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A Combined Model for Prediction of Financial Software Learning Rate based on the Accounting Students' Characteristics

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ABSTRACT

The accounting software is considered to be of the most critical components of accounting information system, with particular significance as of accounting and financial systems. the most important problems with accounting education systems is that students do not adequately learn the financial software required by the accounting profession, which, in turn, reduces the credibility and position of the accounting profession. That the main objective of accounting software education is to educate skilled and expert accountants to enter the accounting profession, which is considered as of the success factors of country's economy. In this study, employ data mining techniques to investigate the accuracy, precision, and recall performance measures and to predict the rate of financial software learning based on accounting students' emotional intelligence (EI), gender and education level. Accordingly, a machine-learning-based multivariate statistical analysis is performed on 100 Iranian accounting students. The results show that emotional intelligence has the most impact on the rate of financial software learning among the variables. Gender and education level were influential. Also, among the five algorithms, the highest precision and recall are achieved by both Decision Tree and XGBoost and are presented as the most appropriate models for the prediction rate of financial software learning.

1 Introduction

Today, the accounting unit in each organization is considered as its heart, and accountants must convert all financial events into numbers and figures through accounting software and record and report them as business unit information to the users for making economic decisions. Therefore, learning financial software and obtaining the necessary professional skills is of great importance for accounting students

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during their education [12]. Since the number of graduates of accounting is increasing, there is a high need for skilled people who are in line with the needs of the professional accountant community and also enjoy the necessary education and skills for employment in the related professions. The surveys show that most accounting graduates, at the beginning of their career, lack the necessary skills to work with financial software and cannot meet the needs of employers and the labor market [2]. Upon their hire, professional institutions have to retrain these individuals to do the work. While all of them have passed computer application in accounting, practically and theoretically, they need to be able to work effectively with financial software [8]. Research shows that in most cases, many graduates cannot deal with work issues after entering professional positions.

In a study by Sanden and Teurlings [7], it was found that the graduates did not have the necessary skills to do their job in a professional position, and they could not implement the skills they had learned well in a work environment and could not meet the employers' needs either [7; 14]. Indeed, the lack of financial accounting software learning by accounting students leads to a decrease in the quality of educational content in accounting, and thus gradually reduces the value of an education in accounting and the students' interest in the field [7]. It also gives rise to the mission of updating the education quality of accounting. Currently, the credibility of universities and professors of accounting is being questioned by the professional accounting world since accounting graduates are leaving school without the necessary skills to work with financial software [6]. Albrecht and Sock [2], in their study, concluded that one of the most important problems in accounting education is that students do not adequately learn the financial software required by the accounting profession [2]. Wallace and Clariana [27] conducted another study titled "Determining the Accounting Students' Computerial Skills Rates." In this research, the skills of accounting students when working with financial software were measured. Based on the results, it was found that the mean scores of the students were significantly lower than the limit of mastery, and the students did not have the knowledge and computer skills to work with industry-specific financial [27]. Undoubtedly, there are numerous individual and educational reasons for accounting students to attain the skills necessary to work with financial software. One of the most controversial theoretical supports for teaching and learning, especially in the area of learning the financial software that has been neglected, is intelligence approaches. For many years, researchers believed that intelligence plays a vital role in learning and academic achievement [10]. But in the last decade, they have found that the sole indicator of measurement of an individual's success is not IQ, but EI. Emotional Intelligence is an effective and determinant factor in real life events, such as success in university and education, career and social relationships [11], because EI is often cultivated and can be developed for various purposes such as education, planning, and behavioral patterns. Therefore, EI, as a personality characteristic, is effective in increasing the learning capacity of individuals [12]. Most research about EI also shows that there is a significant association between this variable and learning and academic achievement. For example, in a study conducted by Lyons and Schneider, it was concluded that higher EI leads to greater learning [20].

Also, studies by Jeon Sang et al. [33] showed that for students at Shanghai University, EI has an impact on academic performance. Thomas, Fabio, Reinhard, Kou, & Andrew also concluded in their paper that EI affects learning. According to Goleman an outstanding psychologist and EI expert, about 80 percent of the reason for success can be attributed to EI [15]. Accounting students should spend a major portion of their educational period in operational settings. A vast majority of profesional competencies expected from accounting students are covered by EI-related skills [10]. Proficiency in working with computers and specialized accounting software are such skills that are essential for any accounting student [10, 13].

On the other hand, Research shows that accountants, as human beings, express their particular behavior and reactions in learning and making various financial decisions, whose interpretation is possible through psychological theories. Therefore, the wide range of learning areas, including the rate of learning of financial software by students, cannot be studied without considering human behavior [5]. However, studies exploring the role of EI in accounting professionals, especially in accounting education settings, are rare. Considering that, based on the results of numerous studies, EI is the most significant factor in predicting individual performance in different educational, occupational, and social fields. We intend to, use the data-mining techniques and artificial intelligence algorithms, present a model that can predict the impact of the behavioral variable of EI, gender, and academic grade on the target variable, i.e., the student’s rate of learning of financial software.

Predictions must be performed with the highest accuracy so that, by measuring EI, gender, and grade, it becomes possible to estimate the rate of learning of financial software with high precision. Obviously, achieving this model using powerful algorithms can be a milestone in employing experts in the accounting departments, or in the selection of auditors, tax and insurance agents in various financial projects for managers. For example, if the level of expertise, practical skills and software capabilities based on input attributes such as EI, gender, education level, etc. are assessed at the beginning of an accountant’s recruitment, the proposed model can predict the efficiency according to system requirements and labor market conditions [26]. It is claimed by Strenberg to say that cognitive capacity is insignificant to scientific achievement would be ridiculous. Such skill requires a relatively high standard to be accepted to a graduate science program at a university .Recently, emotional intelligence (EI) has won an important place in the academic and scientific circles [24]. Emotional Intelligence (EI) comes up with a new pattern which would help educationalists to better understanding and corelating success and educational environment [16]. The obtained results of Reuven Bar-On showed that emotional intelligence is an effective predictor of an employee's career and personal life. He suggested a 5-point scale of emotional intelligence, which looks at the quality of each of the five components of emotional intelligence as follows: intrapersonal skills, interpersonal skills, stress control, the ability to adapt and general mood [34]. In general, Bar-On claims that emotional and cognitive intelligence, both contribute equally to one's overall success in life. In recent years, it has been found that academic success is influenced by such variables as family, school, society, and the environment [23]. Educational experts and psychologists have highlighted the relationship of EI and students’ academic performance. The relationship between EI and educational achievements has been evaluated in many countries. Many studies have reported a close relationship between EI and academic performance [6, 8-12]. However, studies exploring the role of EI in accounting professionals, especially in accounting education settings, are rare.

Accounting students should spend a major portion of their educational period in operational settings. A vast majority of profesional competencies expected from accounting students are covered by EI-related skills [10]. Mentioning the importance of EI in academic performance, it would be promising to prevent the students’ future educational problems by efficient planning to reduce deficiencies and develop the required capacities. EI can be improved throughout life through participation in related educational courses and learning the relevant skills. To achieve this, we have tried to prioritize the variables affecting the rate of financial software learning by using a new combined method, including data mining techniques and artificial intelligence algorithms. It should be noted that although the study of the relationship between EI and learning in developed countries has a relatively long history, the simultaneous study of this relationship in the field of learning financial software among accounting students using data mining and Artificial Intelligence classification algorithms provides the researchers with a unique combination that has so far been explored only in a limited scope [1]. Due to advances in technology, Traditional data techniques cannot analyze vast amounts of data.Therefore data mining is a process can discover patterns and rules underlying the enormous amounts of data [18]. Developing data mining algorithms attracted significant attention that could be applied to various fields such as crime detection, risk scoring, fraud detection, bankruptcy prediction, and market analysis. On the other hand, a few studies have addressed the problems of the learning process in financial software among accounting students using artificial intelligence algorithms and data mining methods in developing countries [9]. Kirkods et al. [27] applied the ANN method to predict bank bankruptcy by assessing the effect of nine financial variables on financial health and reached a 93% prediction strength. Boyacioglu, Kara, & Baykan [28] applied the data mining method and designed a model in predicting bankruptcy in banks. By applying the Genetic algorithm, Shin [29] developed a model that identifies and ranks the factors leading to a financial crisis in organisations, Huang et al. [30] assessed the credit risk of two Korean and American companies by applying Vector Support Machine, a learning machine, where five types of ranking are of concern [30].

However, reviews of the authors of this paper, no study is reported in the literature of developing countries to identify and prioritise role of individual accounting students' features to predict their financial software learning rate and there is a research gap in the field of accounting [18], To contribute to the above gap in the literature, this article seeks to bridge this gap in these countries. This research aims to investigate data mining techniques to extract potential knowledge using five classification techniques, namely, K-Nearest Neighbors (KNN), Decision Tree (DT), XGBoost, Random Forest (RF), and Support Vector Machine (SVM) by which we can predict the students' rate of financial software learning, taking into account their EI, gender, and level of education. In addition, in this study, we measure the accuracy of the available models for prediction and introduce a model with the highest accuracy as the main model. Based on the experiment results, we also seek to identify the most effective feature that affects the students' learning rate of the accounting software. The rest of this paper is organized as follows: In section 2, we take an in-depth look at the theoretical foundations of EI and its definitions; to develop the theoretical foundations of the subject, EI patterns, features, and components of each model are defined and interpreted. In section 3, the role of EI in learning financial software is explained. In section 4, we explain the data mining and artificial intelligence algorithms used in this paper, software and presents the methods of research. Section 5 discusses the prediction results conducted to identify significant features and data mining techniques. Section 6 expands the conclusions and a few recommendations for future studies.

2 Literature Review and Hypotheses Development

2.1 Multidimensional View of Emotional Intelligence

The term "emotional intelligence" was introduced by Mayer and Salovey to psychology literature [24]. They define emotional intelligence as the "the ability to perceive emotions, to access and generate emotions to assist thought, to understand emotions and emotional knowledge, and to regulate emotions reflectively to promote emotional and intellectual growth" [16]. Mayer et al.consider EI as a mental ability, and believe that cognitive and emotional structures work in an integrated manner [22]. The ability to identify and understand emotions and reasoning through them, as well as the ability to control emotions in oneself and others, are the set of abilities that determine the EI of each individual. In their latest definition of EI in 1997, they cited four basic components of EI that include:

- ✓ Perceiving, evaluating, and expressing emotions.
- ✓ Emotional facilitating of thoughts.
- ✓ Understanding emotions and applying emotional awareness.

- ✓ Regulating emotional reaction in order to promote emotional and rational growth.

EI refers to the underlying aspects of an individual's behavior that are entirely different from their intellectual and thinking abilities. [21] Defined EI as an array of non-cognitive skills, abilities, and competencies that affect one's ability to cope with the demands and environmental pressures [21]. Goleman considers EI as a collection of inner elements (level of self-awareness, sense of independence, self-actualization, and decisiveness) and external elements (interpersonal relationships, empathy, and sense of responsibility), and refers to the individuals' capacity to accept facts and to be flexible, and their ability to solve emotional problems and other issues and to deal with stressful events [15]. Mayer believes that EI is a type of mental capacity for giving meaning and application of emotional information. People, in this case, have different capacities. Some are moderate, and others are expert. Part of this capacity is instinct, and another part is the result of what emanates from experiences. This is the second part, which can be promoted by effort, practice, and experience [22].

EI definitions, despite their diverse appearances, all emphasize on a fundamental axis, including awareness of emotions, their management, and their use for academic, professional, and familial achievements. The measurement criterion of EI is its coefficient, and it indicates the ability, capacity or skill of perceiving, measuring, and managing the emotions of oneself and others. One can never predict personal EI solely based on intelligence and academic talent. IQ or educational intelligence is the ability to learn. As an example, IQ at age 15 is exactly as likely to be at age 50, while EI is a flexible and interchangeable skill that can be taught and learned. Over the past few decades, the concept of EI has been introduced in theoretical background and psychology research as a construct that relates to the various behaviors of humans in different environments. Sternberg believes that "we find people who have succeeded in their education and failed in their jobs, or those who have failed in school but succeeded in their work. We see people who get high scores in their intelligence tests but lack skills in their social interactions, and we find people who get lower scores in their intelligence tests but are efficient in practical tests. The general public also differentiates between educational intelligence and practical intelligence (familiarity with life's conditions)" [32].

On the other hand, Studies Amado-Alonso et al. have shown that students who practiced organized sport had better abilities at the intrapersonal and interpersonal level, better adaptability and mood states, and greater emotional intelligence than those who did not. The findings regarding gender and age indicated greater values in girls of emotional intelligence, highlighting the interpersonal dimension, as well as mood state scores, whereas younger studentsshowed greater intrapersonal intelligence and less stress management [4]. EI is concerned with knowing oneself and others, communicating with others, adapting to the surrounding environment that is necessary for success and is considered as a tactical capability in individual performance [27]. Zhange et al. concluded in their paper that individuals with higher EI have the most power of automatic processing of emotional information and tend to have strong critical thinking skills—both factors that can affect the individuals' rate of [34]. Researchers such as Razeghi, et al. believe that emotional intelligence (EI) is a better predictor of a person's success in life than intelligent quotient [28]. On the other hand, a group of EI studies points to gender differences and internal and external abilities derived from EI in men and women. Studies have shown that women's ability to express emotions and empathy is greater than men's; also, in interpersonal relationships, their level of attention to the emotions of other people is greater, and this attention to the emotions of others can be an effective tool in their learning [20]. The findings of AL-Qadri et al. showed that Emotional Intelligence (EI) is essential attribution among school learners of today. In this respect, determination and normalization of the measures to investigate and recognize dimensions levels help educators have a successful intervention and increase students' academic achievement level. The research findings suggested the final formulation of items of the

emotional intelligence scale that can measure the levels of emotional intelligence of students along with a significantly positive relationship to academic achievement. There were statistically significant differences in the respondents' level of emotional intelligence according to the gender variable [3]. The findings of studies are different so that some of them, such as that of Saklofske et al. (2012) which showed that girls had significantly higher EI than boys. Results from other studies oppose those results and emphasize that there is no meaningful difference between the EI of women and men [29].
However, studies show that in addition to the relationship between gender and EI of individuals concerning learning, the level of education also has a profound connection with EI. Research shows that EI has a more effective role in the attainment of higher levels of education in individuals, especially in M.A and Ph.D. courses. The probable reason is that during this period, due to age, EI is higher than other factors, because this variable is an acquiring factor in which learning plays an important role [24].

2.2 Emotional Intelligence Models

EI includes ability and mixed models. In an ability model, EI is fully derived from mental ability and hence is called pure intelligence. In contrast, in a mixed model, EI is considered as a combination of mental abilities and personality traits such as optimism and happiness. Since these abilities are supposed to be half-independent, EI models are likely to vary among individuals; that is, one person may have a high ability in one subject, and a lower ability in another one, whereas another person may show a different pattern [4]. Currently, only John Mayer and Peter Salovey's EI model is presented. Mixed models of EI are presented with different concepts. In sum, the most influential models of EI are:

- ✓ Model of Mayer and Salovey
- ✓ Model of Goleman
- ✓ Model of Bar-On
- ✓ Model of Dulewicz & Higgs

In the following, we briefly describe these models. Mayer, Salvoy, and Carousou made a modified model of EI that examines EI operatively in two cognitive and emotional systems. It works in the form of a fully integrated pattern and consists of four components, each of which represents a class of capabilities that are organized according to the complexity and in a hierarchical manner. They are as following: Identifying the emotions, emotional facilitating of thoughts or use of emotions, understanding the emotions and organizing the emotions or emotional management. In the definition and model of Mayer and Salovey, EI has focused more on the biological and psychological aspects of emotions. EI, in this definition, refers to generalized social abilities that play an effective role in mental health [25]. The model's initial pattern also included three areas of abilities: assessment and expressing the emotion, in oneself, in both verbal and non-verbal dimensions; adjusting the emotion in oneself and others; and the use of emotions in thinking, action, and problem-solving [20]. Goleman's model introduces the components of EI as self-awareness, self-management, motivation, empathy, and social skill.
Self-awareness means "a deep and clear understanding of your feelings, emotions, needs and strengths and weaknesses." Individuals who have confidence and certainty about their feelings show more skill in directing and controlling the events of life and are accurate in their work [16]. Control of emotions in an appropriate way is a skill that is created after consciousness. Efficient people can better get rid of negative emotions such as frustration, anxiety, and irritability, and they are less likely to face difficulties in the ups and downs of life, and when faced with a problem, they can quickly return from a distressful and challenging situation to a favorable condition. Control of emotions for a particular purpose is the basis for the acquisition

of any kind of skill and success, and those who are able to persuade their feelings in a timely manner, in whatever they are entrusted, try to be productive and effective. Empathy is based on self-awareness. The more open we are to our feelings, the more we will be skilled in understanding the feelings of others [31]. Being skilled in managing our behavior and others' behavior to achieve the qualifications of leadership and persuading others. Bar-On model defines EI as "an array of non-cognitive (emotional and social) capabilities, competencies and skills that influence one's ability to succeed in coping with environmental demands and pressure." This model has five components as follows, with 15 factors affecting them. People who find more components in themselves have higher EI.

These five components are as follows: Intrapersonal skills examine the individuals' awareness of their feelings and ability to express them, beliefs and thoughts, and defense of their rights in a desirable manner. Intrapersonal skills include: Emotional self-awareness; courage; self-esteem; self-actualization and independence [30]. Interpersonal skills examine the individuals' ability to adapt to others and social skills and include: Interpersonal relationships: the ability to maintain satisfying mutual relationships with others. Empathy: awareness of others' feelings, as well as understanding and admiring those feelings. Social responsibility/social commitment: the individuals' ability to introduce themselves as useful members with a sense of cooperation in their social group.

Adaptability consists of three factors:

- Problem-solving: the ability to diagnose and define problems and apply effective solutions.
- Reality testing: the ability to assess the relationship between emotional experience and existing objectivity. [30].
- Flexibility: the ability to deal with one's emotions, thoughts, and behavior in different situations and conditions.

Stress management also includes two parts: Stress tolerance means the ability to withstand events and stressful situations, overcome difficult situations without succumbing. Impulse control also means the ability to delay impulses, accept aggressive impulses, be patient, and control the anger in individuals. General mood that Includes two modes: Optimism means the ability to have a life expectancy and a positive attitude toward daily life and happiness means enjoying oneself and others, and having a good feeling at work and in one's free time [4]. Final model is model of Dulewicz & Higgs. Based on their empirical research, Devoux and Higgs have identified the common axial elements in the overall structure of EI, which are:

- Self-awareness, awareness of one's personal feelings and ability to identify and manage them;
- Emotional flexibility, ability to do well and adapt to different situations;
- Motivation, energy, and incentive to achieve short-term and long-term goals and results;
- Interpersonal sensitivity, the ability to be aware of the feelings of others and to reach influential decisions in them;
- The ability to persuade others to change their viewpoints on one issue;
- Acumen, the ability to use insight and interaction in decision making when confronted with information.

Despite the existence of different models of EI, there are statistical and theoretical similarities between their various concepts. At a more general level, all models aim to measure the components involved in understanding and to regulate the personal emotions of an individual and other people. Also, all models agree with the view that there are specific critical components for EI [1].

3 The Role of EI in Accounting Software Learning

Accounting software is considered as the most important component of the accounting information system, and it is of particular importance as an essential support tool in accounting and financial systems [7]. Appropriate accounting software should use the standard connection between modules. It also should help the user to confirm new data and easily extract the old information for analysis of the procedure. Of course, it should have other key features such as flexibility, inventory control, and different levels of security and automatic backup [8]. Considering the various functions of accounting software designed by programmers, the ability to learn software is one of the most prominent features in meeting the future needs of accountants and organizations. Therefore, training is needed for users to learn how to work with financial software in order to achieve the business and financial goals of organizations [19]. In new decision-making theories, emotions are used for the efficiency of wisdom [29]. Emotions help in making wise decisions in three ways:

- ✓ Emotions help people identify and prioritize problems.
- ✓ Emotions help identify the components needed to make a decision.
- ✓ At a deeper level, emotions help provide the ground for making more appropriate goals [29].

In learning the financial software, investigations show that various individual and external factors are influential in individuals' rate of learning. Some of these factors are EI and characteristics such as gender and education level [40]. Accordingly, it is necessary, in learning accounting software, to pay attention to the emotions and identification and to recognize the social, economic, and ethical consequences of applying emotions and their impact on decision making [8;12]. Some research shows that in learning financial software by accounting students, considering the features mentioned, the accounting students and accountants continuously use their emotions based respectively on the type and content of their practical and specialized courses and their profession characteristics [13]. The main objective of accounting software learning is to develop skilled and expert accountants so that they are ready to enter the profession. Effective human resources in each country is considered as a competitive advantage, and one of the factors of success in its economy [8].

Today, data mining has transformed various scientific fields as one of the most widely used technologies. Due to the existence of advanced analyses performed using artificial intelligence algorithms, one can precisely and profoundly analyze the procedure and the hidden order in the data and make predictions on the possible future events based on the current information [32]. Two associations of official accountants and the American Association of Internal Auditors have introduced data mining as one of the top 10 technologies and included it in their list of four research priorities [3]. With such an extraordinary predictive technique, if managers could predict the job applicants' expertise and professionalism based on personal characteristics such as EI, gender, age, and level of education through models and modern algorithms of data mining and artificial intelligence, they could sponsor massive improvements in terms of the productivity of organizations and increase the credibility of the accounting and auditing activities [28].

3.1 Motivation and Contributions

While the main objective of education on accounting software is to educate skilled and expert accountants in order to enter the accounting profession, one of the most important problems with the accounting education system is that students do not adequately learn the financial programs required by the accounting profession. The goal of this research is to develop models for predicting the rate of learning financial software among the students. On the other hand, given that very few studies in developing countries have examined the learning of financial software among accounting students through artificial intelligence algorithms and data mining, and there is a research gap in the field of accounting, so in this article, we are trying to bridge this gap in these countries. Therefore, in this paper, we intend to present a new and combined model from several models based on using the data-mining technique that can predict the effect students' rate of financial soft wares learning, taking into account their EI, gender, and level of education. In addition, in this study, we are to measure the accuracy of the available models for prediction and introduce a model with the highest accuracy as the main model. We also seek to identify the most effective variable on the learning rate of accounting soft wares. In this study, five popular classification techniques in data mining, specifically KNN, DT, XGBoost, RF, and SVM, are employed to build predictive models. The grid-search method is employed to find the best parameters for each of the candidate models [39]. Furthermore, to minimize the bias associated with the small dataset, 5-folds cross-validation technique was used since more training data will be used in each iteration. In this paper, we try to answer the following three questions: Is it possible to predict the rate of students' learning based on the characteristics studied and using artificial intelligence algorithms and data mining technique before teaching financial software to them?

What variables, if the prediction is made, have the most impact on individuals' learning?

Among artificial intelligence models and algorithms, which one has the highest accuracy to predict the rate of learning?

For this purpose, after a thorough review of the previous studies on the learning of financial software, data mining and artificial intelligence, as well as consulting with 15 experts in education, accounting, data mining, and psychology, three variables were selected as effective variables on the target variable. These variables are gender, level of education, and EI; the response variable is the rate of financial software learning by accounting students. Table 1 demonstrates the results in more detail.

Table 1: Description and Type of Attributes of the Final Dataset.

Variables	**Attribute**	**Description**	**Type**
Effective variable1	Education	The level of education Value 0: Undergraduate studies Value 1: Graduate Studies	Numerical
Effective variable2	Gender	The gender of the respondent Value 0: Female Value 1: Male	Numerical
Effective variable3	EI	The emotional intelligence level of the respondent	Numerical
The target variable	The rate of financial software learning by accounting students (grade)	The target variable Value 1: Very low, Value 2: Low Value 3: Medium, Value 4: High Value 5: Very high	Numerical

4 Methods

4.1 Data Collection

To collect data and measure variables, we used the Schutte 's EI Questionnaire [30]. It was created by Schutte in 1998 based on Mayer's EI Model which had been developed in 1992. It consists of 33 descriptive statements such as "When I have positive mood (such as happiness), it is easier for me to solve problems." By responding to these statements, three components of emotion regulation, evaluation, and expression of emotion, and the emotional utilization are assessed, which are shown in Table 2. The method of evaluating the statements is that the respondent expresses the degree of his agreement or disagreement to each statement on a Likert five-point scale, including strongly disagree (1), disagree (2), undecided (3), agree (4), and strongly agree (5). Note that statements 5, 28, and 33 are valued in reverse order from strongly disagree (5) to strongly agree (1). Instructions for responding to the statements are at the beginning of the questionnaire. Having studied the instructions by the respondent in the second part, the respondents' personal profile is included in the answer sheet, and the third part includes the statements about which the respondents should comment. Also, to measure the software learning, we used the students' scores of software application in accounting in 2018.

Table 2: Components of EI Assessment and Their Statements.

Components of the questionnaire	Statements
Emotion regulation	13,14,16,17,20,23,26,27,30,31
Emotion assessment and expression	3,4,9,10,11,15,18,19,22,25,29,33
Emotion utilization	1,2,5,6,7,8,12,21,24,28

Our population is accounting students at Khomeini University in 2018. The questionnaire was distributed among 120 students through attendance at their classes. After collecting the questionnaires, 100 forms were surveyed since the respondents had answered to all statements and completed their profile in the inquiry form. The rest were excluded from further investigation. At first, the required data were collected by distributing the questionnaire among accounting students. The variables included age, educational level, and EI, which were determined by the viewpoint of 15 experts in accounting, artificial intelligence, and psychology. Then, the validity and reliability of the questionnaire were examined and also confirmed. After that, we categorized and normalized the data. The results indicated that the data is normal. The demographic frequency data are shown in Table 3.

Table 3: The Frequency of Demographic Variables.

Education Level			
Bachelor of Accounting (B.A.)		Associate Degree in Accounting (A.A)	
Female	Male	Female	Male
25	25	25	25

Table 3 shows that out of 100 students, 50% are students working on a B.A. and 50% working on an A.A. Also, 50% of them are male and 50% are female. The "target variable" feature is the grade that is given to each student ranging from 10 (very low) to 20 (very high). All records in this dataset are complete without missing values. The dataset contains 100 records. The next section describes data pre-processing and features engineering steps to prepare a dataset for implementing data mining models.

4.2 Data Preprocessing and Feature Engineering

In this study, the data preparation step starts from the pre-processing phase, followed by feature engineering to calculate the target feature and prediction step. Since the goal of this research is to develop models for predicting the rate of learning the financial software among the students, a multiclass dependent variable is needed [35]. The values of the target variable in the provided dataset was transformed from a range of 10 to 20 to a categorical multiclass dependent variable with five classes (one for very low, two for low, three for moderate, four for high and five for very high). The resulting dataset thus contains only five values for the target attribute. After creating the target attribute, we removed the grade attribute. After feature engineering step including the reduction of the target attribute, the final dataset contains an attribute named "target variable" to show the level of learning rate in students on different scales, from 1 to 5. In this scenario, 1 represents the lowest, and 5 refers to the highest grade of learning rate. The distribution of the dependent variable is illustrated in Table 4.

Table 4: Distribution of the Dependent Variable.

Category	Frequency	Percentage
1	14	14
2	18	18
3	30	30
4	28	28
5	10	10
Total	100	100

4.3 Classification Models

In this study, after the data preparation step, five popular classification techniques in data mining are employed to build predictive models, namely, KNN, DT, XGBoost, RF and SVM. The grid-search method was employed to find the best parameters for each of the candidate models. Furthermore, to minimize the bias associated with the small dataset, 5-folds cross-validation technique was used since more training data will be used in each iteration. In addition, a study done by Kohavi suggests 5-folds cross-validation provides the best trade-off between bias and variance [37].

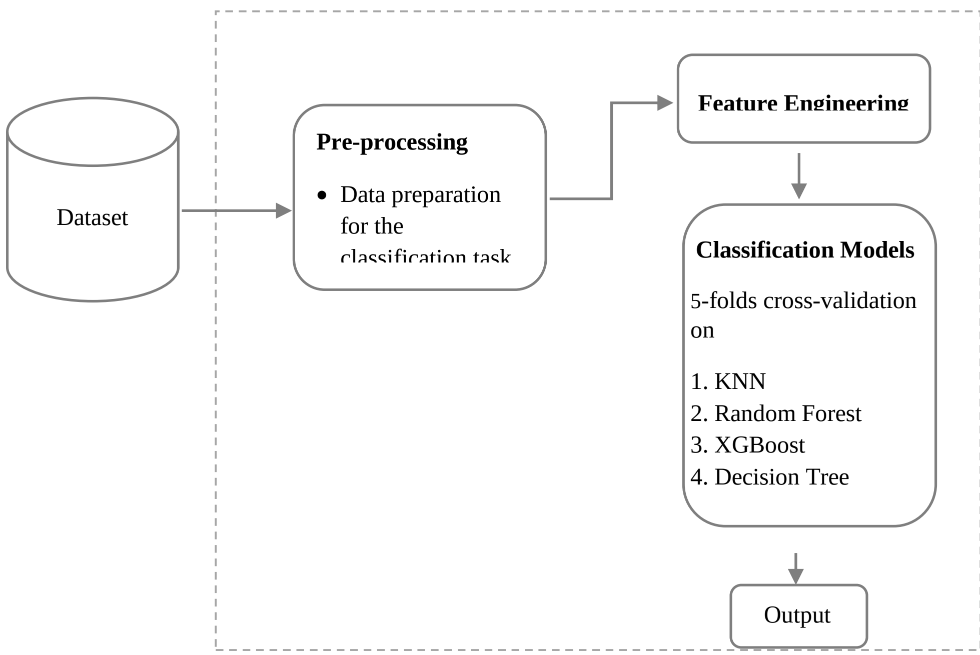

Fig.2: Workflow of the Experiment

In this approach, the complete dataset is randomly divided into k subsets (e.g., five in this study) of approximately equal size and then processed k times. Finally, the overall accuracy of the classification model is calculated by comparing the accuracy if each of the five measures [36]. We also used a stratified sampling method to divide the dataset into train and test sets. In stratified sampling, the sample represents the exact ratio of the main dataset to ensure all categories are represented in the samples [4]. In this study, the Python programming language was used to conduct the experiment [39]. Python is freely available as one of the open source mainstream languages in data science. The experiment was implemented on an Intel Core i7-8700K 3.7 GHz processors and 32GB RAM. Figure 2 shows the workflow of the experiment.

4.4 Prediction Models

We used five different types of classification models for multiclass classification problem in this study, namely, KNN, DT, XGBoost, RF, and SVM. A brief introduction of the selected models is presented in this section. The decision tree is a supervised learning technique for classification and regression tasks in machine learning. Decision trees, also known as hierarchical classifiers, recursively create a tree-like model of decisions to determine the relationships between features in a labeled dataset to interpret the class labels of the unseen samples. A decision tree consists of a set of rules to find an optimal choice while the final leaf node is the best choice for the given problem at hand. Different metrics are used in a decision tree such as information gain and Gini index. These metrics help with splitting the node of a decision tree [5]. The support vector machine (SVM) is a numerical classifier for classification and regression tasks. An SVM attempts to find optimal boundary lines between the classes by separating the training examples into their assigned classes. A boundary line or hyper plane that bifurcates the data in a way that maximize distance from these closest points during training. SVM hyper plane boundary can separate data using linear boundary or quadratic boundary [18].

K-Nearest Neighbor (KNN) is an instance-based learning tool used to tackle both regression and classification problems. KNN identifies the class of an unknown data point based on the characteristics of the nearest objects by a majority vote of its neighbors. The Euclidean distance is used to measure the distance between two data points. However, KNN has some major drawbacks. Furthermore, the speed of the KNN algorithm declines for large amounts of input data since it compares a new data point with every sample in the data. Also, choosing the optimal number of neighbors (K) is a major issue [33]. The random forest is an extension of the decision tree algorithm. Random forest is an ensemble classifier that could be used for both classification and regression tasks. Random forests are based on the combination of different decision trees to make a robust classifier. Random forest selects the best subset of data features randomly and is capable of preventing overfitting of the data. The prediction results are computed based on the majority vote from among all the trees in a random forest. The Random forest classifier offers several advantages such as being computationally fast, reducing variance and bias in classifications and also minimizing the problem of over fitting [5]. XGBoost (Chen & Guestrin, [17]) stands for Extreme Gradient Boosting, developed in 2014 by Tianqi Chen, is a powerful algorithm based on the gradient boosting principles to improve both performance and speed for both regression and classification tasks. By using parallel processing techniques, XGBoost optimizes the computation resources providing higher computation efficiency. XGBoost algorithm an ensemble strategy to build a strong classifier from multiple weak learners consecutively. The main advantages of the XGBoost are regularization, parallel computing, and handling missing values automatically [17].

4.5 Feature Importance

In this paper, using the data mining technique and five data mining models, we seek to predict the accounting students' rate of financial software learning based on the three variables of gender, education level, and EI. Then, we examine which of these three variables has the greatest impact on their accounting software learning rate. Also, among the algorithms used in this paper, which one has the highest accuracy to predict the rate of learning? Therefore, we further analyzed our experiment using XGBoost method to identify the significant attribute in predicting the rate of learning [16].

4.6. Measures for Performance Evaluation

We evaluate the performances of the proposed algorithms through classification by accuracy, precision, and recall analysis. Accuracy is the percentage of correctly predicted instances among all instances as in Eq. (1). Sensitivity or recall is the measure of correctly classified samples to the total number of positive samples as in Eq. (2). Precision is defined as the fraction of correctly classified samples over the total number of samples that are correctly and incorrectly classified (Eq. (3)). We assessed the performance of each classifier with the help of a confusion matrix. There are four possible outputs based on the confusion matrix: True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). The following formula from Equations (1-3) was used to measure the accuracy, precision, and recall.

$$Accuracy(\%) = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{1}$$

$$Sensitivity\ or\ recall = \frac{TP}{(TP + FN)} \tag{2}$$

$$Precision = \frac{TP}{(TP + FP)} \tag{3}$$

5 Experiment Results and Discussion

This section presents the results achieved in the experiments. The performance of five data mining models on 100 records of features was investigated using accuracy, precision, and recall performance measures. In this experiment, the 5-folds cross-validation technique was used to measure the performance of the models. Finally, the accuracy results are shown by averaging the results obtained from the 5 iterations.
Tables 5-6 summarize the highest accuracy, the highest precision, and the highest recall achieved by each data mining technique used in this study. Based on the analysis showed in table 5, we can see that the best performing techniques are DT and XGBoost with 100% for both of them. The second-best models, SVM and KNN, also yield a higher overall accuracy (96%) than the RF model with 76% accuracy. On the other hand, the highest precision and recall (100%) was achieved by both DT and XGBoost.

Table 5: Accuracy Achieved by Data Mining Models

Algorithm	Accuracy
Support Vector Machine	96%
XGBoost	100%
Decision Tree	100%
K-NN	96%
Random Forest	76%

The results also indicate that RF has the lowest accuracy (76%), the lowest precision (91%), and the lowest recall (76%) as compared to the other models. The experimental results prove that the DT and XGBoost methods have produced auspicious results in the classification of the students' learning rates in this experiment. Also, Fig. 3 illustrates the boxplot of the models for testing data.

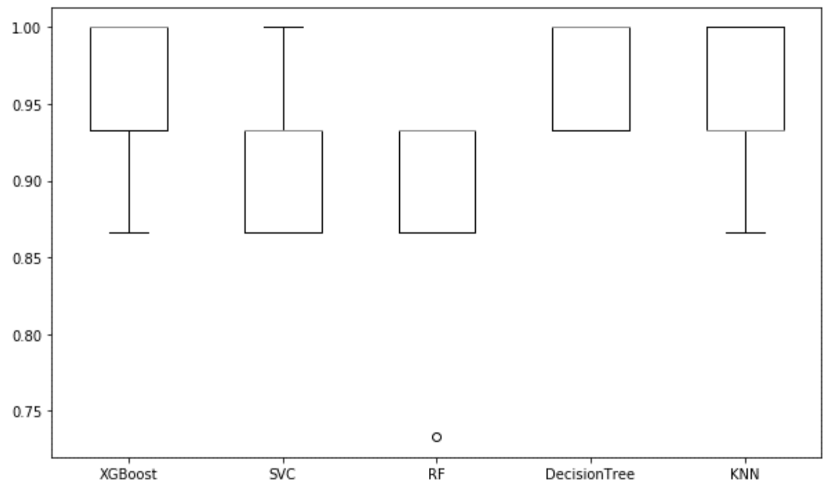

Fig.3: Boxplot of the Models for Testing Data.

In order to identify the most important attribute from the provided dataset in this study, the proposed procedure is to test each possible feature with the XGBoost method.

Table 6: Average Precision and Recall Achieved by Data Mining Models

Algorithm	Precision	Recall
Support Vector Machine	96%	96%
XGBoost	100%	100%
Decision Tree	100%	100%
K-NN	97%	96%
Random Forest	91%	76%

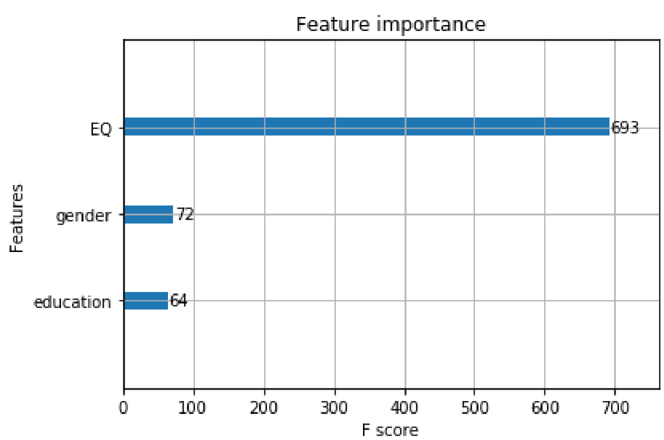

Fig.4: Feature Importance

Figure 4 demonstrates the analysis of attributes that have achieved the best performances using the XGBoost method in descending order of importance to their performance. In this Figure, the EQ attribute has achieved the highest performing feature and in comparison with the other attributes EQ has resulted in the highest accuracy. Similarly, the second and third most important features are gender, and the level of education attributes using the XGBoost algorithm. This indicates that EQ attribute is the most important attribute that has an impact on predictions with high accuracy. Also, the results of the final decision tree of the training dataset in Figure 5 suggested that the EQ variable was useful in differentiating students' learning rate. The Gini index is used as the splitting criteria to measure the attribute selection. Based on the tree results, EQ $\leq$ 130.5 is chosen to split data points based on weighted Gini Index. Furthermore, the boxplot in Figure 5 indicates the performance of selected models and the efficacy of the DT and XGBoost models as our best models in this study.

Also, the results of the final decision tree of the training dataset in Figure 5 suggest that the EQ variable has been useful in differentiating students' learning rate. The Gini index is used as the splitting criterion to measure the attribute selection. At the root level of this tree, we start the prediction based on variables such as EQ, gender, and the level of education. The feature contribution is derived from the target variable and how it changes at successive splits. For example, in the root node of this decision tree, the dependent variable has five classes with 75.

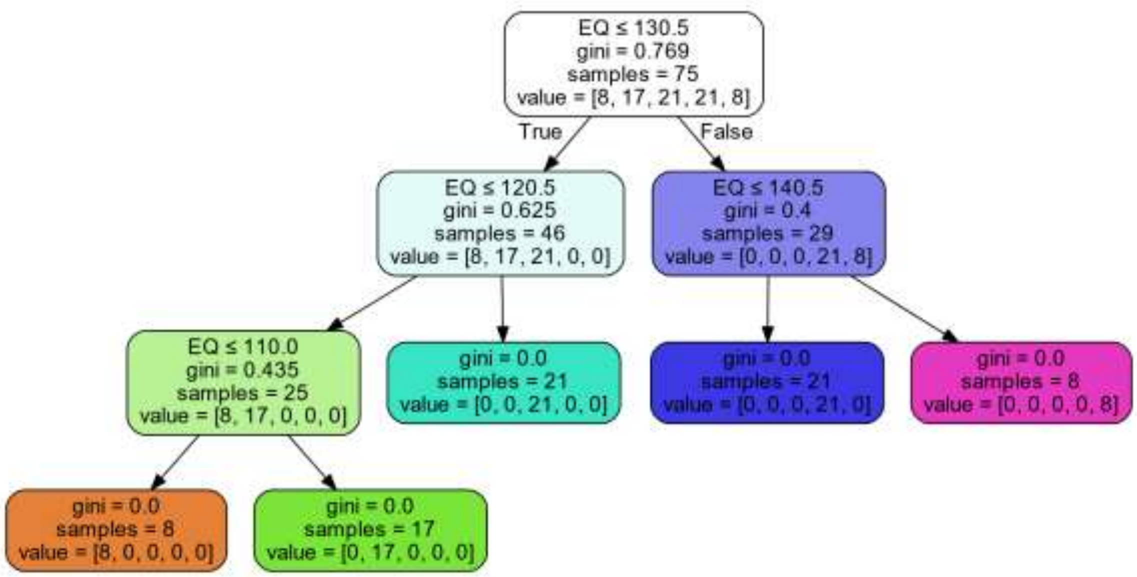

Fig. 5: Decision Tree with the Training Dataset

observations in the provided dataset, eight observations with "very low" value, 17 observations with "low" value, 21 observations of "medium" value, 21 observations with "high" value, and eight observations with "very high" value. For the next level of this tree, if a sample meets the condition, then it goes to the left branch. Otherwise, it goes to the right branch. For example, a sample with EQ of less than or equal to 120.5 and Gini index of 0.625 will be placed in the left branch. Otherwise, if the EQ value is less than or equal to 140.5, the sample will be in the right node. The depth of this tree is three levels. According to the tree results, EQ $\leq$ 130.5 is chosen to split data points based on weighted Gini Index.

6 Conclusions

The need for quick and complex computing and immediate responsiveness to the information needs of the business units and coordination with changes in the economic environment has led the accounting profession to use powerful, industry-specific software. Because the basis of decision making at the micro and macro levels of organizations is based on the presented financial reports, and this information is also provided through accounting information systems using financial software and by accountants, it is crucial for accountants to learn the financial software required for accounting information systems. Hence, an accounting student should be able to learn and implement the accounting information systems, and the necessary financial software by understanding the advancement and development of technology. In this study, using the data mining technique and five data mining models, we seek to predict the accounting students' rate of financial software learning based on the three variables of gender, education level, and EI. To apply the machine learning algorithms to its full potential, effective data preparation is needed to pre-process the datasets. Furthermore, some of the features that do not contribute significantly to the performance of the data mining techniques were removed and transformed into more representative features. Furthermore, along with data preparation, a proper feature engineering method is needed to achieve high accuracy in the students' learning rate prediction using significant features and data mining techniques. The provided dataset includes 100 records in two five different classes. In this study, notable features and the best performing classification modeling techniques that improve the accuracy of the students' learning rate prediction were selected. K-fold cross-validation is used in this study since it works better for small datasets to reduce the bias. The findings were evaluated with different evaluation metrics using accuracy, precision, and recall performance measures.

The top data mining techniques that produce high accuracy in this research are DT and XGBoost with 100% accuracy. Finally, an experiment was conducted using the XGBoost model to identify significant features. Among the variables examined by the technique of data mining and artificial intelligence algorithms, the EI has the most effect on the target variable (the soft wares learning rate). It means that the higher the students' EI, the higher their financial software learning rate. Indeed, EI can be regarded as an essential axis in academic and vocational learning. In accounting that, human power, as the main actor, plays a crucial role in decision making and management of strategies and successes of organizations, paying attention to EI and its assessment among the accountants at the time of employing can, as an effective solution, lead to a significant change in accounting and organizations. As the studies have shown, 90% of those with excellent job performance have very high EI. Those who develop their EI are usually successful in their job because EI and job success are interdependent. Alfuree examined the effect of EI on technology learning. The result of his study shows that EI has a positive and significant relationship with improving the learning process. As Golman has pointed out, EI is a predictable variable for the success of individuals in various fields of academic and vocational learning. If accounting students develop their EI, the rate of learning skills and financial software will be increased, and in the future, they will succeed in their job and improve their performance [27]. After that, gender had more impact on the rate of software learning by accounting students. The results indicate that gender is also an essential factor in learning of financial software and examination of the student learning rate since the personality traits of males and females are shaped by gender and are different. Knowing that women, for example, are more willing to learn financial software than men, or vice versa, can provide useful information for accounting policymakers to employ accountants and auditors in organizations based on their gender. Student's education level had less impact on the financial software learning rate because the principles of working with financial software are taught at lower levels, and there are no financial software training courses at higher levels of education. Therefore, there is no significant difference between the levels of A.A. and B.A. of accounting students. This research, like all studies carried out in this field, had some limitations. The first one had to do with time and place limitations. This research was conducted among Iranian accounting students; therefore, one should be cautious in the generalization of its results to other times and other statistical populations. Although the goals and functions of all financial software are provided based on accounting standards by the needs of the accounting profession and are included in training courses, they may have different contents and teaching methods in different countries. This research has the limitations that are common in all research studies performed using data collection method through the questionnaires, including lack of understanding of the question concept, the failure to return the distributed questionnaires, the possibility of presenting a false image by the subjects, etc., to which much attention should be paid in generalizing the results.

This model, until now, has not been presented in the field of teaching and financial software learning in developing countries and using it can create a modern and extensive change in different areas of financial predictions of the behavior of accountants, auditors, and managers due to their various personal characteristics. Certainly, in accounting that, human power, as the main actor, plays a crucial role in decision making and management of strategies and successes of organizations, paying attention to EI and its assessment among the accountants at the time of employing can, as an effective solution, lead to a significant change in accounting and organizations. There are many ways to enhance this research and address the limitations of this study. This research can be extended by conducting the same experiment on a large-scale real-world dataset. Further research can be conducted to test different ensemble of data mining techniques in the students' learning rate prediction to improve the accuracy of the classifiers. Besides, it is suggested that future research studies can adopt additional theoretical conceptions for measuring the multiple intelligence, creative thinking, reflective thinking, and critical thinking and their influences on the academic achievement of students in different stages. Also, this observed relationship between EI and academic achievement should be investigated by considering emotional intelligence measures in future studies. Additionally, new feature selection methods can be applied to get a broader perspective on the significant features to enhance the accuracy in prediction.

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