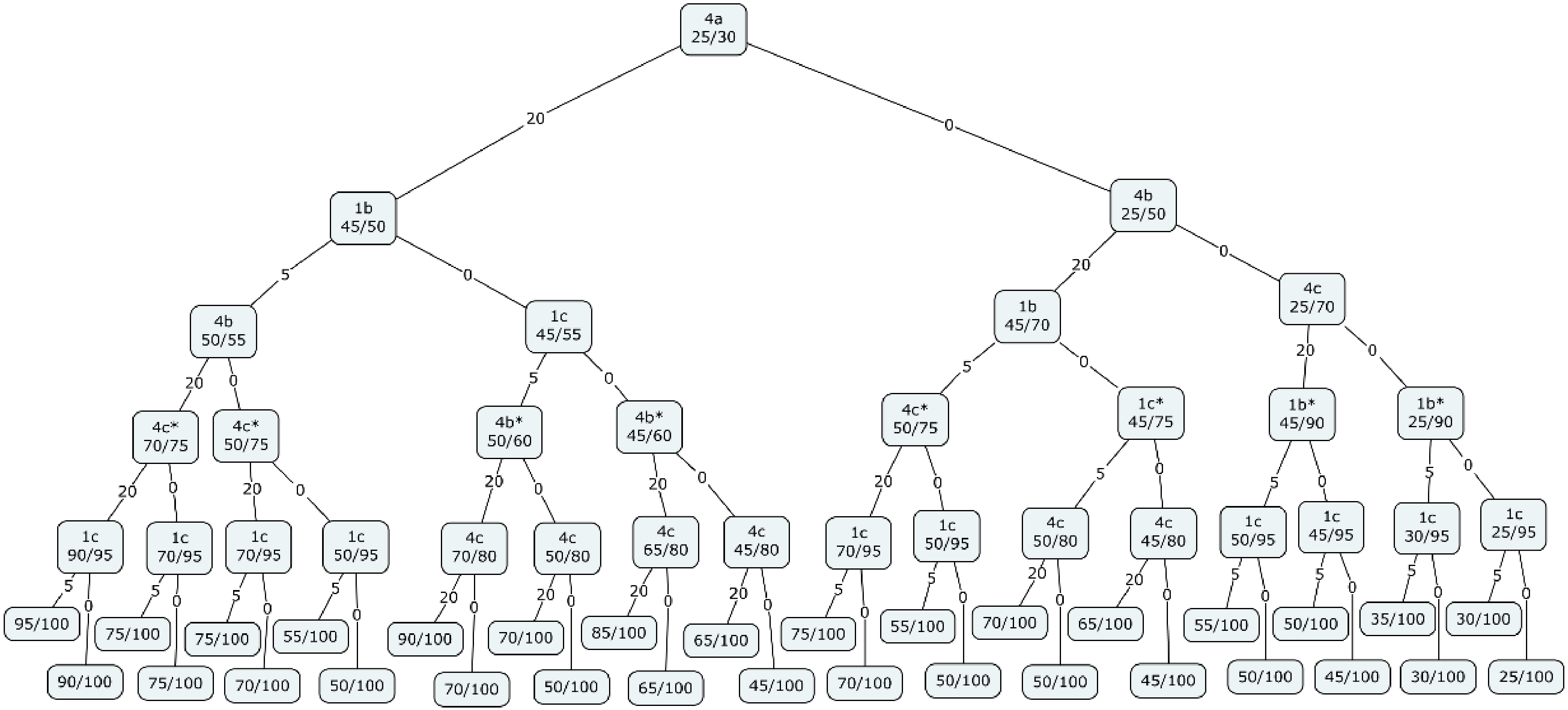


Figure 25: The subtree of the 5th leaf of T'

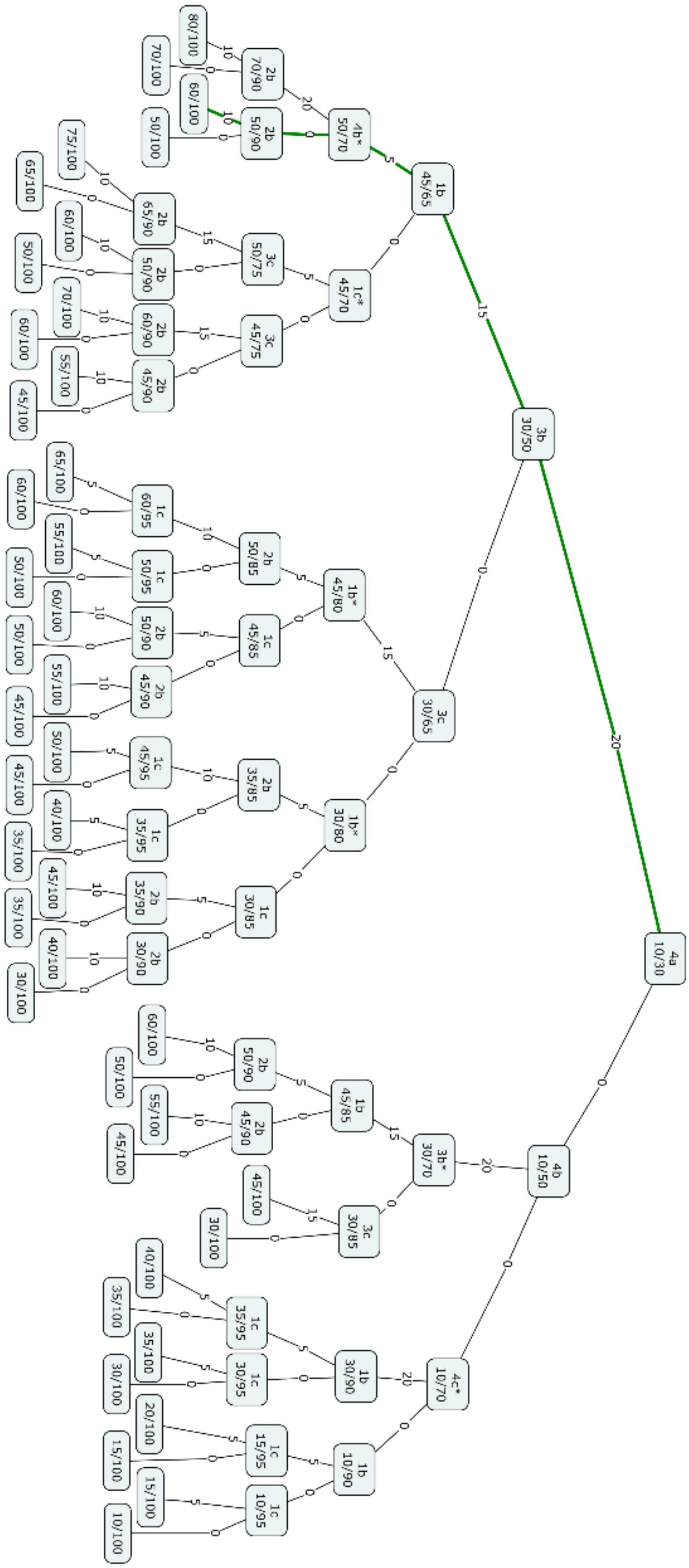


Figure 26: Subtree T_3

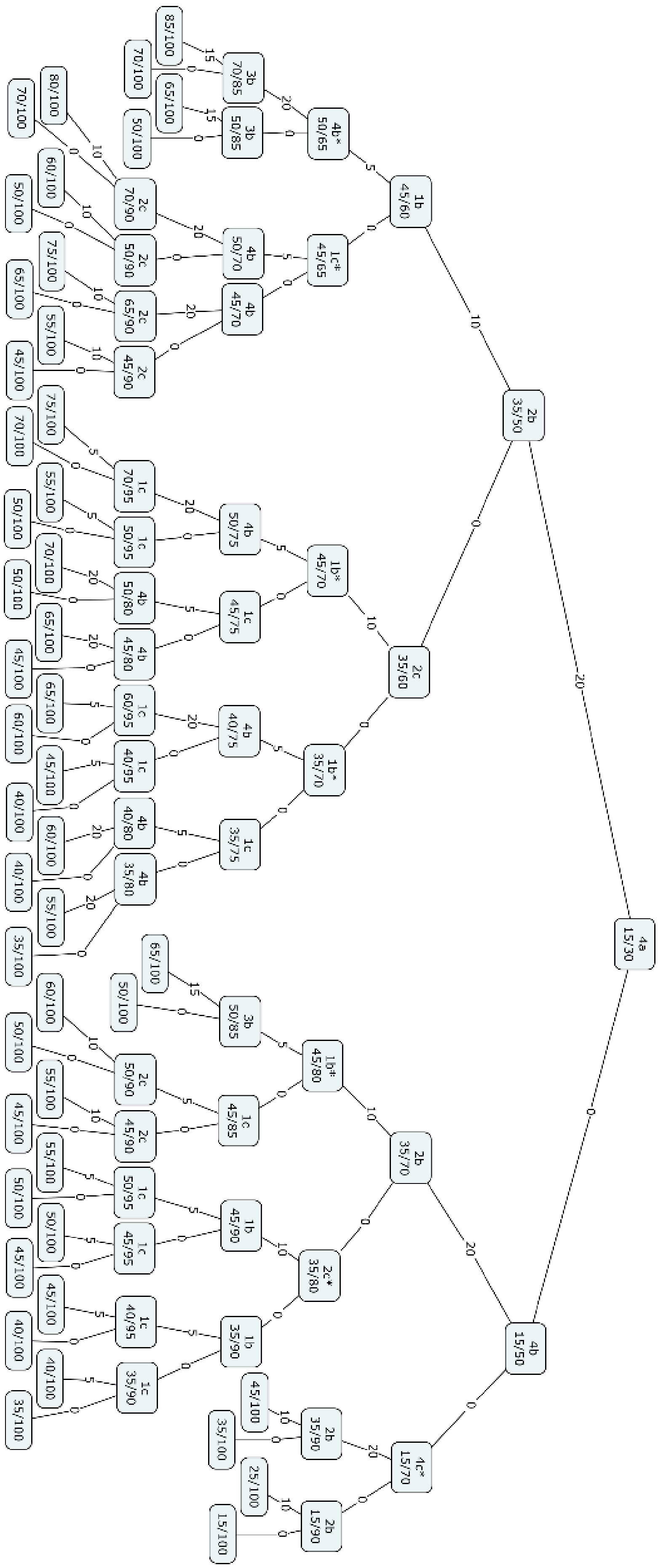


Figure 27: The subtree of the 7th leaf of T'

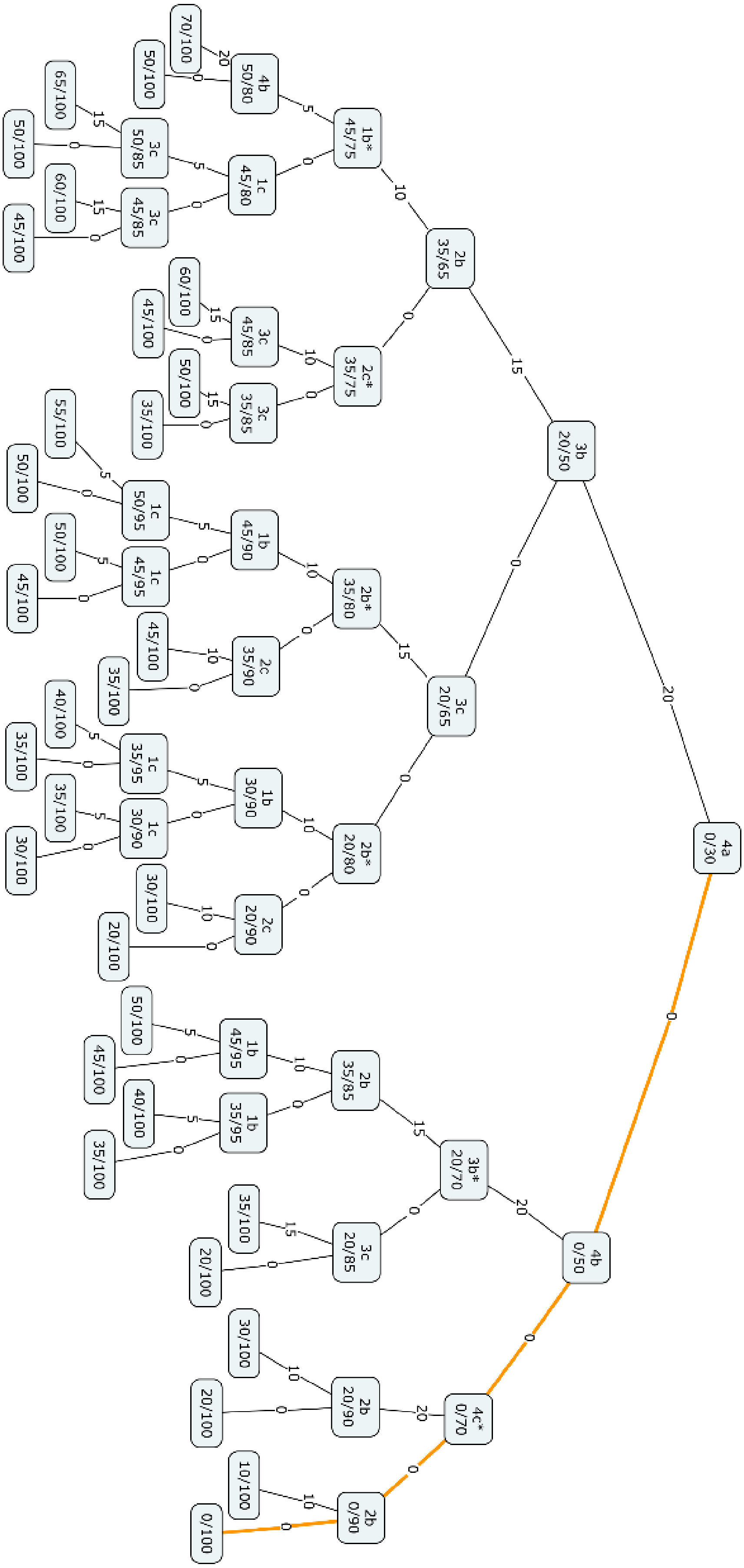


Figure 28: Subtree T_4

3. Predicting Algorithm

3.1 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):

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

Table 7: Initial parameters

The rationale for the algorithm is as follows:

- 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.

- 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.

- 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.

- Finish:

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

3.2 Use Cases

Some cases that are useful in drawing conclusions will be analyzed. Through different paths and parameters that have been identified, different results have been recognized. In the academic performance of students, the well prepared student or the student who needs to study more can be identified through the appropriate exercises.

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 the most important points of the decision tree have been analyzed. 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, it is observed that the student 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.

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), for “MaxGrade” to reach exactly 100 points with as few questions as possible. If the student correctly answers 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 Figures 20 and 21).

Case 2:

In case 2, a student who does not answer the 1st and the 3rd level questions is examined, whereas he/she correctly answers 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 correctly answer 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 Figures 20 and 26).

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 answer 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 cannot 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 answer 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 Figures 20 and 23).

Case 4:

Finally, the last case is about 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 Figures 20 and 28).

3.3 Results

Considering the grades of students' academic performance, the following 4 tables demonstrate the results while considering the variables of assessment.

	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 8: Case 1 (Grades 80-100)

Table 8 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.

	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 9: Case 2 (Grades 51-79)

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.

	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 10: Case 3 (Grades 31-50)

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%.

	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%

Table 11: Case 4 (Grades 0-30)

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.

4. Discussion

The conclusions of this assessment 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, Virvou, & Sakkopoulos, 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 this assessment, the following were concluded: 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 31-50 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.

Part D: Predictive Model for Mathematics

1. System Architecture

Digital learning vs traditional learning has been promoting incorporating blended learning in schools to improve students' knowledge needs. (Boelens, Voet, & De Wever, 2018), (Harrison, & West, 2014). Universities are increasing the use of blended learning because this type of learning offers flexible and effective learning.

The paper (Wang, Quek, & Hu, 2017), implemented blended learning through video conferences to improve teaching-learning conditions. The purpose of the paper, (Cavanaugh, Hargis, & Mayberry, 2016) is to propose the use of a Learning Management System such as Sakai and Moodle to perform online evaluations at any time and place. The organization of school activities through blended learning can improve in traditional classes. (Blaine, 2019), (Prasad, Maag, Redestowicz, & Hoe, 2018). This hybrid model of learning allows the planning of various tasks inside and outside the classroom through technology focusing to improve academic performance and developing students' skills, (Van Niekerk, & Webb, 2016), (Yamagata-Lynch, 2014).

A lot of researchers specialize and focus in such diverse areas as artificial intelligence, fuzzy techniques, genetic algorithms, cognitive science, mathematical modeling, neural systems computer-supported cooperative work, geographic information systems, user interface management systems, informatics, knowledge representation, and applications of intelligent systems, presenting methods of modeling systems, which develop and evolve the educational process according to the student's needs.(Matzavela, Alepis, 2017) (Alepis et al., 2021) (Alepis et al., 2017)

Sønderlund et al. presented a literature review specifically aimed at studying the effectiveness of learning analytics interventions based on predictive models. Of 689 papers, merely 11 studies reported an evaluation of the effectiveness of such interventions, by emphasizing the need for a solid knowledge base on the feasibility, effectiveness, and generalizability of the learning analytics interventions. Gasevic et al. present that “learning analytics is about learning” and recommend learning analytics and educational institutes change direction from the performance-based evaluation of learning analytics. Tempelaar et al. presented that prediction accuracy increases over time and that performance data are especially important. The number of clicks in the week before the course offered extra information and have the highest predictive power. Subsequently, the prediction of student performance gradually improved. The researchers, therefore, argued that the best time to predict student performance is as soon as possible after the first assessment. (Arruerte, 2021) Following the above, there is a gap in personalized learning through hybrid learning or blended learning. (Alepis, Virvou 2014) (Virvou, Alepis 2004) and walk step by step to optimization of learning systems.

In view of the above, this paper proposes an improved application for students with a self-assessment, which is based on a predictive model in order to more accurately predict the grade in the final exams. This application offers the student the opportunity for better preparation before the final exams, applying an intelligent decision tree system. It also offers more flexibility in this type of learning giving more opportunities for students to succeed.

This section and its subsections consist of the backbone of this system. The three main parts of the architecture of an intelligent predictive model are: 1. The database (or Knowledge Base): In order to work, necessary data is needed. This data can come from a variety of sources including the Internet. In this work the data come from students of 6 Greek schools. 2.The model (eg, general decision framework and user criteria): All data collected in the database is managed by different models. These models can be standard or customized depending on the user's preferences. 3.The user interface: Another important element of the structure of a decision-making system is the user. The user communicates and interacts with the system and is considered part of it. End users alone are also very important parts of the architecture. After creating the model, the next step is to evaluate it. To achieve this, test data to calculate the accuracy of the model are used. The model categorizes the test data. Then, the category formed on the basis of the test data is compared with the prediction made for the training data, which are independent of those of the test. The accuracy of the model is calculated from the percentage of test samples that were correctly categorized in relation to the model under training.

If the model is considered acceptable, then it can be used to categorize future data samples, the classification of which is unknown. Decision trees are widely used for categorizing and predicting data. A decision tree is constructed according to a set of pre-categorized data training. Each internal node identifies the control of the attributes and each branch that connects the internals to the offspring corresponds to a possible value for the attribute.

1.1. Predictive Model

Decision systems require a structured approach. Such a framework includes people, technology, and the development approach. The Framework of Decision System consists of four phases:
Intelligence – Searching for conditions that call for decision;
Design – Developing and analyzing possible alternative actions of solution;
Choice – Selecting a course of action among those;
Implementation – Adopting the selected course of action in decision situation.
There are several ways to classify Decision system applications. Not every Decision system fits neatly into one of the categories but may be a mix of two or more architectures.

Holsapple and Whinston (1996) classify Decision system into the following six frameworks: text-oriented Decision system, database-oriented Decision system, spreadsheet-oriented Decision system, solver-oriented Decision system, rule-oriented Decision system, and compound Decision system. A compound Decision system is the most popular classification for a Decision system; it is a hybrid system that includes two or more of the five basic structures.

Decision system components may be classified as:
Inputs: Factors, numbers, and characteristics to analyze
User knowledge and expertise: Inputs requiring manual analysis by the user
Outputs: Transformed data from which Decision system "decisions" are generated
Decisions: Results generated by the Decision system based on user criteria.
An intelligent decision support system should behave like a human consultant:

supporting decision makers by gathering and analyzing evidence, identifying, and diagnosing problems, proposing possible courses of action and evaluating such proposed actions. The aim of the AI techniques embedded in an intelligent decision support system is to enable these tasks to be performed by a computer, while emulating human capabilities as closely as possible. The term "Intelligent decision support system" is thought to originate with Clyde Holsapple and Andrew Whinstonin the late 1970s.

Examples of specialized intelligent decision support systems include Flexible manufacturing systems (FMS), intelligent marketing decision support systems and medical diagnosis systems. The philosophy of this paper follows the above parameters of an intelligent decision system, taking inputs numbers, and characteristics to analyze and outputs data from which Decision system "decisions" are generated. The intelligent decision system that follows accepts the data, specifically inputs from the questionnaire with Mathematics exercises, is randomly classified and returns to the user. The user answer to the exercises and results are extracted, which are shown in the corresponding path of the binary tree. The intelligent system processes the outputs and "decides", through the algorithm, to select intelligently the next question for the user.

The resulting binary decision tree is presented with four snapshots (Figures 29-32), which illustrate students differently prepared for the mathematics exam. Each tree has its own weights/scores per level of difficulty of the question. The questions are divided into 4 difficulty levels. In the first level of questions, there are 20 simple questions for all students. In the second level of questions, there are 10 questions of moderate difficulty. In the third level of questions, there are 6 questions that are more demanding for students. In the fourth level, there are 5 questions of the high cognitive field for the completion of the test. The points for each of the first level questions are 5 points, for the second level 10 points, for the third 15 points and for the fourth 20 points. The final score is 100/100 for the excellently prepared student. In Figure 29, illustrates the excellent student, who correctly answered questions from all levels (8 questions in total), in random order, and he/she collected 100/100 points. In Figure 30, illustrates a student who answers 9 questions and collected 80/100 points. In Figure 31, illustrates a different combination of questions, and the student collected 70/100 points. The Figure 32 illustrates a student who has not been prepared for this exam and his/her score was 0/100.

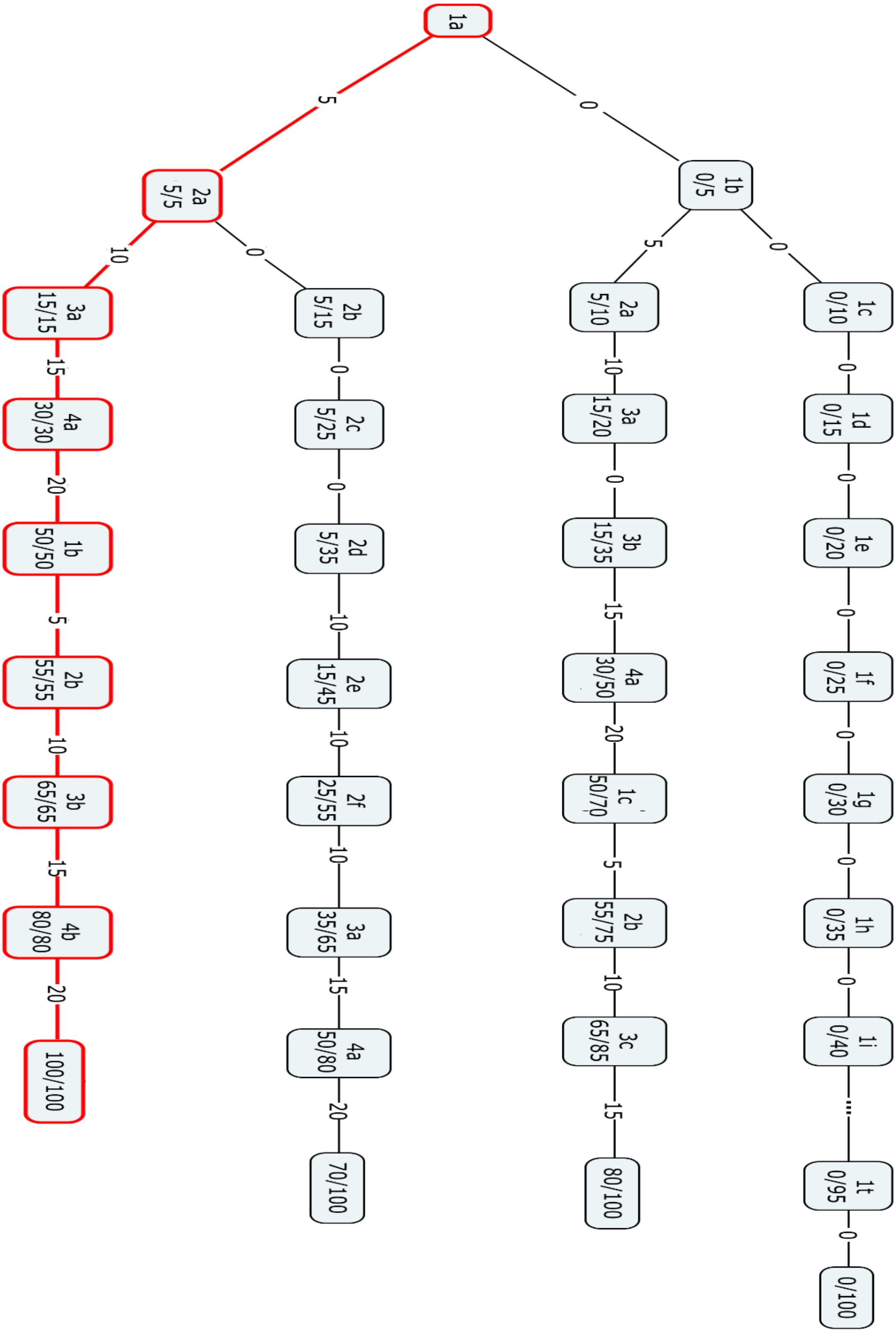


Figure 29: First snapshot of the binary decision tree

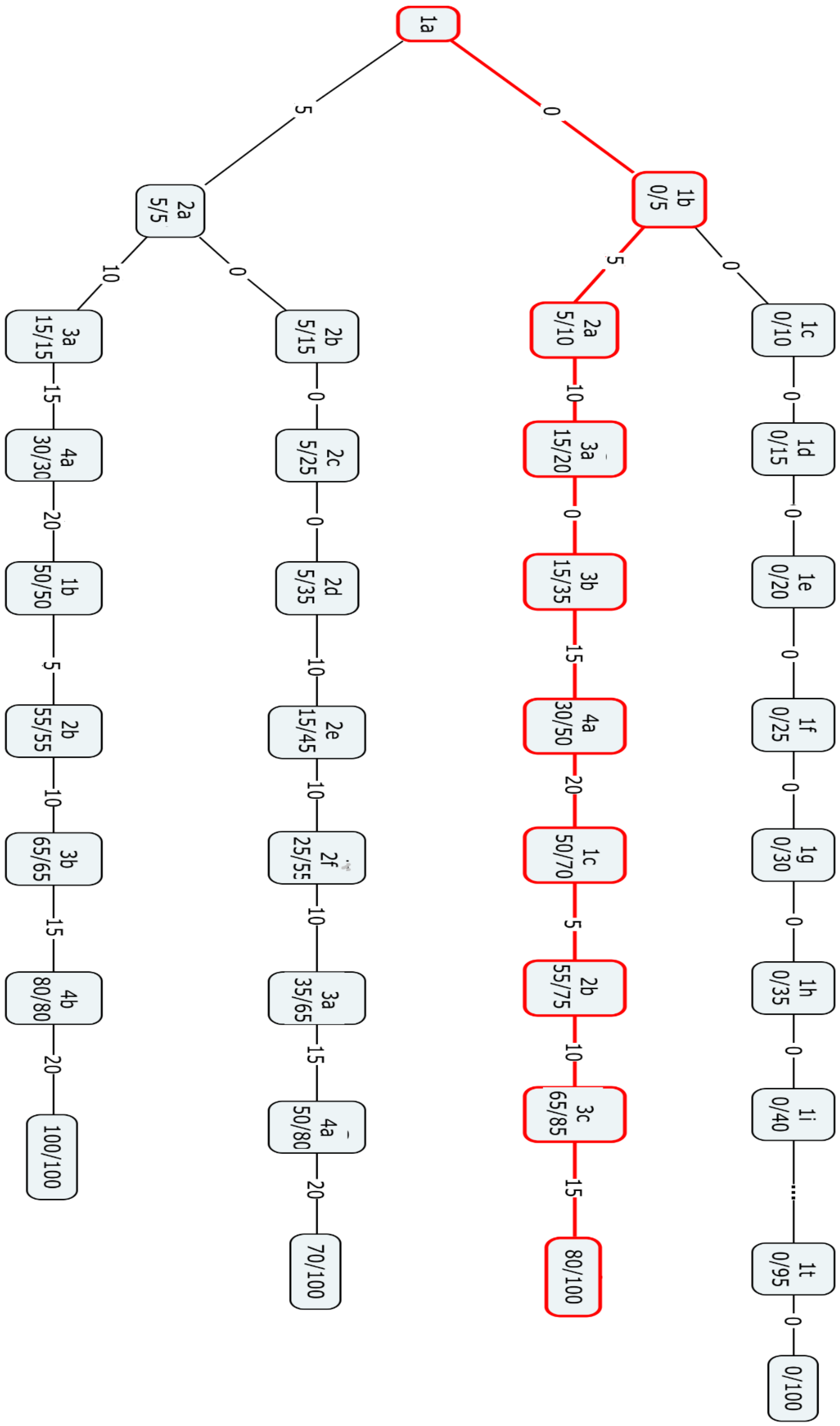


Figure 30: Second snapshot of the binary decision tree

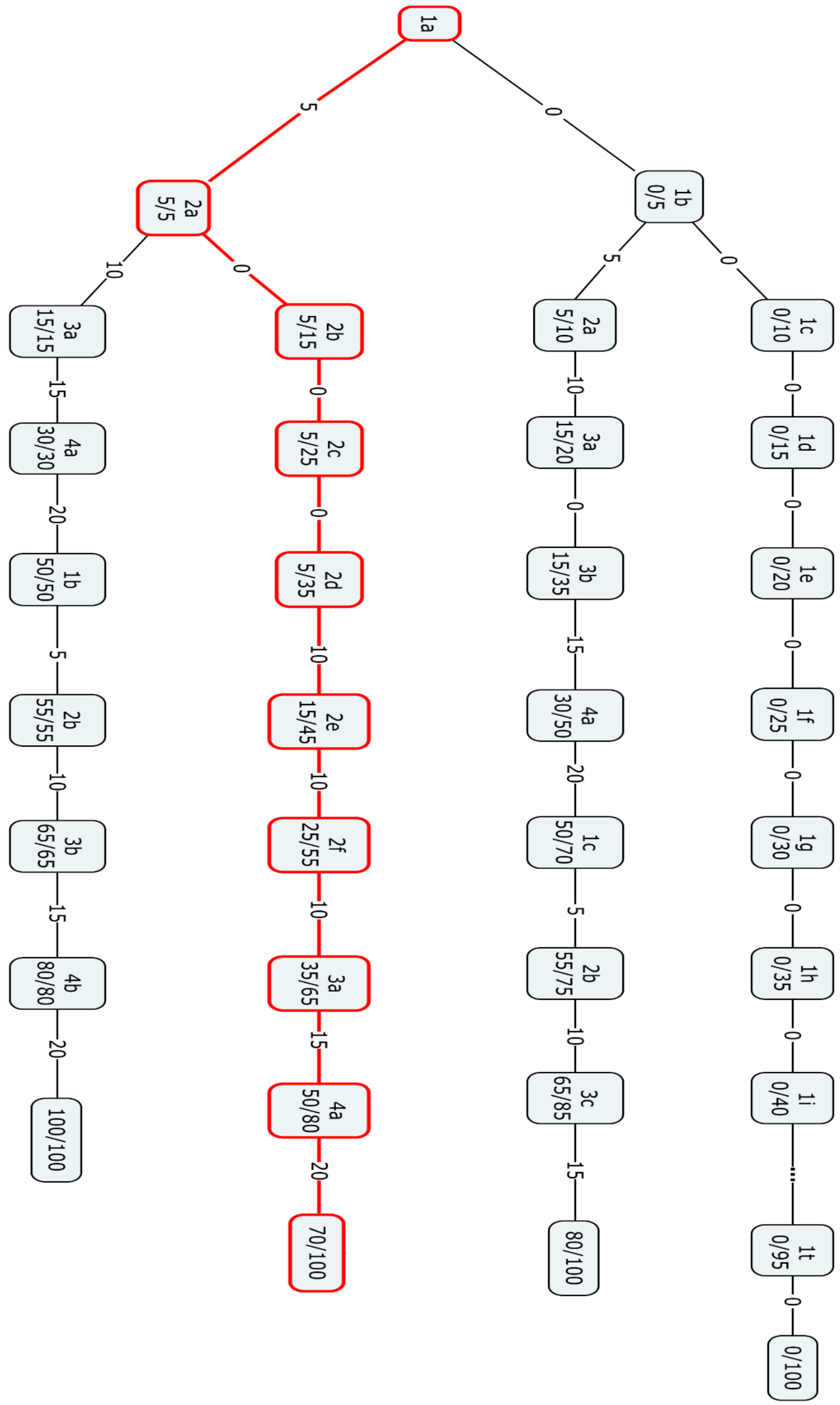


Figure 31: Third snapshot of the binary decision tree

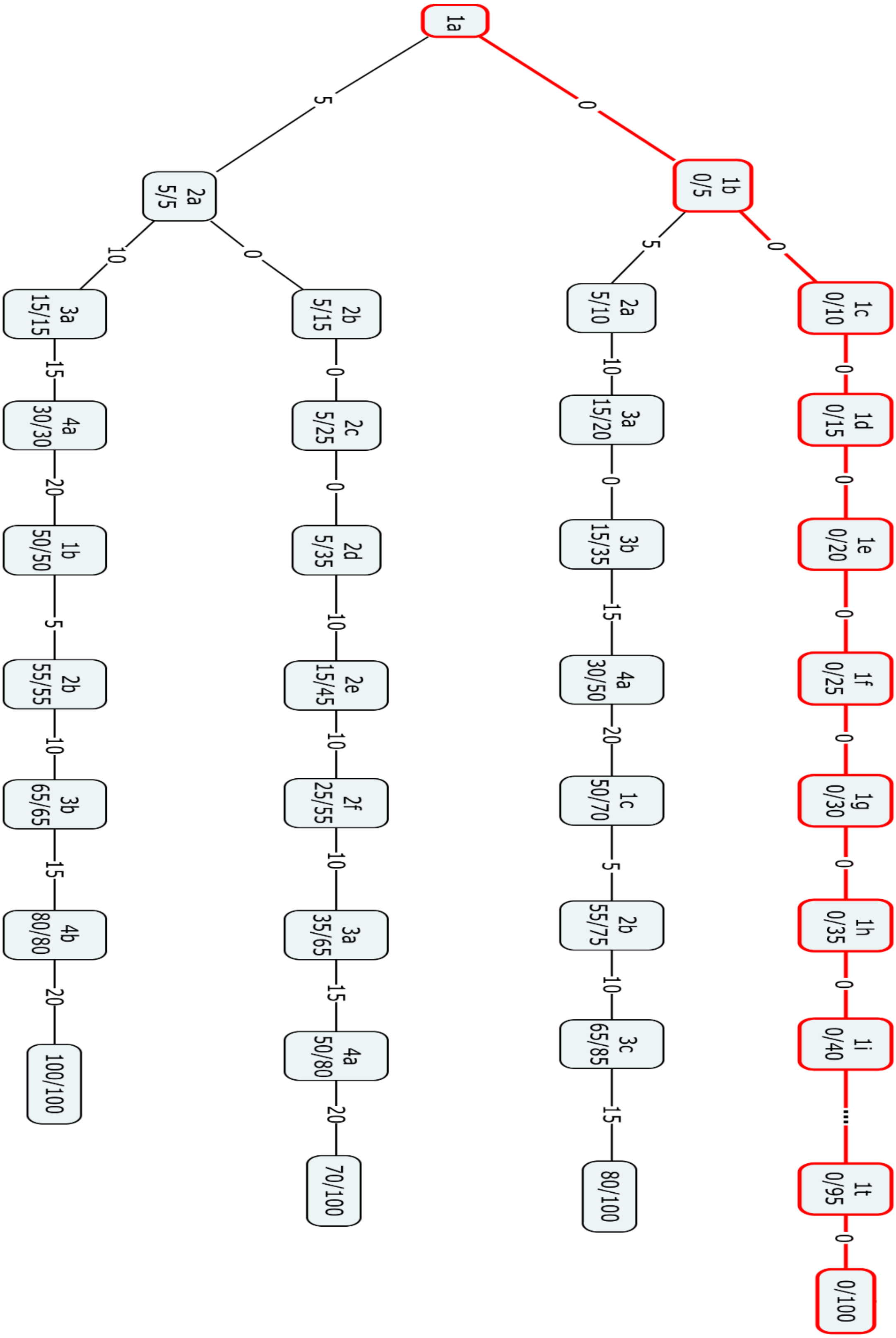


Figure 32: Fourth snapshot of the binary decision tree

1.2 Algorithm of Binary Tree

The mathematician John von Neumann designed a sorting algorithm, nowadays called merge sort (Von Neumann, Kurzweil, 2012) which is amongst the most widely taught sorting algorithms because it epitomizes the important solving strategy known as divide and conquer: the input is split; each non-trivial part is recursively processed, and the partial solutions are finally combined to form the complete solution. Whilst merge sort is not difficult to program, determining its efficiency, by means of a cost function, requires advanced mathematical knowledge. The algorithm was based on merge sort classification (Knuth, 2000).

The merge sort function in classification algorithm is useful in online sorting, where the list to be sorted is taken item by item, rather than taken in its entirety from the beginning. In this application, each new item that is received, is sorted by using any sorting algorithm, and then merge it into the sorted list using the merge sort function. However, this approach can prove to be accurate in time and space if the data is received in small chunks over the sorted list - a better approach in this case is to enter the data into a binary search tree at the time it is received.

The algorithm is as follows:
1) Initializing the variables:
"Level_1[20]" is the array that contains the 20 questions of the first level.
"Level_2[10]" is the array that contains the 10 questions of the second level.
"Level_3[6]" is the array that contains the 6 questions of the third level.
"Level_4[5]" is the array that contains the 5 questions of the fourth level.
"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.
"Levels[4,3]" is a two-dimensional array that contains the number of questions

and the correct answers of each level.
2) The order of the questions in each array (Level_1, Level_2, Level_3, Level_4) is randomized.
3) The first question of the first level is presented and based on the answer "Grade", "MaxGrade" and "Levels[4,3]" are altered appropriately.
4) In this loop, the subroutine is called:
4.i) For each level, it checks the ratio of the correct answers to the total of questions and if it is less than 0.5 then selects the specific level.
4.ii) If the ratio of all levels is greater than 0,5 then the following level of the previous question is chosen.
4.a) It shows the question from the level that was chosen.
4.b) Based on the answer, the variables "Grade", "MaxGrade" and "Levels[4,3]" are altered appropriately.
4.c) If "MaxGrade" is less than 100, the algorithm runs the same loop once more.
5) When "MaxGrade" is equal to exactly 100, the final "Grade" is shown and the algorithm ends.

1.3 Questionnaire

This questionnaire was based on Mathematics, under the supervision of Mathematical Scientists, and on specific chapters. However, the following questionnaire can be implemented with the same algorithm and the integrated predictive model in all courses with similar questions.

	Questions		Questions
1.a	What is the commutative property of the prosthesis?	1.k	Factorize the expression: $(x-1)(x^2-9)-(x+3)(x^2-1)$
1.b	Complete the equation: $a^m a^n=$	1.l	If $x=-\frac{2}{3}$, calculate the value of the expression: $A=9x^3-3x^2-5x-1$
1.c	If $\frac{x}{y}=2$, calculate the value of the expression: $A=\frac{(x^3y^{-2})^2(x^3y)^{-1}}{(x^2y^{-1})^{-2}}$	1.m	If $\frac{55^v 3^v}{33^v}=225$, find the value of v
1.d	If α, b positive numbers, then $\sqrt{a}+\sqrt{b}=\sqrt{a+b}$	1.n	If we double the side of a square, how many times does its area increase?
1.e	Calculate the expression: $\Delta=\sqrt{21+2\sqrt{1+\sqrt{9}}}$	1.o	Calculate the expression: $\sqrt{2}\sqrt{8}+\sqrt{36\cdot 121}$
1.f	Solve the equation: $\frac{x\sqrt{5}}{\sqrt{2}}=\sqrt{8}$	1.p	Convert the following fraction that has an implicit denominator to an equivalent fraction with an explicit denominator. $\frac{6}{\sqrt{48}}$
1.g	Do the arithmetic operations: $(-2x2)^3+(-x3)^2+7x^6$	1.q	This number is given $a=\frac{3\sqrt{2}\sqrt{6}+\sqrt{6}\sqrt{8}}{\sqrt{5}\sqrt{15}}$ and $a=2$
1.h	Find the numerical expansion: $(\sqrt{2}+\sqrt{5})^2$	1.r	These polynomials are given $A(x)=x^3-3x^2-3x$ and $B(x)=2x^3+3x^2-2x+1$ Find the polynomial: $\Delta(x)=A(x)-B(x)$
1.i	Do the arithmetic operations: $\frac{1}{(2-\sqrt{3})(2+\sqrt{3})}$	1.s	Do the arithmetic operations: $1-(2x+1)(5x-3)$
1.j	Calculate the polynomial: $P(x)=(x-1)^2-(3x-2)^2-2x(5-4x)$	1.t	These polynomials are given $P(x)=x^3-3x$ and $Q(x)=x^2-2$ Find the product of: $P(x)\cdot Q(x)$

Table 12: First level questions

	Questions
2.a	Find the numerical expansion: $(-3x-5)^2$
2.b	Find the numerical expansion: $(11x^2y-12w^3)(11x^2y+12w^3)$
2.c	If $x-\frac{1}{x}=-2$, calculate the expression: $x^2+\frac{1}{x^2}$
2.d	If the numbers x, y are inverse, calculate the expression: $A=(x+2y)^2 - (2x-y)^2 + 3x^2 - 3y^2$
2.e	This polynomial is given $A(x)=(x-1)(x+1)(x^2+1)-(x^2-1^2)$ Find its value
2.f	Factorize the expression: $4x^2(x-2)-12x(x-2)+9x-18$
2.g	Calculate the value of the expression: $A=55\cdot 87 - 55\cdot 32 - 45^2$
2.h	Factorize the expression: $(x-1)^2 - 6(x-1) + 9$
2.i	Factorize the trinomial: $x^2 - 6x +8$
2.j	Simplify the expression: $\frac{x^2-4+x(x-2)}{2x^2-8x+8}$

Table 13: Second level questions

	Question
3.a	Characterize the following equation in terms of its correctness: $\frac{x+2y}{z+2y}=\frac{x}{z}$
3.b	Find the product: $\frac{x^2-1}{x^2-3x}\cdot\frac{x^2-9}{3x-3}$
3.c	Do the arithmetic operations: $\frac{y}{y-1}\cdot\frac{y^2-36}{y+1}\div\frac{y+6}{y+1}$
3.d	Calculate the expression: $\frac{3x}{x-1}-\frac{x+2}{x-1}$
3.c	Calculate the expression: $\left(1-\frac{2x}{x^2+1}\right)\left(x+\frac{x+1}{x-1}\right)$
3.e	Solve the equation: $\frac{2x-1}{3}-\frac{x-2}{6}=x-2$

Table 14: Third level questions

	Questions
4.a	Solve the equation: 1-2x(x-1)=1-2x
4.b	Solve the equation: $(2x-1)^2 – x(x-1) = 2 + x^2$
4.c	Simplify the expression: $\frac{3x^2-5xy-2y^2}{9x^2-y^2}$
4.d	Solve the equation: $\frac{1}{x^2-5x+6}-\frac{1}{x-3}=\frac{1}{x^2-4x+4}$
4.e	Solve the inequality: $1-\frac{2x-1}{6}<\frac{x-2}{3}-\frac{x}{2}$

Table 15: Fourth level questions

The questionnaire consists of questions of four different levels for self-assessment in Mathematics. The whole cognitive background for the specific course is examined prior to the final exam, which allows the students to improve their performance, while the institutions can extract useful educational results. The questionnaire consists of questions in random order for each student, in order to prevent, as far as possible, cheating in the test and for the grades to remain objective. The answer types are 3: multiple-choice, right/wrong, and open text. In the digital classroom, these intelligent systems predict the results of students' grades with great accuracy, aiming at optimizing personalized learning.

2. Mathematical Analysis

The intelligent decision system first solves two important problems, and their solutions are defined below, in order to predict the number of different outputs provided by the system.

Problem 1: There are 4 levels of questions: level 1 contains l1 = 20 questions of value 1, level 2 contains l2 = 10 questions of value 2, level 3 contains l3 = 6 questions of value 3 and level 4 contains l4 = 5 questions of value 4. Let S20 be the number of question sets that can be formed such that the total value of questions equals 20. If k1, k2, k3, k4 is the number of questions selected from levels 1, 2, 3, 4 respectively, then it is clear that these numbers satisfy.

k1 + 2k2 + 3k3 + 4k4 = 20 (1)

Moreover, there exist $\binom{l_i}{k_i}$ ways to choose ki questions from level $i \in \{1,2,3,4\}$
More formally S20 is the number of partitions of 20 into parts no greater than 4, where
ki counts the number of parts equal to i and each partition of type (k1, k2, k3, k4) has weight

$$w(k_1, k_2, k_3, k_4) = \prod_{i=1}^{4} \binom{l_i}{k_i}$$

For example, a valid partition is 1+ 1+ 1+ 3+ 3+ 3+ 4+ 4 = 20, its type is (k1, k2, k3, k4) =
(3, 0, 3, 2) and it corresponds to w(3, 0, 3, 2) different question sets. Each such question set
contains 3 level 1, 3 level 3 and 2 level 4 questions. Note that these questions can be
ordered in $\frac{(k_1+k_2+k_3+k_4)!}{k_1!\,k_2!\,k_3!\,k_4!}$ different ways but, under the above definition, the order of
the questions is irrelevant, since S20 counts question sets and not question lists. Therefore

$$S_{20} = \sum_{k_1+2k_2+3k_3+4k_4} \prod_{i=1}^{4} \binom{l_i}{k_i} = [x^n] \prod_{i=1}^{4} \sum_{k\geqslant 0} \binom{l_i}{k_i} x^{ik_i} = [x^n] \prod_{i=1}^{4} (1+x^i)^{l_i}$$

Denote by f(x) the product of the last equality, i.e.,

f(x) = (1 + x)20(1 + x2)10(1 + x3)6(1 + x4)5

It follows that:

S20 = [x20]f(x) = 2845201114

The above coefficient is easily computed using any symbolic computation system.

Problem 2: In the above solution, zero values were allowed for any of the ki’s. But what if each question requires that at least one question from every lower level is contained in the solution? Let S'20 denote the number of solutions in this case. In order to solve this problem, it is defined:

$$f_i(x)=\prod_{j=1}^{i}\left((1+x^j)^{l_j}-1\right), i\in\{1,2,3,4\}$$

so that the coefficient of x20 in fi(x) equals the number of solutions containing questions of maximum level i. Then, it can be calculated as before,

[x20]f1(x) = 1,

[x20]f2(x) = 109208162,

[x20]f3(x) = 1158309895,

[x20]f4(x) = 1061692900

and

S'20 = [x20](f1(x) + f2(x) + f3(x) + f4(x)) = 2329210958.

3. User Interface Design

The user interface of the application was created with the aim of being user-friendly and providing flexibility and adaptability to the needs of students. A self-assessment provides a clear picture of the student's preparation for the lesson. By using the application, the student knows in advance his performance and his rate of self-improvement. The goal is to reduce the percentage of students who drop out or repeat the course, which is time consuming and costly. The assessment begins by tapping on the icon of the app (Fig. 33).

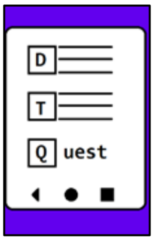


Figure 33: Icon of the app

In the beginning, the ID of the certificated student is checked (Fig. 34) by typing the PIN, which ensures the identification, and the timer of the process is initialized.

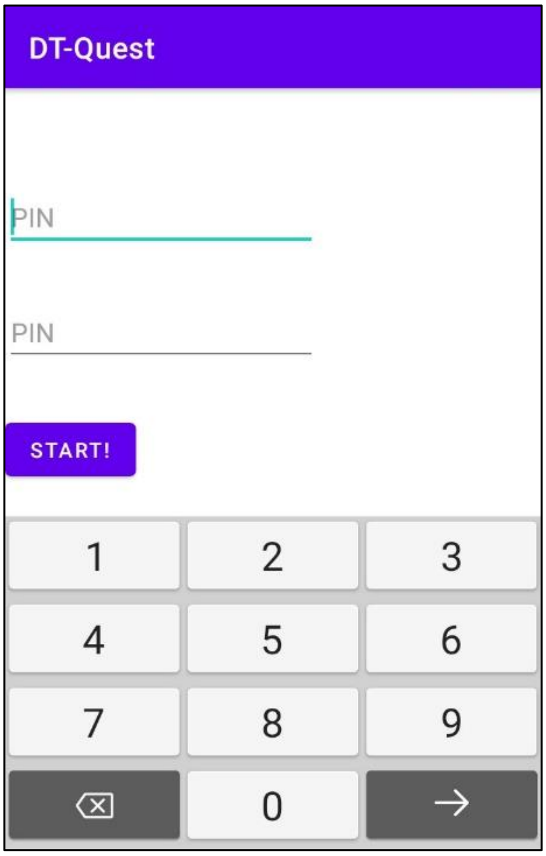


Figure 34: The login screen

The remaining time is presented on all pages of questions, on the upper side of the screen. The following 3 Figures (from 35 to 37) correspond to the 3 types of questions that were implemented.

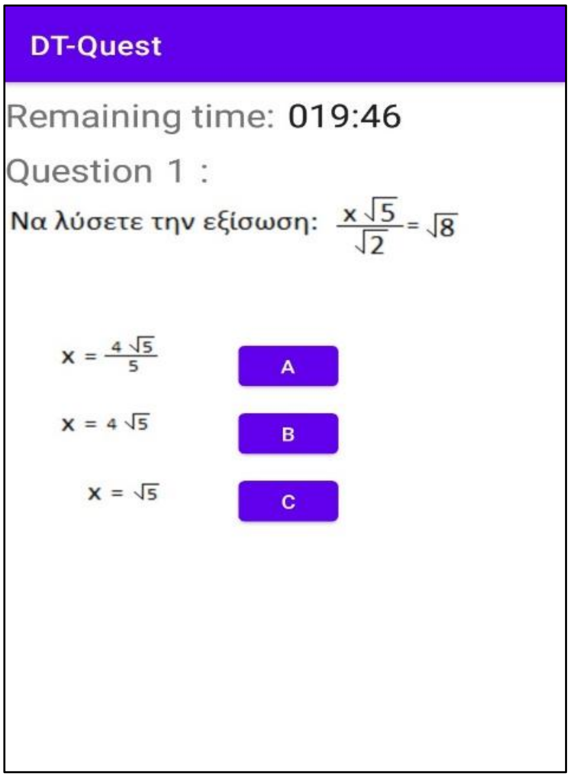


Figure 35: A multiple-choice question

Figure 35 shows a multiple-choice question, with 3 choices, whereas an open-ended question is demonstrated in Figure 36, where the students can write text for the answer.

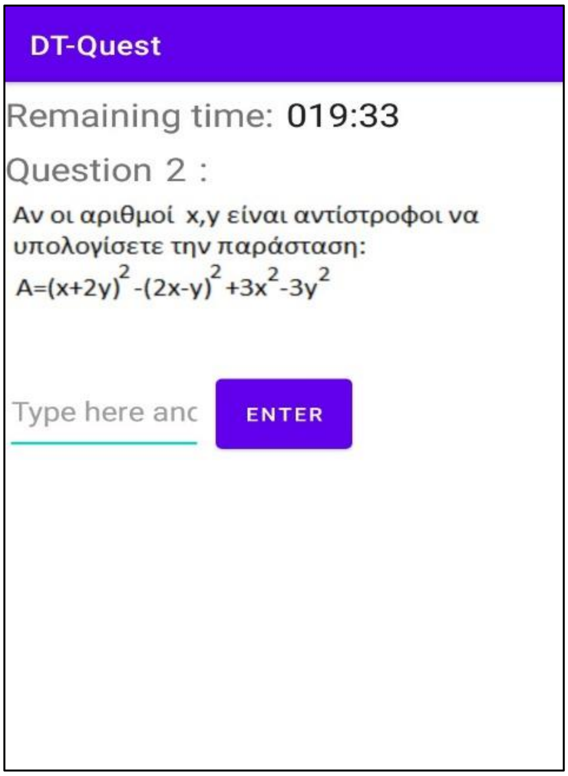


Figure 36: Open-ended question

The 3rd type of question, a True or False question, is displayed in Figure 37.

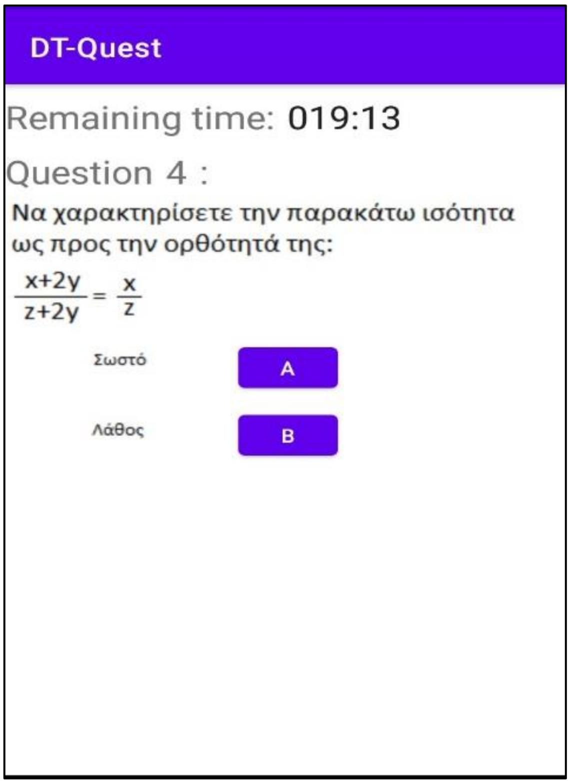


Figure 37: A true or false question

The final score is calculated instantly and disclosed on the last page, without any delay (Fig. 38). The benefits to the students appeared when the application was widely used in 6 Greek schools. Before each competition they knew their performance which was proportional to the study.

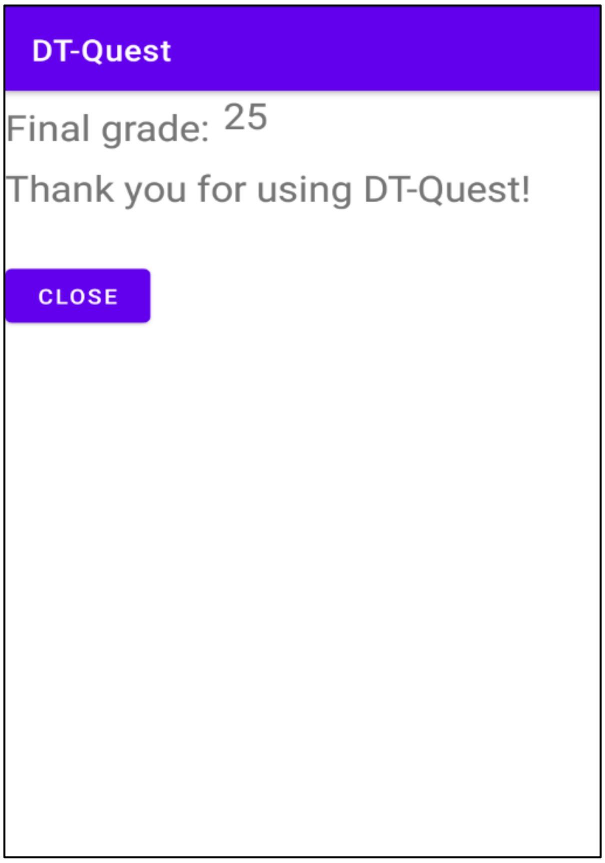


Figure 38: End of self-assessment

The exercises were given to 177 Mathematics students from 6 Greek schools, with a questionnaire for evaluation. The results were encouraging when asked whether they liked the application with a percentage of yes 97.17%. The next question is whether their performance was improved with a percentage of yes 96.61%, whether it was easy to use with a percentage of yes 98.87% and whether they would recommend it to others with a percentage of yes 96.04%.

3.1 Assessment of Application

The table below shows the questions that participants were asked to answer in order to evaluate the application. Also, the specific table refers to the percentages of positive and negative responses.

Q1	Do you like the application?	Yes: 97.17%	No: 2.83%
Q2	Was your performance improved?	Yes: 96.61%	No: 3.39%
Q3	Was it easy to use?	Yes: 98.87%	No: 1.13%
Q4	Would you recommend it to others?	Yes: 96.04%	No: 3.96%

Table 16: Assessment of the application (percentage analysis)

The resulting system was presented to and evaluated by students, through the completion of questionnaires.
The quantitative analysis follows:

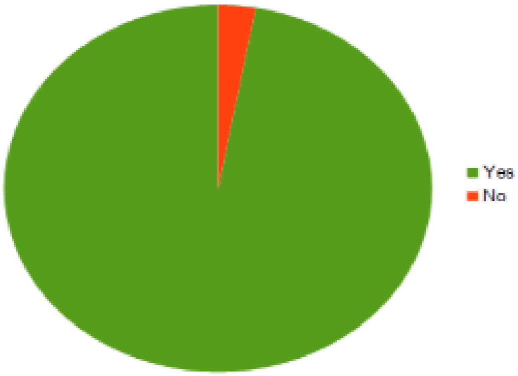
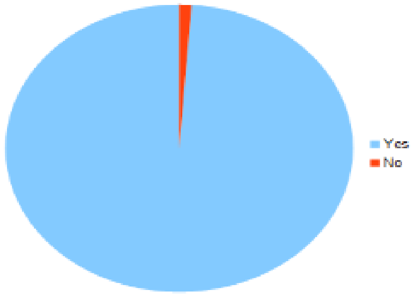
Q1	Do you like the application?	Yes: 172 No: 5	
Q2	Was your performance improved?	Yes: 171 No: 6	
Q3	Was it easy to use?	Yes: 175 No: 2	
Q4	Would you recommend it to others?	Yes: 170 No: 7	

Table 17: Quantitative analysis

Subsequently, by analyzing the enthusiastic results, the utilization and feasibility of the application were confirmed. Such an application can find space in learning environments for students' personalized needs. The use of analytics improves the overall learning design quality and helps educators avoid committing design errors.

4. Discussion

As online and blended learning have 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 Ph.D. thesis 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 the proposed system (Matzavela, & Alepis, 2021) impressed the students. This was rather expected, since the 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 the system by the students. Indeed, the 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 levels.

The main aim of this system is the prediction of students' academic performance before/after the final exams through intelligent decision systems. Before the exams, the self-assessment provides to students’ enhancement of their performance while focusing on the difficult study points. After the exams, each institution determines the individual profile of the student and his/her knowledge needs in digital class and m-learning environments.

The specific app focused on Mathematics, while it could be useful for all lessons with the appropriate parameterization of the questions. (Virvou et al., 2013) The structure of the system has been supported by a mathematical analysis where the number of combinations of random questions is analyzed. Due to the vast number of combinations of questions, the risk of students cheating in the exam is minimized.

According to the paper (Matzavela, & Alepis, 2017), the major percentage of learners of all different age groups prefer adaptive learning in a physical class, whereas digital education influences the students' attributes and the dropout in courses. For the above reasons, digital classroom learning needs to be optimized at the classroom and examination level. The paper (Matzavela, & Alepis, 2021) states that the decision tree method has various advantages: It is simple to understand and interpret, it is easy to display graphically, and it is capable to handle both numerical and categorical data.

The implementation of this app in digital education has been evaluated by students with excellent results. The present study offers improvements in students' self-assessment, which positively affects their performance, and reduces rejections in a course by institutions. This application can be integrated into online learning, such as mobile learning, hybrid learning or blended learning. aiming for an intelligent decision system with a predictive model that accurately predicts a student's optimal grade.

Subsequently, the DT-Quest 2 app was created according to the above benefits for students and institutions for m-learning environments. Future studies could be based on intelligent decision systems, (a path of machine learning), which contribute to all fields of education as well as of economics, business, medicine, etc. Institutions, by focusing on studies that accurately predict student grades, enhance the quality of the studies they provide, and minimize dropout of courses.

The evidence provided to support the above claim is the architecture of a system that includes the creation of a decision tree algorithm that achieves the optimization of the results in exams and the utilization of them on behalf of the institutions. The specific assessment focused on Mathematics, while it could be useful for all lessons with the appropriate parameterization of the questions.

The system was created according to the benefits for students and institutions for m-learning environments. Future studies could be based on intelligent decision systems, a path of machine learning, which contribute to all fields of education as well as others, for example, economics, business, medicine, etc.

Conclusions And Contribution to Science

Researchers increasingly use technological advancements emerging from learning analytics to support digital education, whereas a surprisingly big interest has the global community for adaptive learning in the online educational systems. Learning analytics can be employed to provide educators with information to reflect on their patterns of students' behavior concerning others, or to identify students requiring extra support and attention, or to help teachers plan supporting interventions for functional groups such as course teams. Given the above, this paper employs learning analytics and presents the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs. The conclusions that are drawn by the system concerning the aspects of students' characteristics seem to be satisfactory and valid and can be utilized for the enhancement of personalized education.

In this Ph.D. thesis, the utilization of m-learning, on days of the pandemic COVID-19 and afterward, is presented. This approach discusses important research issues such as: to maximize the educational benefits of distance learning, while based on the needs and preferences of individual learners. The aspects of m-learning were analyzed extensively, including unique features, and the data generated a set of parameters of m-learning. The most important parameters are gender, usefulness, acceptance, perceptions, mixed methods, social media, interaction, ease of use, behavior, and attitude. Each of these parameters is presented and analyzed separately in this paper and it is focused on the synthesis of the questionnaire for extracting specific results. The major percentage of learners of all different groups prefer adaptive learning in a physical class, whereas digital education influence the student's attributes. It is within the future of authors to create a dynamic questionnaire for self-assessment or student academic performance with random tests supported by decision tree learning. The benefits of the above approach could be effective in the individualization of m-learning according to students' features, the limitation of drop out and the concretization of a predictive model, which categorizes the answers of each student, to be able was incorporate in an algorithm for tutoring systems.

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 created algorithm, 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.

The growing digitization, personalization, and internationalization of education launch the demand for applications for students and institutions, which drive the development and evolution of digital learning.

The learning problems: classification, regression, recognition, and prediction are a challenge to intelligent systems. Predicting the results and especially the grades of students in the digital classroom tends to be required with great accuracy for 2 important reasons: for more objective performance and reduction of students who drop out.

New technological environments for education have been on the rise which influence the further support of the students' profile. Their impact on students' competencies, such as the ability to adapt to new situations, oral and written communication, autonomy, teamwork, creativity, critical thinking, brings about great changes in distance education.

According to the paper (Matzavela, & Alepis, 2017), the major percentage of learners of all different age groups prefer adaptive learning in a physical class, whereas digital education influence the student's attributes and the dropout of courses. For the above reasons, digital classroom learning needs to be optimized at the classroom and examination level, while students have called for more personalization and digitization at all courses.

The paper (Matzavela, & Alepis, 2021) refers that 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.

The implementation of this Ph.D. thesis in digital education has been evaluated by students with excellent results. These novel approaches offer improvements in students' self-assessment, which positively affect their performance, and reduce rejections in a course by institutions. These applications can be integrated into online learning, such as mobile learning, hybrid learning or blended learning. aiming for an intelligent decision system with a predictive model that accurately predicts a student's optimal grade.

- **Further research**

This Ph. D. thesis describes a novel approach to effective learning for each student that automatically predict the learner's assessment, allowing her/him to complete the educational program in her/his own abilities and pace.

The encouraging results of the application and implementation of the particular approach to an integrated m-learning environment, motivate the implementation of the predictive model to educational environments of other knowledge domains, also. Therefore, future work includes the development of a predictive algorithm, which will allow the construction of m-learning courses of any knowledge domain that will integrate the adaptation and learners' knowledge and their individual needs of the presented approach.

Furthermore, as it is referred in the conclusions, the presented predictive model is applicable to systems in which the user’s changeable state and/or preferences are affected by the existing dependencies among the system’s elements (like concepts, preferences, choices). Consequently, the proposed decision system can be extended to provide the ability to construct modules, which integrate the presented novel approach for adaptive systems (like smart cities).

Another interesting field of further research is to extend the presented novel predictive model making it possible to model students' behavior and learners’ emotions, also. Motivation, self-assessment, and characteristics of the student affect the learning process and the student’s performance.
Therefore, it would be very interesting to add more predictive modeling techniques to the presented approach in order to model more learners’ aspects.

Furthermore, the integration of Artificial Intelligence is an interesting prospect for future work. The integration of AI into the presented predictive model will allow the system to learn about the learner’s cognitive states, decrease the dropout, the transitions between them, and the reasons for these. In other words, the decision system will simulate the thinking and decision-making processes of an expert.

Thereby, the system will be able to make more valid adaptation decisions on individual criteria.

The contribution of this research to science is described below:

- **Contribution to AI**

  AI embodies a heterogeneous set of techniques and algorithms. Various applications and techniques fall under the broad umbrella of AI, ranging from neural networks to speech/pattern recognition, to genetic algorithms, to machine learning (algorithms that enable systems to learn). Enormous amounts of data are available for model training. The quality and the scale of the datasets are the determinants of the robust performance of prediction/classification. Researchers devote efforts to designing and carrying out exhaustive experiments to collect real-world data, representing typical working conditions. In this process, the types of variables and how the data are measured constitute a part of the intellectual inputs by humans. Publicly available datasets function as a baseline for defining AI challenges and for fair comparison of novel AI algorithms. Machine Learning shows superiority in the following aspects. In this Ph.D. thesis, the datasets of learners' assessments can be evaluated for optimizing AI algorithms.

  The integration of Artificial Intelligence is an interesting prospect for future work. The integration of artificial intelligence into the presented prediction model allows the system to learn about the student's cognitive states, reduce dropouts, transitions between them and the reasons for them. In other words, the decision system will simulate the thinking and decision-making processes of an expert.

  Thus, the system will be able to make more valid adaptation decisions based on individual criteria.

- **Contribution to Intelligent Decision Systems**

  Intelligent Decision Systems are a path of Machine Learning, which instructs the datasets and contributes significantly to adaptive learning. A decision tree algorithm achieves the optimization of the results and the utilization of them on behalf of the institutions. Learning analytics by decision tree algorithm can be employed to provide educators with information to reflect on their patterns of students' behavior concerning others. Methods for generating decision trees from data, allow for a tree-shaped representation of the learning results, 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. In the area of machine learning and data science, decision tree learning is considered 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.

- **Contribution to Predictive Model Algorithms**

  Predicting Algorithms instruct the systems for the representation of the learner's knowledge, which is usually performed as a subset of the knowledge domain. However, the representation of the learner's knowledge is a moving target. The student's knowledge level of a domain concept usually is affected by her/his knowledge level of other related.

  The novel predictive model has been structured into a binary tree that follows a specific path and can predict the last levels of the algorithm, extracting safe results. The implementation of this predictive model is available to maximize the educational benefits of distance learning, while based on the needs and preferences of individual learners improving educational quality, which is vital in attracting students. Supplementally, can be expert in all knowledge aspects and other domains e.g., meteorological predictions, consumer behaviors, smart cities.

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Appendix

Papers that were published during the elaboration of my Ph.D. thesis:

- **In International Journals**

Matzavela, V., & Alepis, E. (2023). An application of self-assessment of students in mathematics with intelligent decision systems: questionnaire, design and implementation at digital education. Education and Information Technologies, 1-16. Springer

Matzavela, V., & Alepis, E. (2021). Decision tree learning through a predictive model for student academic performance in intelligent m-learning environments. Computers and Education: Artificial Intelligence, 2, 100035. Elsevier

Matzavela, V., & Alepis, E. (2021). M-learning in the COVID-19 era: physical vs digital class. Education and Information Technologies, 26(6), 7183-7203. Springer

- **In International Conferences**

Matzavela, V. (2019). M-assessment: Dynamic questionnaires and decision trees in the background. In 2019 1st Summit on Gender Equality in Computing (ACM).

Matzavela, V., & Alepis, E. (2017, August). A survey for the evolution of adaptive learning in mobile and electronic devices. In 2017 8th International Conference on Information, Intelligence, Systems & Applications (IISA) (pp. 1-5). IEEE.

Matzavela, V., Chrysafiadi, K., & Alepis, E. (2017, April). Questionnaires and artificial neural networks: a literature review on modern techniques in education. In 2017 IEEE Global Engineering Education Conference (EDUCON) (pp. 1700-1704). IEEE.

- **Number of citations per paper**

M-learning in the COVID-19 era: physical vs digital class - Citations: 69

Decision tree learning through a Predictive Model for Student Academic Performance in Intelligent M-Learning environments - Citations: 32

Questionnaires and artificial neural networks: a literature review on modern techniques in education - Citations: 9

A survey for the evolution of adaptive learning in mobile and electronic devices - Citations: 7