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Predicting student performance using data mining and learning analysis technique in Libyan Higher Education

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ABSTRACT

The Technology has an increasing impact on all areas of life, including the education sector, and requires developing countries to emulate developed countries and integrate technology into their education systems. Recently schools in Libya are facing an issue trying to figure out why students perform poorly in certain subjects and how can they know how they will perform next in the future in coming semesters in perspective subject. There are several methods proposed to predict the student's performance, using data mining techniques. In this paper, there are plans to create Data Mining Techniques in Education (i.e., DME) prediction model clustering, classification and association rule mining in many universities and schools in order to provide students and teachers with the most advanced platform. Although relatively late, the Libyan government finally responded to this challenge by investing heavily in rebuilding the education system and launching a national plan to presented method in terms of predicting students' performance based on their grades in Math and English. The results are divided in to three main sections clustering analysis using k-mean algorithm, classification analysis was done using two rounds first using Gain Ratio Evaluations to find out the top attributes that used by J84 algorithm in second round of classification, and rule association analysis using A priori algorithm. Rule association analysis is applied for the clusters generate by clustering analysis to generate the rules associated with each cluster. For each section, a list of inputs is presented with the scale used for the values followed by the results of the algorithm and explanation for the finding.

Keywords: Data Mining, Performance Predicting, Education, Electronic Systems, E-Learning

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1. Introduction

The academic performance of higher education (HE) students is designed to solve problems related to low academic performance, high dropout rates, delayed graduation, and other difficult problems [1]. Simply put, student achievement refers to the short-term achievement level and long-term goal in education [2]. However, the academic world will measure academic performance from a variety of perspectives such as student achievement, grade point average (GPA), and future employment prospects[3].

The literature proposes many computational tasks aimed at improving the performance of school and university students, especially those based on data mining and learning analysis techniques [4]. However, there is still confusion about the effectiveness of existing intelligent models and methods. Stand up for learners and enable teachers to intervene and implement the learning process at an early stage. Successful interventions include but are not limited to student counseling, progress monitoring, development of intelligent guidance systems, and policy formulation [5].

These efforts are mainly driven by advances in computer science in the fields of data mining and learning analysis[6]. A recent comprehensive study showed that approximately 70% of studies examined student predictions based on student performance and grades, while only 10% of studies tested student predictions based on learning outcomes [3]. This loophole prompted us to review the work done, which used learning outcomes as a proxy for student academic performance. Predicting student performance is crucial. When the student's performance is lower than the standard, start to predict the student's performance.

So, the school had to find a way to solve the problem of poor grades. One way to solve this problem is to implement the system. Based on data mining, it depends on the contributions of the authorities, such as their own strengths and weaknesses in predicting student performance [7]. In this document, we invite students to predict their academic performance based on exams and test scores for the semester and school year. Each student is individually taken to assess academic performance and determine the ability to predict future academic performance [8]. The accepted majors in divination are English and Mathematics. They are key factors in predicting the results of physics, biology, information technology, and chemistry. Mathematics and English have become the main subjects for predicting academic performance because they involve all subjects, while physics and chemistry are based on the numbers and principles of the English language. These two themes are the focus of the test.

This research aims to predict student performance based on students' math and English scores. Data from student exams and tests in all semesters is used for analysis to predict whether students will perform poorly or succeed in future semesters and years. Physics, chemistry, biology and information technology are used for comparison and prediction [7]. These subjects are compared with mathematics and English to help determine the performance of future students to prevent students from losing and changing schools or universities. learn. There are tables and figures. It introduces the elements used in this research.

2. Background and related work

This section introduces the key concepts of learning outcomes and student performance, and then identifies gaps in the literature that predict student learning outcomes.

2.1. Student outcomes

Outcome-Based Education (OBE) has become a new school of thought in the field of education, which has recently been widely accepted and accepted [9]. This educational paradigm shifts the focus of teaching from traditional teacher goals to so-called student outcomes. In short, student performance is related to the knowledge, skills, and values that students must achieve at graduation or the end of the course [10]. The result representing the target ability can be achieved at the course level, i.e. H. Course results, or at the plan level, d. H. Plan results, define and measure. An activity called course mapping. Computer-based tools have been developed to achieve OBE goals [11] and effectively record educational evaluation activities [12]. By including intelligent models that can predict the learning outcomes of academic semesters, practicality can be improved.
Measuring student learning outcomes in higher education will undoubtedly bring many benefits, including setting student and teacher plan expectations, evaluating the quality of courses and plans in practice, and providing key indicators of academic success [13, 14]. Various quality assessment tools such as[15] , and quality assurance systems such as [18], have been proposed to implement result-based educational concepts and achieve program certification. In addition, the ability to predict student performance provides other valuable benefits. The ability to make corrective interventions during the learning process; however, there are several articles that focus on intelligent prediction of student performance. The result is unclear. Research has shown that these factors differ between academic factors such as teaching quality[16] and online interaction [17] and non-academic characteristics such as family participation[18] and student motivation [19]. Our goal is to understand the prospects of predicting student performance through data mining and machine learning through systematic investigation, identify the main problems that make it difficult to predict student performance, and make appropriate recommendations.

2.2. Student performance

Despite major changes in the teaching and learning system, namely OBE, academic achievement is still the main challenge of higher education[14], especially considering the low grades and high dropout rate even in world-class universities [20] Previous reviews have shown that cumulative grade point average and course grades are the most commonly used predictors of student performance and achievement [21, 22]. In fact, there are several studies that use the next quarter’s results as the main measure of student performance, such as [23, 24]. However, it’s not uncommon to measure student performance in other ways, including dropout rates,

student studies, and positions. -Course results [25]. We believe that students' performance should not be judged solely on the basis of grades. It should be explored in a broader context, especially by observing the performance of the cohort to promote the learning process of student outcomes. Research suggests checking predictive student performance in order to draw conclusions about student performance[26].
The intelligent methods used for learning analysis to predict student performance are usually divided into supervised learning, unsupervised learning, data mining and statistical methods [3, 25]. Each category includes many of intelligent algorithms such as artificial neural networks, support vector machines, nearest neighbors, and random forests. The attributes that predict student performance are widely discussed in the literature, leading to a combination of academics (for example, preliminary grades). Entrance and entry scores) and non-academic (e.g. emotional intelligence and resilience) factors [27, 28]. However, the factors that affect course grades and project results remain a mystery. Measurable student outcomes are designed to improve the quality of the learning process and educational program [10]. In fact, these results provide an estimate of what students can do with the knowledge they have learned. Direct assessment methods are designed to find specific evidence of student learning, while indirect assessment methods are based on allowing students to reflect on their learning experience. It is necessary to determine the goal and proficiency a priori, and then match the student's performance with the corresponding proficiency [13]. In our work, we examined the studies that predict the attainment of student outcomes, irrespective of their form.

2.3. Existing comments on student performance and documentation gaps

Our comprehensive review of previous surveys found that, as far as we know, there is no systematic review of the literature designed to predict student performance from the beginning. Outstanding research conducted to predict student performance and highlight their priorities and weaknesses. In fact, our search returned numerous surveys on the use of in Education Data Mining techniques (i.e., EDM) to unravel student modelling activities and predict academic performance. Comments are subject to some limitations, such as (1) they are generally very broad, (2) they do not focus on using student performance as an indicator of student performance, (3) they have quality issues (e.g. methods are not fully defined) (4) they are not highly indexed. The position is published. These weaknesses are highlighted in Table 1.

Table1. Source of educational dataset in the studies.

Source	Number	Number of Studies (Percentage of Occurrence)
School	One	1 (1.61%)
	Multiple	11 (17.74%)
University	One	36 (58.06%)
	Multiple	2 (3.22%)
Not Specified		12 (19.35%)

Other less relevant research in this field focuses on the impact of homework on student performance [29] and the impact of using interactive whiteboards on student performance. Students [30], predictors of academic success. In the first year of study[31] and factors for successful completion of training [32]. In contrast to the above survey, our research chose to conduct a systematic review by implementing a comprehensive review process that allows us to synthesize specific answers to clearly defined research questions in the context of predicting student learning outcomes.

3. Methodology

The EDM model mentoring programs plan review is a comprehensive and systematic review that explores and explores various characteristics of student mentoring; however, this is not directly related to the experience and process of the mentee (before and after using the mentor interaction). Quantitative methods to measure the performance of the model, including triangulation, such as interviews, articles, and questionnaires, to understand the model more comprehensively. These are the concepts of learning quality necessary for successful learning through knowledge and skills in natural sciences, mathematics, and physics. Through action descriptions, formal concepts that enhance student confidence, problem-solving skills, testing and learning experience, mathematics and physics, and appropriate interest in peer study plans, students are introduced to the nature of university mathematics. The term includes cognitive and social participation as well as components. The instructor also received training on the use of online communication resources and tools (online activities, videos and screen presentations, questionnaires) and the methods for involving students in the online world. Discuss physics subjects (taught in the Mentis curriculum) as well as student goals, EDM learning, and career development. They can also access an online repository of multimedia and entertainment materials grouped by course topics.

3.1. Data collection

During the extended pilot project of the Orientation Program, data was collected, in which a questionnaire about their desire to be a mentor was filled out before posting about their trust in coaching ability (measured by alcohol value), such as in STEM students and high school students Guidance on the qualitative research of the plan and expected types; the interviewer can easily read the scale descriptor list aloud ("1-strongly agree to disagree, 2-disagree") for the nature of the tasks and discussions they will participate in and the expected questions [33]. This will introduce in more detail the challenges you will encounter with the instructor and discussion topics, as well as the expected challenges. The questionnaire also lists strategies that teachers can use to improve the quality of learning relationships, such as peer learning methods and discussion areas described in the literature. They are adapted from literature on the characteristics of effective mentors, such as the design of student interests and factors related to social and cognitive consistency measures (such as case studies and the use of self-awareness). -distribute). At the end of the weekly course, the tutors completed a post-meeting questionnaire, detailing what is covered during the meeting, how it is organized, student participation and mobility, and how to proceed. During the coaching week, the participant's subsidiary response uses a unique personal code. In addition, the questionnaire provides a list of strategies that the mentor can use to improve the quality of the mentoring relationship, as described in References and Dialogue/Discussion. They are based on the characteristics of good mentors (such as focusing on student interests), including cognition and social perceptions. Communication variables (e.g. use of practical examples, self-disclosure).

3.2. Predication

Forecasting involves developing a EDM model that uses predictors and predictors. The predictor variable represents a specific piece of data, and the predictor variable is a combination of other pieces of data. Researchers divide predictions into three categories, namely classification, regression, etc., and density estimation. He described these three categories as classification methods using decision trees, logistic regression and auxiliary vector machine regression [33]. The focus of regression is on continuous variables as predictors. Linear regression, neural network and vector machine regression support are also used. In order to estimate the density, the probability density function is a predictor variable and a kernel function is used.

3.3. Clustering

In clustering, a set of data points is determined, which together form a logical grouping. Observation shows that the result is that some clusters are formed from the complete data set. When the category within the group is unknown, the use of grouping becomes more valuable. The cluster set can be evaluated based on how closely the cluster set matches the data. He explained that the purpose of clustering is to find data points that together form a natural group and a complete data set [33-35]. By dividing the data set into logical groups, researchers can evaluate how the group set interprets the meaning of the data.

4. Method

Based on these research goals, the main research goals are proposed, which may be an ideal choice for developing a EDM model that uses prediction and predictors to better understand the relationship between learning behaviors, including its positive and negative results. The main research objectives can be answered by the following additional research objectives:

I. Do mining educational data help to identify students' performance early?

II. Do students' performance in the science and mathematics subjects' courses can serve as indicators of a good or low students' performance in the Physics exam?

III. Which behavioral patterns/attributes lead to positive or negative performance?

To address these research objectives, this study employs the Science, Technology, Engineering and Mathematics using EDM model clustering, classification and association rule mining for the following aims:

I. To predict student performance in Physics courses based on their performance in Math and Physics courses.

II. Examine the impact of behaviors learning on the students' performance.
III. Develop a model that will help extract knowledge about progressions of students' performance during their studies and relate them with their performance in the indicator courses. The results of the experiments are expected to provide answers to the primary research objective.

The following assumptions are made in this study.

• This study supposes that the model can help teachers deliver and students achieve good marks in Math and Science subjects, who were likely to be more successful and perform better in the Physics exam.
• Thus, to pass in these subjects, students must have at least a reasonable level of understanding of Math and Science subjects. In this regard, this study supposes that the students who could get a good mark in the Mathematics, Physics and Science were likely to be good students and successful. Hence, they perform better in the other courses.
Finally, this research examines the correlation between monthly test scores and overall academic performance. In most courses in Malaysia, monthly exams are the most important part of training. In these monthly exams, students can get familiar with the actual exam situation by solving questions similar to the final exam. In this sense, this research shows that taking monthly exams has a significant impact on students' preparation for final exams; therefore, better results in final exams. In order to draw concise conclusions and conclusive facts on the two most widely used data mining methods, namely clustering and classification methods, we use particle swarm optimization and terrain classification algorithms respectively. Use a series of linear discriminant analysis and logistic regression (classifier and clustering) system. The prediction system based on data mining proposed in the thought is described in Figure 1.

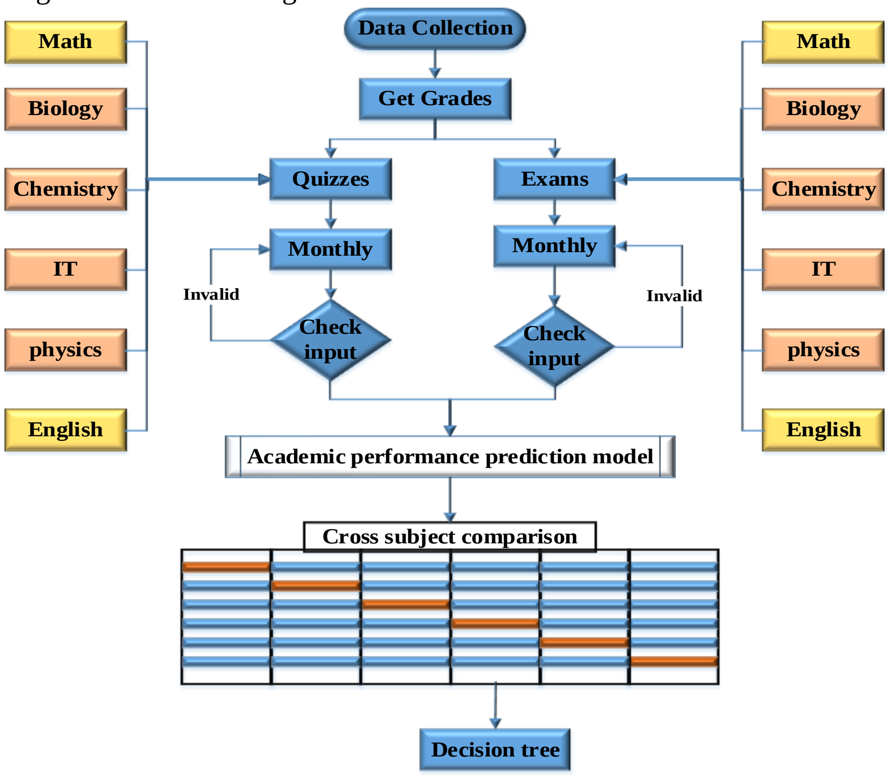

Figure 1. Presents the EDM model processing [36]

4.1. The framework has the following main phases

I. The normalized data set is very important in classification. Generally, classification algorithms involve scaling the output to fit a narrower acceptable range. When dealing with functions of multiple scales, normalization is usually required. This is an important part of being loud, unreliable and loud. The decimal method is used here to standardize the data in this study.

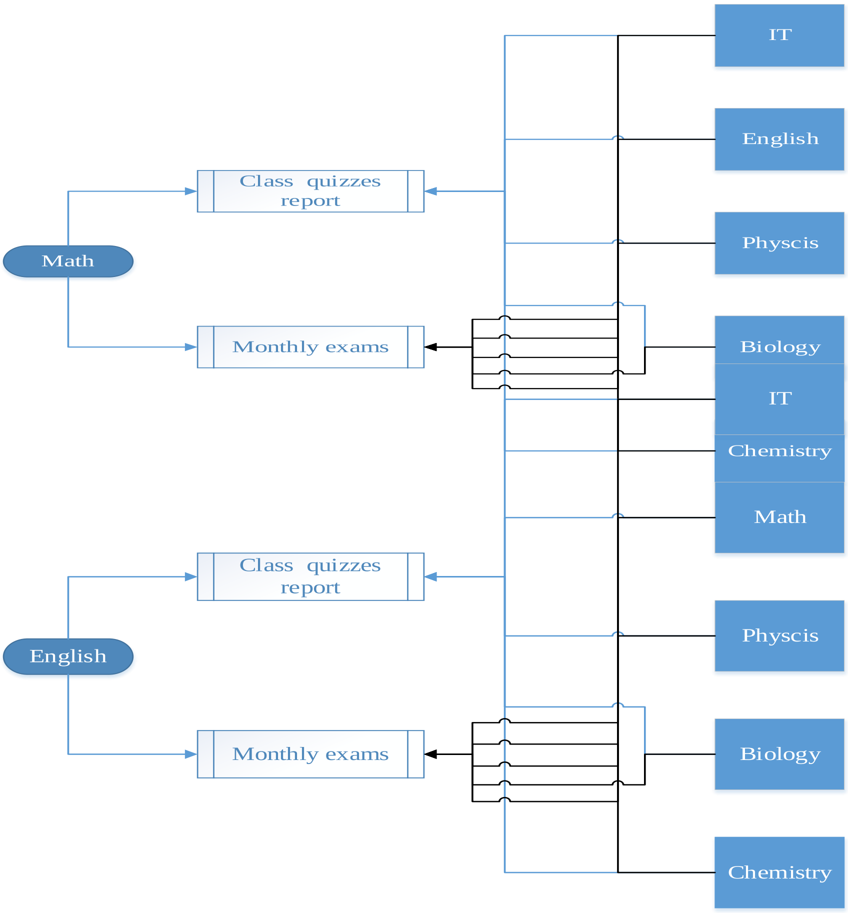

Figure 2. Math against all subjects and English against all subjects

II. Data grouping: Use algorithms such as K-Means to perform the selection step. In order to obtain data from the refined subset, the ensemble classifier is trained using the correction data obtained from each process.
III. Classification: In this step, use Scikit training to create a packaging kit. In order to improve the classification accuracy, the ensemble method combines logistic regression and linear discriminant analysis in Figure 2.

5. Results

Therefore, the data is mainly recorded in the EDM model of "pre-orientation expectations and trust in its guiding ability". It then summarizes the model's views on the relationship quality, frequency, and relevance of the specific forecasting strategy placed by the model. Finally, the qualitative data results are described in the student's exam summary, including the understanding of the tutor’s participation. The performance of students in mathematics and physics is compared with high scores, medium scores and low scores Table 1. [33].

Table 1. Comparison of the student's success in Mathematics versus Physics

Mathematics			Physics		
High	Moderate	Low	High	Moderate	Low
55	110	35	101	67	32

5.1. Mentors’ perceived relationship quality indicators

From this study, mentors reported that the relationship gained strength, where the mentor-mentee link got stronger throughout the 9-week online mentoring program (Table 2). Mentors’ evaluations of mentee advantages were the greatest of all relationship variables, whereas negative signs (frustration and feeling distant) stayed low. Mentors’ assessments of communication ease and frustration levels had large standard deviation coefficients, indicating that their mentoring experiences were varied. All of the relationship indicators changed during the mentorship program. The graph below depicts how mentors' experiences and perceptions of their mentees changed over nine weeks of mentoring (Figure 2). Although all measures increased as mentoring assignments proceeded, relationship quality as well as the prevalence and significance of specific mentoring strategies over the mentoring placement. In the end, we present qualitative data results on mentors' session summaries, including the perception of the mentors and the subjects involved. views decreased somewhat in certain weeks. In the sixth and eighth week, mentors' perceptions of distance grew. Similarly, frustration with mentoring climbed in the eighth week but stayed below neutral for the remaining weeks. The perceived ease of communicating with mentees rose in the fifth week and then began to drop in the following weeks. It dropped to its lowest point in the eighth week, then increased in the last week of mentorship. Mentors indicated that mentees' desire to learn held strong throughout the program, with a significant rise in the final mentoring session. This tendency was replicated in mentors' perceptions of mentee advantages received from involvement. Eventually, except for the seventh and ninth week, the strength of the mentor-mentee link remained neutral. Mentors' perceptions of the connection strengthening maintained at their greatest in the program's middle and final weeks, with lower levels in the second and sixth week. The research on peer mentorship acknowledges that scientific role models have a good influence on high school students. Enhanced academic achievement [34, 37], richer attitudes toward science [38, 39] and self-confidence are all advantages of mentoring [40].

Table 2. Average ratings for relationship great signs over nin weeks of mentoring

Indicator	Mean	Standard Deviation
Relationship getting stronger	M=3.89	SD= 0.1
Feeling distant	M=2.89	SD= 1.1
Feeling frustrated	M=2.23	SD= 1.157
Strength of bond	M=3.78	SD= 0.551
Willingness to learn	M=3.67	SD= 0.500
Benefiting from mentoring	M=4.03	SD= 0.486
Ease of communication	M=3.88	SD= 0.992

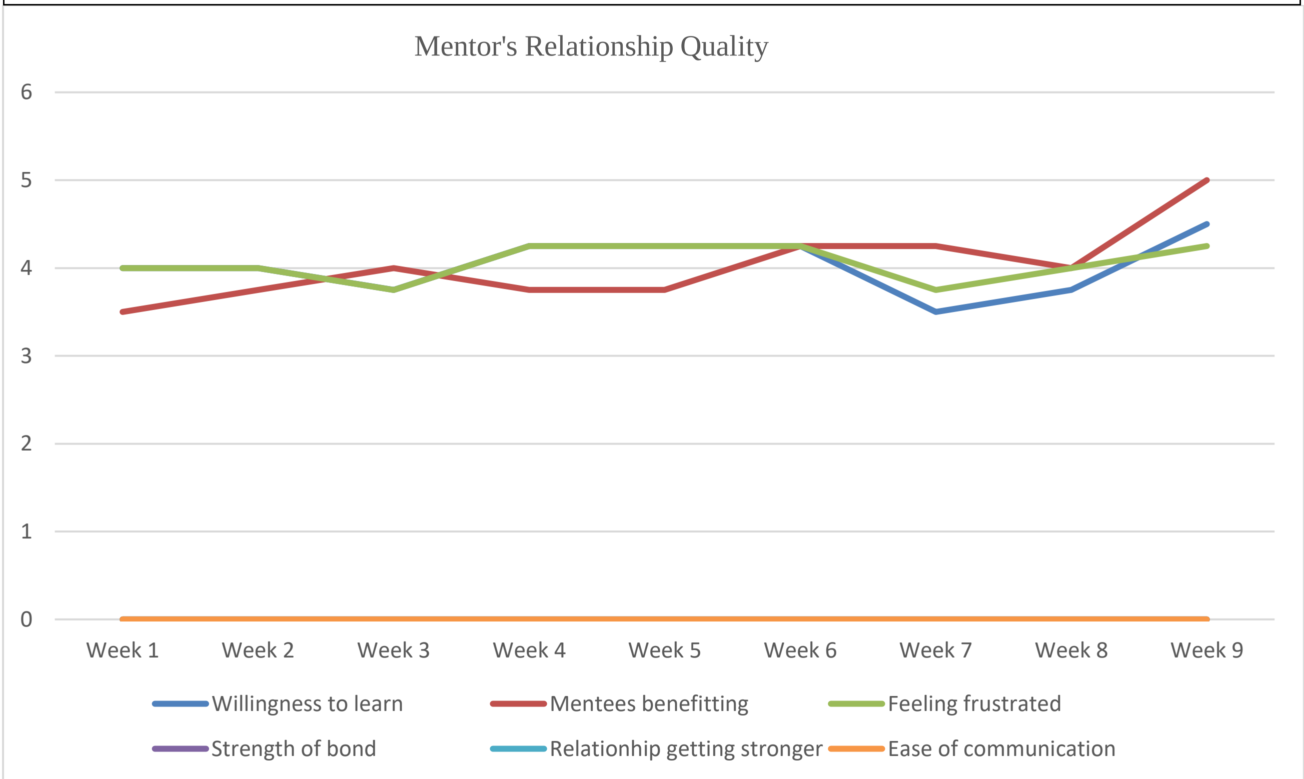

Figure 2. Mentors' relationship quality mean scores over nine weeks of the mentoring period

5.2. Strategies employed by mentors

In this plan, the importance of guidance is average (Table 3). The responses of the instructors vary, which means that different instructors have different views on the relevance of each method. Ask students what they want to talk about in class and what they want to do in class), discuss scientific and mathematical concepts with the instructor and use practical examples (such as math applications). Teaching methods are rarely cited in terms of relevance, unless instructors claim it is a common way to share their personal learning challenges. Similarly, instructors have different opinions on the importance of this strategy, which may be due to the small sample size which may lead to high variability.

Table 3. Average importance of mentoring strategies and actions

Indicator	**Mean**	**Standard deviation**
Asking for students' input	M=4.33	SD=.713
Understanding students' science interests	M=3.77	SD=1.183
Mentor sharing own school experiences	M=3.49	SD=1.422
Mentor sharing university experience	M=3.33	SD=1.179
Mentor sharing own interests and aspirations	M=3.37	SD=1.266
Mentor providing resources	M=3.52	SD=1.463
Mentor explaining science topics	M=4.22	SD=1.354
Mentor using practical examples (e.g. real-life applications)	M=4.33	SD=1.308
Mentor using examples to raise mentees' interest (e.g. suited to mentees' interests/aspirations)	M=3.88	SD=1.341
Showing study strategies	M=1.86	SD=1.530
Mentor sharing own learning challenges	M=2.55	SD=1.638
Talking about science career opportunities	M=2.89	SD=1.671

The achievement of the mentors' experiences as part of a pilot EDM model mentoring program that matched university students and secondary school students in regional areas. It sought to contribute to the peer mentoring literature by exploring mentors 'strategies and challenges associated with providing EDM model mentoring through online communication tools. However, the findings of these researches suggest that online mentoring programs could be employed to increase students' engagement in EDM model if particular aspects of the mentor-mentee relationship are taken into consideration when designing and implementing these programs. Therefore, there is a need for presented the prediction model can provides an overview of the methodology by which this study was conducted. The study states the objectives tested and their results, which were directly measured and proved. Next, it introduced the research design and data source, followed by a discussion of how the datasets and applying the technology, engineering, and mathematics mining using EDM model in conducting the experiments. This is in agreement with [41, 42] who stated that EDM model, such as clustering, classification, and association rule mining, can offer more meaningful results, way beyond the statistical analyses.

6. Discussion

Clustering analysis, for this research students are clustered based on their performance to find out the association rules that describe each cluster. The experiment was run three times on variation from 2 to 4 clusters. The evaluation of best number of clusters was based on the result of Euclidian distance between clusters. The best number of clusters was 3 clusters [43]. As the Simple K-Means clustering algorithm was used numeric values and can use nominal values by converting it to numeric values using optimal scale function. Subjects' marks percentage and final year results are chosen to apply clustering. The analysis will be conducted in sections, first section is final exam grades of all subjects included in the test. Second section is quizzes grades of subjects. Next Association rules analysis that contains four sections [19, 35, 44]. First section is Math exam comparison against all subjects, second section is English exam comparison against all subjects, third section is Math quiz comparison against all subjects, fourth section is English quiz comparison against all subjects, following sections present the analysis.

7. Conclution

In this paper, it was discussed the ability to predict the student performance by using data mining technique. We successfully described how EMD models (including data mining algorithms) are promising in organizing student data and provided a system that can help teachers maintain student performance throughout a semester. To another level, so as to achieve the purpose of investigation.

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