Predicting University Dropout through Data Mining: A Systematic Literature

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Predicting University Dropout through Data Mining: A Systematic Literature

Mayra Alban1* and David Mauricio2
1Technical University of Cotopaxi, Faculty of Computer Science and Computer Systems, Ecuador; mayra.alban@utc.edu.ec
2National University of San Marcos, Artificial Intelligence Group, Perú; dmauricios@unmsm.edu.pe

Abstract

Objectives: To make a systematic review of literature on the prediction of university student dropout through data mining techniques. Methods/Analysis: The study was developed as a systematic review of the literature of empirical research results regarding the prediction of university dropout. In this phase, the review protocol, the selection requirements for potential studies and the method for analyzing the content of the selected studies were provided. The classification presented in section 3 allowed answering the main research question. What are the aspects considered in the prediction of university student desertion through data mining? Findings: University dropout is a problem which affects universities around the world, with consequences such as reduced enrolment, reduced revenue for the university, and financial losses for the State which funds the studies, and also constitutes a social problem for students, their families, and society in general. Hence the importance of predicting university dropout, that is to say identify dropout students in advance, in order to design strategies to tackle this problem. Novelty/Improvement: This is the first work to perform an integral systematic literature review about university dropout prediction through data mining, with studies from 2006–2018.

Keywords: Data Mining, Dropout Factors, Dropout Prediction, Machine Learning, University Student Dropout

1. Introduction

There is currently an increasing interest in researching the topic of university dropout around the world1, with one of the main concerns being elevated rates of occurrence2. Dropout negatively affects institutions in the reduction of enrolment and the non-achievement of institutional objectives3. As a consequence, students, universities and governments are affected in both economic and social terms. Furthermore, dropout becomes a critical topic when university administrators do not possess the tools necessary to identify students who are at risk of leaving the institution. In turn, potential corrective measures are reduced4, which might have enabled student retention at higher education institutions5. In the same way, the early prediction of student dropout has become a major challenge, as well as identifying the factors which contribute to this increasingly occurring phenomenon6. One possible reason that there are still high university dropout rates may be associated with the fact that most of the prediction models applied to solve this problem are difficult to interpret7. A significant effort has been made to close the university dropout gap and thus reduce dropout rates. Nonetheless, this effort has been insufficient8; according to the Organization for Economic Cooperation and Development (OECD), in 2016, European dropout rates ranged between 30% and 50%, while in the United States the student dropout rate was 37%9.

In some Latin American countries, such as Columbia, dropout rates exceeded 40%, while in Brazil they reached approximately 54%. In Costa Rica, the dropout rate reached 50%2, with public universities presenting higher dropout rates than private ones10. One of the measures to deal with university dropout is based on predicting its rates; therefore, data mining is used, aimed at developing methods to identify patterns among large datasets and
Predicting University Dropout through Data Mining: A Systematic Literature

In general, this process follows four stages, which range from data pre-processing to result evaluation (Figure 1).

Prior literature survey on data mining and education have covered topics such as: learning management systems, intelligent tutoring systems, adaptive educational systems, learning analytics, student modeling, and predicting academic performance. However, none of these considers the topic of university dropout, despite the large number of studies regarding factors that influence university dropout and techniques for dropout prediction. For this reason, the present study aims to answer the following question: What aspects are considered in predicting university student dropout through data mining?

In order to perform this systematic review, we considered the methodologies applied by, which consist in three stages:

**Planning:** This stage identifies the need for research and the determination of a review protocol.

**Implementation:** This stage implements the plan; the defined protocol is applied as well as the inclusion and exclusion criteria.

**Results:** This stage presents the results and statistical analysis of the selected documents.

### 2.1 Planning

Five research questions were proposed in order to determine the aspects that have been developed to predict university student dropout.

- Question 1 (Q1): What techniques are used for data pre-processing?
- Question 2 (Q2): What factors affect dropout?
- Question 3 (Q3): What techniques are used for factor selection?
- Question 4 (Q4): What techniques are used for prediction and what are their levels of reliability?
- Question 5 (Q5): What tools are used?

Articles from conferences and journals indexed in Scimago Journal Country Rank (SJR) with impact factor were reviewed in the following databases: Science Direct, ACM Digital Library, IEEE Xplore, Springer, DOAJ, Taylor and Francis, Emerald, Proquest and Ebsco. For document selection, the inclusion and exclusion criteria presented in Table 1 were applied.

The following search criteria were considered: “dropout student” OR “drop out student” OR “dropping student” AND “data mining”, which were applied to the title, abstract and keywords in the search period between January 2006 and December 2017.

### Table 1. Criteria for document selection

| Inclusion | Exclusion |
|-----------|-----------|
| Models to provide a solution to the problem of university student dropout. | Prediction documents that are unrelated to university student dropout, such as primary, secondary and postgraduate education. |
| Documents that present factors influencing university dropout. | Documents not related to data mining. |
| Papers that include prediction based on data mining. | Documents that do not have numeric experimentation. |
| Papers that present metrics to assess the quality of predictive models. | Documents that are not found within the established search period. |
| Papers that respond to the research questions. | |

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**Figure 1.** Data mining process for university dropout prediction.
Mayra Alban and David Mauricio

Indian Journal of Science and Technology

Vol 12 (4) | January 2019 | www.indjst.org

3. Result

Table 2 summarizes the total identified and selected documents by information source, Science Direct being the main source of information, with 40% of the primary selected studies. Meanwhile, Emerald and ACM Digital Library present rates of 4.47% and 1.49%, respectively. Figure 3 exhibits the increase in studies during the past 12 years and the interest that researchers have in solving the problem of university dropout prediction. 87% of the primary selected documents come from journals (58 studies out of 67), and 13% correspond to publications in conferences (9 studies of 67), as presented in Figure 4. From the selected documents, we identified three aspects regarding university dropout prediction: factors, techniques and tools, all of which are specified in the framework of the present study.

**Dropout factors:** The reasons for which students leave studies.

**Data mining techniques:** The objective of these techniques is to discover patterns, profiles and trends through

Table 3. Techniques for data pre-processing

| ID  | Technique                                      |
|-----|-----------------------------------------------|
| TDP1| Multivariate analysis of variance[22]         |
| TDP2| Bagging[26]                                   |
| TDP3| Discretization[22,37,39]                      |
| TDP4| Attribute-based filtering[40,53]              |
| TDP5| Single imputation[41]                        |
| TDP6| Multiple imputation[47,48]                    |
| TDP7| Normalization[22,37,26,43,42,12]             |
| TDP8| Oversampling[22]                             |
| TDP9| Simple random sampling[43,42]                 |

2.2 Implementation

We performed the search process based on the strategies proposed in section 2. Once selected, each document’s content was reviewed in order to determine whether it matched the established selection criteria. The systematic literature review process is presented in Figure 2.

Figure 2. Systematic literature review process.

**Table 2.** Selected papers

| Source                  | Identified papers | Selected papers |
|-------------------------|-------------------|-----------------|
| Science Direct          | 378               | 27              |
| ACM Digital Library     | 326               | 1               |
| IEEE Xplore             | 41                | 10              |
| Springer                | 260               | 6               |
| DOAJ                    | 71                | 5               |
| Taylor and Francis      | 27                | 5               |
| Emerald                 | 110               | 3               |
| Proquest                | 148               | 4               |
| Ebsco                   | 320               | 6               |
| **Total**               | **1681**          | **67**          |

Figure 3. Temporal trend of selected publications on university dropout.

Figure 4. Publications on university dropout prediction.
Predicting University Dropout through Data Mining: A Systematic Literature

Indian Journal of Science and Technology
Vol 12 (4) | January 2019 | www.indjst.org

4

Vol 12 (4) | January 2019 | www.indjst.org

Predicting University Dropout through Data Mining: A Systematic Literature

Indian Journal of Science and Technology
Vol 12 (4) | January 2019 | www.indjst.org

4

Table 4. Personal dimension factors

| ID   | Factors                                      |
|------|----------------------------------------------|
| PDF01| Adjustment                                   |
| PDF02| Age 2, 20, 25, 28, 44–55                    |
| PDF03| Change of goal 21, 23, 24, 56               |
| PDF04| Choice to change current course 23          |
| PDF05| Country or city of origin 19, 37, 29        |
| PDF06| Dependents                                  |
| PDF07| Disability                                  |
| PDF08| Domicile 24, 70, 31, 20                    |
| PDF09| Encouragement and support from parents 25   |
| PDF10| Engagement of students 28, 43, 56, 58       |
| PDF11| Ethnicity 2, 39, 26, 25, 33, 12, 47, 68, 79, 71, 60 |
| PDF12| Gender 2, 11, 22, 20, 28, 44, 45, 50, 39, 33, 61, 62, 48, 70 | 81 |
| PDF13| Has a computer                              |
| PDF14| Health problem                              |
| PDF15| Interest level in the current course 13     |
| PDF16| Intrinsic motivation 41, 79                 |
| PDF17| Leadership                                 |
| PDF18| Level of commitment 40                     |
| PDF19| Living on campus                           |
| PDF20| Loneliness 57                               |
| PDF21| Marital status 5, 22, 49, 68, 29, 73       |
| PDF22| Measure of student persistence 45, 69      |
| PDF23| Pessimism                                  |
| PDF24| Residency 20, 66, 31                       |
| PDF25| Self-efficacy                               |
| PDF26| Student satisfaction 28, 44, 52, 57         |
| PDF27| Tuition fee source 22                      |
| PDF28| Vocational involvement 24                  |
| PDF29| Work experience                             |
| PDF30| Year of birth 40                            |

Table 5. Academic dimension factors

| ID   | Factors                                      |
|------|----------------------------------------------|
| ADF01| Absenteeism 24                               |
| ADF02| Academic ability 75, 61                      |
| ADF03| Academic overload 22                        |
| ADF04| Academic performance 5, 61, 81              |
| ADF05| Age at admission 65                         |
| ADF06| Average formative assessment result 20       |
| ADF07| Best test score GPA 1.5, 64, 69, 34, 37, 44, 46, 47, 48, 56, 57, 59, 33, 70, 80, 81 |
| ADF08| Cohort 26, 60, 70, 71                       |
| ADF09| Curricular involvement 48                   |
| ADF10| Degree 27, 36, 48, 59, 59                   |
| ADF11| Degree aspiration 22, 28                    |
| ADF12| Degree program length 24                    |
| ADF13| Drop out intention 22                       |
| ADF14| Educational goal 28                         |
| ADF15| English language literacy 41                |
| ADF16| Enrolled in other institution 28             |
| ADF17| Entry qualifications 7, 69                   |
| ADF18| Experience 22                               |
| ADF19| Final examination test 20, 77, 26, 46, 58, 65 |
| ADF20| First and second mid-term exam grade 45      |
| ADF21| First semester credit load 23               |
| ADF22| Motive for choice 24                        |
| ADF23| Number quiz 55                              |
| ADF24| Participate in extra curriculum activity 28, 31 |
| ADF25| Points from secondary 49, 58, 12             |
| ADF26| Progression outcome 2                       |
| ADF27| Readiness 2                                 |
| ADF28| Recognized credits 41, 60, 29               |
| ADF29| Resources use 22                            |
| ADF30| Satisfaction with course 31                 |
| ADF31| Score of academic integration 45, 59, 65    |
| ADF32| Scores 25, 38, 69, 29, 65, 79, 84           |
| ADF33| Self-evaluation 51, 64                      |
| ADF34| Student enrolment status 28, 73, 12          |
| ADF35| Study center 45, 73                         |
| ADF36| Study level 20, 41, 30, 33                  |
| ADF37| Study shift 43                              |
| ADF38| Success rate 54                             |
| ADF39| Support for learning 22                     |
| ADF40| Total failed courses 50                     |

data analysis using pattern recognition technologies and advanced data analysis techniques.

Data mining tools: This refers to software used to extract patterns, trends and regularities to discover and better understand the data and predict future behavior 12.

a) Q1: What techniques are used for data pre-processing?

In the pre-processing stage, eleven techniques were identified (Table 3). This stage allows the management of anomalies as well as the correction of atypical and
missing values\textsuperscript{17}. The purpose of these techniques is to improve the properties of the variables and solve data anomalies to optimize the search process of data mining algorithms\textsuperscript{18}. This is based on three activities: integration, cleaning and transformation of the information. All of the studies\textsuperscript{20} involving the pre-processing stage are concentrated around the activity of data transformation, with the techniques of normalization and discretization being the most commonly used. However, integration and cleaning activities are also important; as in\textsuperscript{19,20} indicate; selecting the wrong variables in the data mining process can negatively affect prediction accuracy for these techniques.

b) Q1: What factors affect dropout?

We identified 112 factors to predict university dropout, which were classified according to the five dimensions (personal, academic, economic, social and institutional) proposed by author\textsuperscript{21}.

**Personal factors:** These constitute characteristics that determine student behavior such as feelings, thoughts or actions, which are decisive in the development of their educational environment. We identified 31 factors in the personal category, and these corresponded to approximately 28\% of the total identified factors, as shown in Table 4. For many authors, personal factors are the main cause of students dropping out of university, and Table 4 evidences this fact. Age and gender are the most frequently used factors for prediction; this is because they are considered internal factors of variability which are simple to define and measure\textsuperscript{22}.

**Academic factors:** These refer to the development of students in their formative process. We identified 40 academic factors, which correspond to 36\% of the total identified factors, presented in Table 5.

Analysis of these factors shows that the university entrance test is the most frequently used factor in the literature. However, it bears mentioning that the learning process at university has a close relationship with preceding study levels, impacting further educational achievements\textsuperscript{23}. In the same way, the score that a student obtains in the university entrance examination is considered an indicator to explain success or failure in academic trajectory at university\textsuperscript{5}. In this sense, many studies have analyzed the predictive validity of this factor, considering it a predictor of cognitive and attitudinal characteristics that is of the utmost importance for students to succeed at university\textsuperscript{24}.

**Economic factors:** These are related to students’ ability to satisfy the economic requirements that present themselves during the academic program. In this dimension, 15 factors were identified that affect dropout, and they correspond to approximately 13\% of the total analyzed factors, which are presented in Table 6. These economic dimension factors refer to material comforts and the ability of parents to allocate more and better resources for the academic performance of their children, which has a significant impact on academic achievements\textsuperscript{25}.

**Social factors:** These are aspects that affect students as a whole, and which are determined by their place and space, as presented in Table 7.

On the other hand, the social dimension focuses on the importance of the interaction between students and their social environment; interaction in relation to the institution, academic norms, and study habits\textsuperscript{26}.

**Institutional factors:** The factors that correspond to this category relate to the structural and functional characteristics of an institution, which are presented in Table 8; these represent approximately 3.53\% of the total analyzed factors.

c) Q3: What techniques are used for factor selection?

We identified ten techniques for factor selection, which are presented in Table 9. The objective of these techniques is to select the most relevant factors used as input
variables for dropout prediction models. Approximately 55% (23 out of 42 studies) used descriptive statistics, as this technique produces the characteristics of dispersion, location and distribution of the variables. Additionally, the technique is frequently used to identify patterns regarding student characteristics and behaviors related to dropout. Of these 23 studies, 14 are oriented towards variable correlation and apply this type of analysis to evaluate the association and relationship of quantitative data in terms of directionality, through correlation coefficients. On the other hand, 12% (5 out of 42 studies) apply Principal Components Analysis to reduce the dimensionality of the observed variables to a number of hypothetical variables; thus, groups of variables that correlate with one another are created. These variables are transformed into independent factors that are implemented in dropout prediction models.

We identified 14 data mining techniques, which had been classified into artificial intelligence and statistical method techniques; these are presented in Tables 10 and 11. Approximately 79% (22 out of 28 studies) used Decision tree classifiers. According to this technique is used due to its flexibility when processing data of a numerical and categorical nature, its monotonic transformations of explanatory variables, and the ease of interpreting results. Furthermore, it presents better accuracy rates. In and mention that the algorithm ID3 (Decision tree classifier) is effective in classifying data from student history registers and is more sensitive in comparison to other algorithms.

Neural network classifiers and support vector machines hold the second highest frequency of use, since these data mining approaches are considered powerful tools for solving classification problems and are used frequently for their simplicity and ease of understanding. Four statistical techniques were identified, corresponding to a total of 36 references, or 3% (4 out of 14 techniques) of the total studies analyzed. Of these, 54% (21 out of 39 studies) applied Linear Regression and Logistic Regression, as

**Table 7. Social dimension factors**

| ID   | Factors                                    |
|------|--------------------------------------------|
| SDF01| Campus accommodation                       |
| SDF02| Category (marginalized or vulnerable section of society) |
| SDF03| College status                             |
| SDF04| Community support                          |
| SDF05| Employment status                          |
| SDF06| Family problems                            |
| SDF07| Family type                                |
| SDF08| Father’s educational level                  |
| SDF09| Housing indicator                          |
| SDF10| Level of involvement in social media        |
| SDF11| Means of transport                         |
| SDF12| Migrated before                            |
| SDF13| Mother migrated                            |
| SDF14| Mother’s educational level                  |
| SDF15| Occupation                                 |
| SDF16| Parent occupation                          |
| SDF17| Political status                           |
| SDF18| Social status                              |
| SDF19| Stress                                     |
| SDF20| Student use of drugs                       |
| SDF21| Use of recreational facilities              |

**Table 8. Institutional dimension factors**

| ID   | Factors                      |
|------|------------------------------|
| IDF1 | Campus environment           |
| IDF2 | High school type             |
| IDF3 | Institutional involvement    |
| IDF4 | University infrastructure    |

**Table 9. Techniques for the selection of factors**

| ID   | Techniques                    |
|------|-------------------------------|
| TSF01| Analysis of variance          |
| TSF02| Descriptive Statistics        |
| TSF03| Feature extraction algorithm  |
| TSF04| Genetic Algorithm             |
| TSF05| Hosmer and Lemeshow           |
| TSF06| Locality Preserving Projection|
| TSF07| Maximum Likelihood            |
| TSF08| Neighborhood Preserving Embedding |
| TSF09| Principal Components Analysis |
| TSF10| Kaiser Meyer Olkin           |
| TSF11| U Mann Whitney               |

d) Q4: What techniques are used for prediction and what are their levels of reliability?
these are frequently used techniques for classifications based on data characteristics, and are flexible in the use of categorical and continuous predictor variables. On the other hand, regarding the accuracy of data mining techniques, the authors considered metrics such as sensibility, specificity, and accuracy. Of these, accuracy is determined by the ratio of True Positives (TP) to True Negatives (TN) among the total of registers, as formulated in equation (1).

$$\frac{TP + TN}{TP + TN + FP + FN} \times 100$$  \hspace{1cm} (1)

where, FP is the number of false positives and FN the number of false negatives. Tables 12 and 13 report the accuracy levels of the data mining techniques that reached a ratio higher than 60% and have a dataset composed of a number higher than 100 students.

The results show that the most accurate techniques are the Decision Tree Classifier, with the classifiers C4.5, ID3, and CART, reaching an accuracy of 98%, 97.5%, and 97%, respectively. The results evidence that the most accurate technique is Linear Regression (87.8%). However, these results cannot be generalized, as they depend on the dataset and the considered variables.

e) Q4: What tools are used?

We identified four tools in studies with artificial intelligence techniques, and seven tools in those using statistical methods; these are presented in Tables 14 and 15, respectively. The results highlight that the most widely used tools are WEKA and SPSS Modeler, most likely due to their wide variety of automatic learning algorithms for data mining tasks, flexibility in predictive modeling, and their facilities and functionalities.

4. Discussion

Of the 67 studies identified on university student dropout prediction, 18% contemplate the pre-processing phase. Therefore, this underlines the importance of this phase in obtaining variable properties, solving data anomalies, and increasing accuracy rates. We found that 90% of the studies regarding dropout prediction contemplate factor dimension, which evidences its relevance to the scientific community. Age, gender, ethnicity, and entrance exam performance are the most commonly used factors and correspond to the personal dimension. Although the total factors are wide-ranging, their behavior changes from one context to another; therefore, there is much controversy over which factors prove to be most efficient in university dropout prediction. With respect to factor selection techniques, 34% of studies used descriptive statistics and 7% used principal components analysis. This is one of the most relevant phases when predicting dropout due to its reduction in variable dimensionality. Thus, it allows us to adequately select the most predominant factors used as input variables in dropout prediction models. With regards to the techniques used to predict dropout, currently, statistical techniques are most commonly used. However, these are gradually being replaced by artificial intelligence techniques, since the latter present higher accuracy rates. Nevertheless, these rates vary according to the factors and educational context, the educational environment, and the theoretical framework of the analysis.

5. Conclusions

This study presents a systematic literature review on the aspects of data mining considered for predicting university dropout. We identified 1,681 primary studies related to the topic, from amongst which 67 documents were selected according to the established inclusion and exclusion criteria, identifying five important dimensions: factors, pre-processing techniques, factor selection techniques, prediction, and tools. This study makes an
inventory of 112 factors that influence dropout prediction. These factors were classified into five dimensions: personal, academic, economic, social, and institutional; the most commonly studied was the personal dimension, which considers factors such as age, ethnicity and gender. Furthermore, we identified ten pre-processing techniques, the most widely used being normalization and discretization. There were ten techniques for factor selection, of which descriptive statistics and Principal Component Analysis were the most referenced. Additionally, four

Table 12. Accuracy of artificial intelligence techniques

| Dataset size | Techniques | Accuracy (%) |
|--------------|------------|--------------|
| 200          | Feed forward neural network | 82 |
|              | Probabilistic ensemble PESFAM | 62 |
|              | SEDM | 94 |
| 193          | Feed forward neural network | 84 |
|              | Support vector machine | 83 |
|              | Probabilistic ensemble simplified fuzzy ARTMAP | 97 |
| 170          | Naive Bayes | 81 |
|              | J48 | 70 |
| 240          | ID3 | 92.50 |
|              | ID3 (Renyi) | 97.50 |
| 150          | Support vector machine | 89.84 |
|              | Decision tree classifier | 86.32 |
|              | Rule induction | 81.98 |
| 3,200        | Naive Bayes | 85 |
|              | Artificial neural networks | 62 |
|              | Decision trees and random forest | 63 |
| 62,375       | Artificial neural network | 84 |
|              | Decision tree classifier | 82 |
|              | Bayesian networks | 76 |
| 300          | C4.5 | 98 |
|              | CART | 97 |
|              | Logistic regression | 86 |
| 775          | Excalibur (J48) | 80 |
|              | SNA (PART) | 92 |
| 3,617        | General Bayesian network | 89 |
|              | C4.5 | 86 |
| 21,654       | Artificial neural networks | 85 |
|              | Support vector machine | 90 |
|              | Decision tree classifier | 89 |
|              | Logistic regression | 80 |
|              | Logistic regression | 84 |
|              | Naive Bayes | 83 |
|              | Support vector machine | 67 |
|              | Decision tree classifier | 83 |
| 128          | Decision tree classifier | 84 |
|              | Logistic regression | 84 |
|              | Naive Bayes | 82 |
|              | Artificial neural network | 82 |

Table 12. (Continued)

| Dataset size | Techniques | Accuracy (%) |
|--------------|------------|--------------|
| 189          | K-Nearest neighbor | 87 |
|              | Decision tree classifier | 79 |
|              | Naive Bayes | 76 |
|              | Artificial neural network | 73 |
| 32,538       | Logistic regression | 66 |
|              | Random forest | 62 |
|              | K-Nearest neighbor | 64 |
| 200          | ID3 | 90.90 |
|              | C4.5 | 89.09 |
|              | CART | 86.06 |
|              | ADT | 87.27 |

200          | K-Nearest neighbor | 74 |
|              | Radial basis function | 70 |
|              | Support vector machine | 79 |
|              | Support vector machine | 65 |
|              | Logistic regression | 65 |
|              | Random forest | 86 |
|              | Gradient boosting decision tree | 88 |

Table 13. Accuracy of statistical techniques

| Dataset Size | Technique       | Accuracy (%) | Reference |
|--------------|-----------------|--------------|-----------|
| 237          | Logistic regression | 71.80 | 23 |
| 6,733        | Logistic regression | 56.60 | 29 |
| 293          | Logistic regression | 85.50 | 29 |
| 1,064        | Logistic regression | 85.80 | 26 |
| 588          | Linear regression | 87.80 | 29 |
| 37,006       | Discriminant analysis | 69.10 | 24 |
| 134          | Discriminant analysis | 81.30 | 27 |
| 209          | Discriminant analysis | 78.20 | 24 |

(Continued)
Table 14. Tools used in studies applying artificial intelligence techniques

| Tools          | AI1            | AI2            | AI3            | AI7            | AI9            |
|----------------|----------------|----------------|----------------|----------------|----------------|
| WEKA           | 46.3, 61, 63, 67, 69, 79 | 63, 61, 63, 67, 69 | 61, 63, 67, 69, 65, 67 | 61, 67, 65, 67 | 67             |
| SPSS Modeler   | 63, 76          | 63, 76          | 63             | 63             | 63             |
| Matlab         | 61, 63          | 61, 63          | 61             | 61             | 61             |
| SAS Enterprise | 61             | 61             | 61             | 61             | 61             |
| Rapid Miner    | 61             | 61             | 61             | 61             | 61             |

Table 15. Tools used in studies applying statistical techniques

| Tools          | S1            | S2            | S3            |
|----------------|---------------|---------------|---------------|
| WEKA           | 28, 63, 68    | 62            | 67            |
| SPSS Modeler   | 79, 63, 70    | 83, 38, 27    | 63            |
| Matlab         | 63            | 63            | 63            |
| R              | 63            | 63            | 63            |
| ISFE SYSTEM    | 63            | 63            | 63            |
| SAS Enterprise | 63            | 63            | 63            |
| Excel          | 63            | 63            | 63            |

Sixteen techniques were identified for dropout prediction, and these were classified into statistics and artificial intelligence. The statistical techniques presented a higher frequency of use, while the artificial techniques presented greater accuracy rates. Finally, there are many data mining tools, of which the most used are WEKA and SPSS Modeler.

Consequently, it is clear that university dropout prediction is of interest to the scientific community, evidenced by the large volume of works on the topic, and its socio-economic impact. To address the problem of dropout, highly accurate techniques are being developed, however we cannot identify one technique that is clearly superior, for prediction accuracy depends mainly on the context, data and technique characteristics; any potential alternative must consider these factors.

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