

# Developing Classification Model to Investigate the Problem of Computing Students Studies Length

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**Abstract**—Students are the key asset for any higher education institutions and their success in achieving the best academic performance within study planned period are resulting in producing graduates with high educational and professional quality skills. These graduates will become great leaders, manpower and play an important role in country's economic and social development. In most Higher Education Institutions, the students' studies length problem has not been investigated comprehensively despite the seriousness of this problem and its impact in the long and short terms. The aim of this research is to develop mining classification model based on decision tree to support academic administrators in decision making by defining features of linger students which could be used to develop an early warning system that has the ability to predict the students "who" might exceed the planned study length period. Data from faculty of computers and information technology at Uuniversity of Tabuk, KSA, has been collected using a survey method; students from male and female sections are participated in this survey. Then the data is preprocessed, after preprocessing of the data, C4.5 algorithm has been applied to discover the classifications.

**Index Terms**—Data mining, classification, computer in education, C4.5, linger students commas.

## I. INTRODUCTION

Students are the key asset for any higher education institution. Normally, the students' success is measured and evaluated by achieving the best academic performance within study planned period which is positively affects in graduates' educational and professional quality skills. These graduates will become great leaders, manpower and play an important role in country's economic and social development [1], [2].

In most higher education institutions, the length of study problem has not been investigated comprehensively despite the seriousness of this problem and its impact on the short and long term. The students who beyond six or seven years in their academic program are called "linger" students [3], this definition exclude medicine domains.

Currently, the higher education in Kingdom of Saudi Arabia (KSA) is growing rapidly through expansion the number of universities and undergraduate students; this may

increase the consciousness regarding the quality of education and attained learning outcomes within the planned studies period.

Table I illustrates the number of admitted students for bachelor degree in 2015-2016 according to ministry of education statistics, KSA [4]. Further, the summary statistics about admitted and graduated students from University of Tabuk in 2014-2015 are demonstrated in Table II [5].

From these mentioned tables we can extract that there is a large gap between number of new comer students and graduated student as well as enrolled and graduated students. Although, this big ratio of variant could be justified by an expansion in admission of new students still there is big gap between expected graduate students and actual graduate students.

In the current era, data mining has given a great deal of concern in the wide range application fields such as education [6], finance [7], manufacturing [8], healthcare [9], business [10], telecommunication [11], agriculture [12], and customer relationship management [13]. Furthermore, the most commonly data mining tasks include: classification, clustering, association rules, regression analysis, and decision tree [14], [15]. The field of data mining is growing rapidly and has become one of the most important computing techniques due to its ability to extract and discover meaningful knowledge from a large amount of data and the potentially useful relationships inside these data [16]-[23].

Data mining techniques could be used to build an intelligent classifier model to categorize students based on linger problem which help the education policy makers to take the appropriate decision when required. Further, this model will help in predicting the current students those who show similar behaviors that may lead to linger in their study, and then take the needed precaution to help them in advanced.

The majority of previous studies that are deal with students' studies length problem are used statistical theories to reach the results. Statistical theories are used to prove or disprove predefined assumptions. Hence, in the majority of previous studies, the data had been collected to serve these predefined assumptions. On the other hand, the rest of previous studies have used machine learning to deal with students' studies length problem. Machine learning is concerned with finding hidden relationships between variables without need for predefined assumptions. Machine learning is used for exploring hidden knowledge inside the data. It is hidden because there are no any previous assumptions.

In machine learning, there are two main approaches: classification and clustering. Classification is defined as grouping data based on predefined criteria and clustering is defined as grouping data without any predefined criteria.

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In this paper, we have developing classification model to investigate the problem of computing Students Studies Length. The aim of this classification model is to extract the features of both types of students: linger and non-linger

students. These features will help to defined expected linger student, i.e., this model could be used as an early alarm of problem of students studies length.

TABLE I: STATISTICS OF ADMITTED STUDENTS FOR BACHELOR DEGREE IN 2015-2016, KSA

Study Type	Available seats			Admitted seats			Vacant seats			Admission Percentage	Vacant Percentage
	Male	Female	Total	Male	Female	Total	Male	Female	Total		
<b>Regular</b>	102,6	121,1	223,7	90,5	112,1	202,6	112,0	10,0	21,8	90.3	9.7
<b>Affiliation</b>	22,9	16,4	39,2	13,6	6,9	20,5	15,0	10,7	25,6	44.5	55.5
<b>Parallel</b>	1,9	820	2,7	2,0	1,0	3,1	268,0	227	495,0	86.2	13.8
<b>e-learning</b>	9,4	6,1	15,5	0	0	0	9,4	6,1	15,9	0.00	100.0
<b>Total</b>	136,8	144,4	281,2	106,2	120,0	226,225	36,5	27,0	63,4	78.1	21.9

TABLE II: SUMMARY STATISTICS FOR ADMITTED AND GRADUATED STUDENT FROM UNIVERSITY OF TABUK IN 2014-2015

Gender	New comer students	Enrolled	Graduated last year
Male	4,2	11,4	1,4
Female	4,9	18,2	2,8
Total	9,1	29,6	4,2

This model has been developed on five steps: 1) investigated the related works to design the questionnaire. 2) Collected the filled questionnaires. 3) Develop classification model based on C4.5 algorithm, the collected questionnaires have been classified in two groups: linger students and non-linger students. 5) Finally, features of both classes have been extracted. Applying classification model to define the most affective factors lead to the length of study problem can contribute in improving quality education and academic performance.

This paper is organized as follows. Section II reviews of literature related to application of data mining in length of studies problem. The method and design steps used in the study are described in the Section III. The results are discussed in Section IV. Section V concludes the paper and gives recommendations for future direction.

## II. LITERATURE REVIEW

In literature, there have been very few studies conducted with the aim of discovering the factors lead in studies length problem and graduation dropout rate, N. Zavale *et al.* [24] utilize a logistic regression analysis to measure and explain the graduation rate at Eduardo Mondlane University (UEM), Mozambique. The data of undergraduate students from 2003 to 2006 are collected to measure the graduation rate, where 8 independent variables (6 variables as student-specific and 2 concerning socio-demographic profile) are selected as core factors affecting in graduation rate. The findings of paper shows that: Firstly (i) More than 25% percent of students graduate within the prescribed duration of programs (ii) 30 percent of students graduate within the duration +2 additional years. (iii) Less than 10 percent of students graduate within the duration +4 years (iv) 40 percent of students do not graduate within the allowed maximum time, i.e., program duration +4 years. Secondly, from the 8 selected variables the following variables are significantly affect the graduation rates of UEM students: gender, admission grade, number of

failed courses, program duration, and regime.

The investigation about length of studies problem based on clustering and the extraction of association rules has been conducted in the Greek Higher Education by P. Belsis *et al.* [3]. The students' data are collected through questionnaires in the lab classes. The study focuses on students who "linger" a low priority for registration in the lab classes and with limiting the number of times of attending lab based courses. Interesting results and rules are obtained and discussed. E. Katsikas, and T. Panagiotidis [25] focus on the symptom of long duration of studies in Greece. This study employs administrative and survey data to assess the relationship between students' socioeconomic background and educational outcomes. Regression and quantile regression methods are applied to examine the relationship between students' status i.e. working and non-working. The results show that the working students have not been not attained lower grades than non-working peers; the negative effect of the studies length on grades is not related to both students status, and the impacts of both students status are similarly.

The study aims to examine the influence of family financial assets during the time of student's college enrollment has been conducted by M. Zhan and D. Lanesskog [26]. The data is gathered from the National Longitudinal Survey of Youth. The findings show that the family assets are positively impacted on the chances of college graduation among the students. S. Robertson *et al.* [27] explore issues and processes of measuring progression and graduation rates in an RN-to-BSN (BSN stands for Registered Nurse and RN stands for Bachelor of Science in Nursing) population and to identify factors that facilitate/hinder their successful progression to work toward establishing benchmarks for success. Using the data collected from 14 California schools of nursing with RN-to-BSN programs, RN-to-BSN students were identified as generally older, married, and going to school part-time while working and juggling family responsibilities.

The work in [28] deal with this question: Do expenditures other than instructional expenditures impact graduation and persistence rates in American higher education? to answer this question a simulation based on panel data from institutional level and a variety of econometric approaches are used to analyze the influence graduation rates of undergraduate students. The most important result shows that expenditures for student service effect on graduation rate and the effects are higher for students with lower entrance test

scores and higher Pell Grant expenditures.

From the above literatures, two groups of previous studies have been discussed. First group was focused on measurement of graduation rate as way to determine the gap between the numbers enrolled and graduated students, and the other group was focused on investigation the factors affecting

study length problem. Table III(A) and Table III(B) summarize some of the main related studies.

Our work is focused on investigating the factors affecting study length problem similar to [24] but with covering most of related factors.

TABLE III(A): SUMMARY OF RELATED WORKS

#	Author(s)	Year	Objective(s)	Sample	Method(s)
1	N. Zavale <i>et al.</i>	2017	<ul style="list-style-type: none"> <li>Measuring the graduation rate from statistical data</li> <li>Test the statistical significance of the selected variables in affecting the graduation rate</li> </ul>	Data from student records system	Statistical analysis And Stepwise logistic regression analysis
2	P. Belsis <i>et al.</i>	2014	<ul style="list-style-type: none"> <li>Defining linger students</li> </ul>	Survey Students about lab attendance	Clustering and the mining of Association rules
3	E. Katsikas, and T. Panagiotidis	2011	Defining the symptom of long duration of studies	Collecting data from student records and Survey	Regression and quantile regression

TABLE III(B): SUMMARY OF RELATED WORKS

#	Author(s)	Year	Objective(s)	Sample	Method(s)
4	M. Zhan, D. and Lanesskog	2014	<ul style="list-style-type: none"> <li>Investigates the relationships of family assets and debt with college graduation.</li> <li>Estimating models that control for a wide range of student, parental, and institutional variables</li> </ul>	Survey	Regression analyses
5	S. Robertson <i>et al.</i>	2010	<ul style="list-style-type: none"> <li>Exploring issues and processes of measuring progression and graduation rates in an RN-to-BSN population</li> <li>Identify factors that facilitate/hinder their successful progression</li> </ul>	Collecting data from the nursing education literature and survey	Benchmarking
6	D. A Webber, and R. Ehrenberg	2009	Analyze whether non-instructional expenditure categories influence graduation and first-year persistence rates of undergraduate students	Collecting data from several systems	unconditional quantile Regression model

### III. DATA OF FACTORS AFFECTING STUDY LENGTH PROBLEM

The questionnaire method was adopted to collect empirical data for this study. The questionnaire was targeted computing students in two academic departments in faculty of computers and information technology, university of Tabuk, KSA. Table IV(A) to Table IV(F) in appendixes section show the questionnaire variables which are issued based on four perspectives: Linger Information, basic information, personal information, academic information, and learning and teaching Information.

### IV. DEVELOPING THE CLASSIFICATION MODEL

In order to investigate the factors affecting length study problem a questionnaire was distributed. In total, more than 250 male and female students are targeted to participate in this study. 175 students completed the survey for a response rate of 70%, which is considered as a very good response rate. Then the classification processes were performed by means of the data mining software RapidMiner 5.3.013.

The C4.5 algorithm was used to generate decision tree to mining the gathered data, and after the processes of constructing the complete decision tree, eight rules have been generated. Four rules deduce linger students and four rules deduce non-linger students. Table V shows rules deduce linger students. Table VI shows rules deduce the non-linger

students.

In the following, features of two classes have been presented. Each class has group of subclasses. The combined features of each subclass represent either linger student or non-linger student. First features of linger students, and then followed by features of non-loner students. Table V(A), V(B), V(A), and V(B) represents the results of our classification model.

TABLE V(A): RULES DEDUCE LINGER STUDENTS

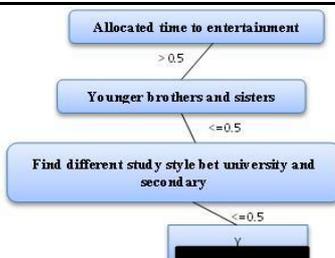
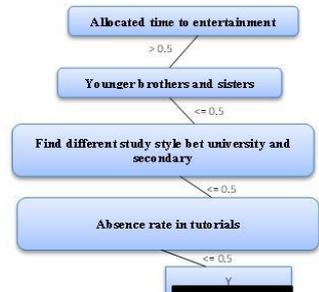
#	Rule statement	Tree of rule
1	If (Allocated time to entertainment = No) and (Younger brothers and sisters = Yes) and (Find different study style bet university and secondary = Yes) then Linger	 <pre> graph TD     A[Allocated time to entertainment] --&gt; &gt; 0.5  B[Younger brothers and sisters]     B --&gt; &lt;= 0.5  C[Find different study style bet university and secondary]     C --&gt; &lt;= 0.5  D[Y]                     </pre>
2	If (Allocated time to Entertainment = NO) and (Younger brothers and sisters = yes) and (Find different study style bet university and secondary = yes) and (low absence rate in Tutorials) then Linger	 <pre> graph TD     A[Allocated time to entertainment] --&gt; &gt; 0.5  B[Younger brothers and sisters]     B --&gt; &lt;= 0.5  C[Find different study style bet university and secondary]     C --&gt; &lt;= 0.5  D[Absence rate in Tutorials]     D --&gt; &lt;= 0.5  E[Y]                     </pre>

TABLE V(B): RULES DEDUCE LINGER STUDENTS

#	Rule statement	Tree of rule
3	If (Allocated time to Entertainment = N0) and (Younger brothers and sisters = yes) and (Secondary_ratio > 70) and (Study Plan Explanation = no) and (high absence rate in Tutorials) and (linger reason = course nature) then linger	
4	If (Allocated time to Entertainment = No) and (Younger brothers and sisters = yes) and (secondary_ratio > 70) and (find different study style bet university and secondary = no) and (Marital status = no) and (low absence rate in Tutorials) then linger	

Features of Linger Students Class: Table V can be summarized in the following sub classes.

**Sub-Class one:** They ignore to allocate specific time for entertainment, they have young sisters and brothers, and they feel there is different study style between university and secondary school.

**Sub-Class two:** They ignore to allocate specific time for entertainment, they have young sisters and brothers, they feel there is different study style between university and secondary school, and they have low absence rate in Tutorials.

TABLE VI(A): RULES DEDUCE NON-LINGER STUDENTS

#	Rule statement	Tree of rule
1	If (Allocated time to Entertainment = N0) and (Younger brothers and sisters = yes) and (Find different study style bet university and secondary = no) and (Were the delivered course materials are sufficient = yes) then not Linger	
2	If (Allocated time to Entertainment = N0) and (Younger brothers and sisters = yes) and (Find different study style bet university and secondary = yes) and (high absence rate in Tutorials) then not Linger	

TABLE VI(B): RULES DEDUCE NON-LINGER STUDENTS

#	Rule statement	Tree of rule
3	If (Allocated time to Entertainment = N0) and (Younger brothers and sisters = yes) and (Secondary_ratio < 70) then not Linger	
4	If (Allocated time to Entertainment = No) and (Younger brothers and sisters = yes) and (Secondary_ratio > 70) and (find different study style bet university and secondary = no) and (Marital status = no) and (Marital status = yes) then not Linger	

**Sub-class three:** They ignore to allocate specific time for entertainment, they have young sisters and brothers, they have secondary ratio greater than 70, they do not get explanation for their study plan, they have high absence rate in Tutorials, and they think that they are linger students due to the nature of their courses.

**Sub-class four:** They ignore to allocate specific time for entertainment, they have young sisters and brothers, they have secondary ratio greater than 70, they feel there is different study style between university and secondary school, they are not married, and they have low absence rate in Tutorials.

Features of Non-Linger Students Class: Table VI cloud be summarized in the following sub classes.

**Sub-class five:** They ignore to allocate specific time for entertainment, they have young sisters and brothers, they feel there is no different study style between university and secondary school, and they feel that the delivered course materials were sufficient.

**Sub-class six:** They ignore to allocate specific time for entertainment, they have young sisters and brothers, they feel there is different study style between university and secondary school, and they have high absence rate in Tutorials.

**Sub-class seven:** They ignore to allocate specific time for entertainment, they have young sisters and brothers, and they have secondary ratio less than 70.

**Sub-class eight:** They ignore to allocate specific time for entertainment, they have young sisters and brothers, and they have secondary ratio less than 70, they feel there is no different study style between university and secondary school, and they are married.

V. DISCUSSION AND CONCLUSION

In this paper, C4.5 algorithm has been used on student data to classify students based on their study length. Features of

linger students have been deduced in four sub classes and same for non-linger students. As conclusion, linger student could be described by combination of factors such as in sub-class one, sub-class two, sub-class three, or sub-class four. Linger student could be any one of these subclasses. For instance, from sub-class one, the students who have these three characteristics together in the same time: 1) there is no schedule for entertainment, 2) they have young sisters and brothers, 3) and feel there is different study style between university and secondary school, those students with these characteristics have high potentially to be linger students.

On the other hand, non-linger students also could be described by combination of f characteristics, such as in sub-class five, sub-class six, sub-class seven, or sub-class eight. For instance, from sub-class six, the students who have these four characteristics together in the same time: 1) there is no schedule for entertainment, 2) they have young sisters and brothers, 3) feel there is different study style between university and secondary school, and 4) they have high absence rate in Tutorials, those students with these characteristics have high potentially to be non-linger students.

The previous two examples illustrate features or characteristics of linger and non-linger students. There are strong similarity between these two classes, for instance, in the previous examples the only difference between linger and non-longer students is that non-linger has one more characteristic which is “high absence rate in Tutorials”. Although characteristic which is “high absence rate in Tutorials” seems strange to be labeled with non-linger student but this is which has been extracted from the data.

In the following, we have used First Order Logic (FOL) for mathematical representing the results from Tables V and VI.

**Suppose:**

A = Allocated time to Entertainment; B = Has younger brothers and sisters; C = Find different study style bet university and secondary; D = Low absence rate in Tutorials; E = Secondary\_ratio > 70; F= Study Plan Explanation; G= Marital status; H = The delivered course materials are sufficient; I= Secondary\_ratio < 70; J= linger reason = course nature;

$$\forall A,B,C: (\sim A) \wedge B \wedge C \Rightarrow Linger \quad (1)$$

$$\forall A,B,C,D:(\sim A) \wedge B \wedge C \wedge D \Rightarrow Linger \quad (2)$$

$$\forall A,B,E,D:(\sim A) \wedge B \wedge E \wedge (\sim F) \wedge (\sim D) \wedge J \Rightarrow Linger \quad (3)$$

$$\forall A,B,C,E,D,G: (\sim A) \wedge B \wedge E \wedge (\sim C) \wedge (\sim G) \wedge D \Rightarrow Linger \quad (4)$$

$$\forall A,B,C,H:(\sim A) \wedge B \wedge (\sim C) \wedge H \Rightarrow \sim(Linger) \quad (5)$$

$$\forall A,B,C,D:(\sim A) \wedge B \wedge C \wedge (\sim D) \Rightarrow \sim(Linger) \quad (6)$$

$$\forall A,B,I:(\sim A) \wedge B \wedge I \Rightarrow \sim(Linger) \quad (7)$$

$$\forall A,B,C,E,G: (\sim A) \wedge B \wedge E \wedge (\sim C) \wedge G \Rightarrow \sim(Linger) \quad (8)$$

The above eight equations summarized mathematically the results from tables five and six. Equations one to four could be combined as:

$$\forall A,B,C,D,E,G,J: ((\sim A) \wedge B \wedge C) \vee ((\sim A) \wedge B \wedge C \wedge D) \vee ((\sim A) \wedge B \wedge E \wedge (\sim F) \wedge (\sim D) \wedge J) \vee ((\sim A) \wedge B \wedge E \wedge (\sim C) \wedge (\sim G) \wedge D) \Rightarrow Linger \quad (A)$$

Equations five to eight could be combined as:

$$\forall A,B,C,D,E,G,I,H: ((\sim A) \wedge B \wedge (\sim C) \wedge H) \vee ((\sim A) \wedge B \wedge C \wedge (\sim D)) \vee ((\sim A) \wedge B \wedge I) \vee ((\sim A) \wedge B \wedge E \wedge (\sim C) \wedge G) \Rightarrow \sim(Linger) \quad (B)$$

From equations (A) and (B) we can see the following observations

- Students do not allocate time for entertainment which reflects that students do not have interesting in time management.
- The position of student in his family is critical factor.
- Linger students have alienated feeling, which means they found difficulty to cope with university environment.
- The impact of tutorials attendance rate in linger students is unclear. In sub-class 2 there is low absence rate feature while in sub class three there is high absence rate feature. This ambiguity might be happen due to subjectivity of the questionnaire. The questionnaire is left free to students to answer based on their opinion. In fact, after analyzing the feedback we found that it is better to use an external source of information, such as formal records of attendance.
- Linger students need more effort in study plan explanation.
- The impact of secondary school ratio is unclear. This ambiguity might be happen due to subjectivity of the questionnaire.

This study will help in improving the quality of education and decision making by determining early the students "who" might exceed the planned study length period. We recommend future studies to use directed questionnaire and support it by independent and external source of information to avoid to biases.

APPENDIX

TABLE IV(A): VARIABLES DESCRIPTION

Variable	Description	Possible Values	Perspective
Linger	The student is linger or not	Yes, No	
Linger Source	The source of delaying in study	Personal matter, Courses nature, Teaching methods, university environment, Tabuk environment	
Graduation Semester	The expected graduation semester	Current semester, Next semester, After next semester	Linger
Preparatory Year	Student face an academic problem or not	Yes, No	Information
Previous Linger	Student is delayed previously or not	Yes, No	
Course(s) That Caused Problems	The course(s) that caused academic problem	Programming, Mathematics, English,	

TABLE IV(B): VARIABLES DESCRIPTION

Variable	Description	Possible Values	Perspective
Gender	Gender of student	Male-Female	Basic information
Age	Age of student	Less than or equal 20 years, Greater than 20 years	
Origin	Origin place of student	Inside Tabuk- outside Tabuk	
Current Accommodation	The current accommodation of students	With Family- Single	
Marital Status	The marital Status	Married, Single, divorced, widower	
Offspring	No of children	None, 1, 2, 3, more than 3	
Family Position	The student is oldest brother or not	Yes, No	
Siblings	No. of sisters and brothers	None, 1, 2, 3, more than 3	
Father Qualifications	Qualifications of the student's father	Illiterate, Primary School, Middle School, Secondary School, University, Master Degree, PhD Degree	

TABLE IV(C): VARIABLES DESCRIPTION

Variable	Description	Possible Values	Perspective
Mother Qualifications	Qualifications of the student's mother	Illiterate, Primary School, Middle School, Secondary School, University, Master Degree, PhD Degree	Basic information
Father Alive	Student father is alive or not	Yes, No	
Father Job	The job of the student's father	Service, Educational, Commercial, Military, Freelance, Retired	
Mother Job	The job of the student's mother	Housewife, Service, Educational, Commercial, Retired	
Family Income	The monthly income is enough or not	Yes, No	

TABLE IV(D): VARIABLES DESCRIPTION

Variable	Description	Possible Values	Perspective
Smoking	The student is smoking or not	Smoking, Not smoking	Personal information
Chronic Diseases	Student has a chronic diseases or not	Yes, No	
Vision State	The vision of state of student is using glasses or not	Glasses, No Glasses	
Physical Disability	The student has Physical disability or not	Yes, No	
Transportation to The University	The type of transportation that the student used to go to the university	Shared Transportation, Bus, Private car	
Place of Break Time	The student place in break time	Library, Cafeteria, Outside university	
Time Plan	Student has a time plan or not	Yes, No	
Lessons Review Commitment	Time student has a commit of review lessons time	Yes, No	
Entertainment Time	Spent time in entertainment game	Less than or equal 2 hours, 4 hours, Grater than 4 hours	
Enthusiasm for Study	Students has an enthusiasm feel for the study or not	Yes, No	
A source of Enthusiasm	The source of no enthusiasm feeling	Courses nature, Teaching methods, university environment, Tabuk environment.	
Future Goal(s)	Student has a future goal(s) or not	Yes, No	
Relation with Outstanding Students	Student has a relation with outstanding colleagues or not	Yes, No	
Future Position Type	The desired position of student in future	Related to computer, Not related to computer	

TABLE IV(E): VARIABLES DESCRIPTION

Variable	Description	Possible Values	Perspective
University Entry Ratio	The average ratio for the university entry ratio	80%-89%, 70%-79%, 60%-69%, 50%-59%, 40%-49%	Academic information
Current GPA	The current cumulative average of student	More than 4.5, 3.5-4.4, 2.5-3.4, 2-2.4, Less than 2	
Current Level	The current level of student in the university	First, Second, Third, Fourth	
GPA	The current cumulative average of student	More than 4.5, 3.5-4.4, 2.5-3.4, 2-2.4, Less than 2	
Current Major	The current major of the student in the faculty	Computer Science, Information Technology	
Major Satisfaction	The level of student satisfaction about major	Bad, Medium, Good	
Dissatisfaction Source	The source(s) of dissatisfaction	Courses nature, Teaching methods, university environment, Tabuk environment.	
Major Selection	Student who select the major or not	Yes, No	

TABLE IV(F): VARIABLES DESCRIPTION

Variable	Description	Possible Values	Perspective
Lectures Absent Rate	The student absent rate of lectures is high or not	Yes, No	Learning and teachings information
Labs Absent Rate	The student absent rate of labs is high or not	Yes, No	
Tutorials Absent Rate	The student absent rate of tutorials is high or not	Yes, No	
Courses Objectives Clarity	The courses objectives are clear or not	Yes, No	
Teaching Methods and Efficiency	The teaching methods are enough and effective or not	Yes, No	
Course's Materials and textboxes Availability	The courses materials and textboxes are available and effective or not	Yes, No	
Classrooms, Labs and Library	The classrooms, labs and library are equipped or not	Yes, No	
Lectures, Labs and Tutorials Time	The time of Lectures, labs and tutorials time are appropriate	Yes, No	
Lectures, Labs and Tutorials Time Sufficiently	The time of Lectures, labs and tutorials time are sufficient	Yes, No	

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