# The Influence of Clarity on Career Choice and Academic Success in First Year

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*Abstract*—In this study, we use various machine learning algorithms to understand the link between the grades that students achieve and their choice of career path within a first year biological sciences degree. This research will shed light on the students' academic success in relation to their motivation to pursue a career within the field which they are studying.
Student success is classified into two classes, pass or fail, using the student career choices, their interest factor that leads to the career choice, the learning style they use in university, and their results in first year. We used six machine learning models to classify the students under two classes (Fail or Pass). The Support Vector Machine model had an accuracy of 74% which was the best model compared to the other 6 models, it had 10-fold cross-validation. The Simple Logistics model achieved the second-best accuracy of 73% also with 10-fold cross-validation.

*Index Terms*—Machine Learning, Career Choice, Student success, South Africa

## 1. Introduction

The South African educational system has become more equitable over the years after the institutionalised system of racial segregation, the apartheid system, came to an end in 1994. Disciplines such as science are now growing the pool of talent entering the domain. Despite the fact that the number of first-year students in higher education is increasing, data reveal that only a small percentage of those individuals qualified for a degree [1]. Challenges with decisions on career choice could be the underlining issues for the high rate of retention of students in science. We could gain more insight into why high attrition rates are still prevalent today by determining to what extent first-year students who are confident of their career path perform better than first-year students who are uncertain of their career path.

This research study will help in the prediction of a first-year student's success in the field of science based on their career path decisions and interests. The aim is to predict a student's academic achievement in biological science, depending on several findings of career path choices and desires. We will also determine the best machine learning model to predict student success using the student's career choice, influences on their career choice, and the study methods they use to pass their exams.

Using the collected information of students about their foremost career choices we classified what career path they would like to pursue, whether they wanted to pursue science or non-science career pathways and what are the factors that triggered interest in their chosen career pursuit, and their first year mark. We classified the student's success into two classes: Pass or Fail. We represented the results from the six machine learning models using accuracy and confusion matrices.

The contributions of this paper are: institutions can use an early detection tool to determine students who are at risk, contributes literature by demonstrating that one of the most important factors for academic success is student motivation and interest. The learning approaches students use helps them to learn more effectively. First year students have little guidance at university and they use the learning approaches they learnt in high school, and so they rely on their high school experience to assist them in putting together their notes. It is also possible that the learning approaches of students could be linked to their motivation to pursue a career within their field of study. Thus, this link could influence the grade that students achieve [2]. Universities are aware of the importance of student data to predict attrition rate as a result of scientific advancements in Machine Learning. Several studies apply a number of machine learning models, and from those models, the model with the best accuracy is used to identify students at risk [3], [4].

We use the students' career choice (science or non-science), factors that triggered their career path, the learning style(s) they use in university, and their first semester results to predict their success. The machine learning model with the best accuracy is the support vector machine, which achieved an accuracy of 74%. The second-best model is the simple logistics model, with an accuracy of 73%, which uses 10-fold cross-validation. The summary of the data collected is shown in tables 1, 2, and 3. Since these are first year students, it is not surprising that 36% prefers to use their own notes for studying. The quality of notes is related to the student academic achievement [2]. The data was collected from students who enrol into a general Biological Sciences degree 92% of them want to work in the field of science and 53% are self-interested in the field.

The structure of the document is as follows. The Related work section has an overview of previously published work, allowing us to find relevant theories, methods, and research gaps; the Methodology section highlights the data processing, features, and classification models used in this paper; the Results section explains the results; and the Conclusion section outlines the study, highlights our contributions, and makes suggestions for further research.

## 2. RELATED WORK

This section reviews prior published work on the topic of student success and/or machine learning models. We will first look at the data used by several papers who had significant contributions towards predicting student success. Secondly, we will look at the list of prominent features which have been successful to predict success, and finally we will look at the machine learning models used to classify.

### A. Data

A number of studies have been conducted to predict student success and, different papers defined student success in different ways and different, in terms of features, data sets have been used to predict student success [5]. Most departments within higher education institutions have access to demographic data for their student cohorts (e.g. gender, race, langauge) and some recent studies still use demographic data to predict student success [6], however surveys such questionnaires can be used to collect more nuanced data [7]. To predict student success, Zeineddine at el [3] analyzed information from admissions, registrar, and student service departments containing records of 1491 students.

The data collected by researchers can sometimes be biased, usually representing selection biased, where, for example, only a large percentage of academically achieving students are selected to predict student success. Zeineddine et al [3] collected 1491 records of student data and 1014 had a good academic standing. A data balancing technique had to be applied to ensure data balancing an unbiased prediction of the machine learning models. The use of SMOTE (Synthetic Minority Oversampling Technique) to balance the data has been used in recent student attrition studies [8].

### B. Features

Student's career choice is very complicated because there are a number of factors that influence their choice, and background knowledge of a career is essential for fostering and developing interest in that career [9]. Family and friends have the most influence towards a student's career choice, followed by gender, media, financial difficulties and others. [10]. Research and consultations; training, exposure, and industrial attachment are ways to gain knowledge about a career. Mentorship, commitment, motivation, and socialising with people in the field of interest are other ways for people to gain foreknowledge for their careers.

Learning styles consist of different ways in which students gather and assimilate information. Age, achievement level, culture, and gender all affect learning styles [11]. There is a strong correlation between learning effectively and academic success and most students use the approach writing notes [12].

York, Gibson, and Rankin [5] explores the use of the term academic success in different educational research. Using the Inputs-Environments-Outcomes model academic success consists of academic achievement, knowledge building, skills, competence, persistence and retention [13]. Academic success is the measure of student's outcomes of academic work, such as course grades. Learning includes the student's cognitive development and effective skills.

The definition of academic success is complex and broad [5]. Academic attributes are mostly used in research for predicting and analyzing student success, other studies use external factors like demographic information, family, financial resources, and more. Most studies use easily accessible student features like age, gender, ethnicity, study program, course load, on/off-campus residency, academic probation, and school educational system [3]. While other studies take it further by considering the students' views on the methods they use to learn and the students' views of their learning experience, for example, see [14]. Using questionnaires, researchers are able to get more insight into students. Thus, more researchers rely on questionnaires (constructed using certain models) instead of simple biographical data accessible through the high institution's database. Recent studies consider using more detailed features and this proves and disproves models that explain and predict student attrition. McKenzie, Kirsten Schweitzer, and Robert [15] collected and annotated documents with textual citations during the literature review, with particular attention paid to how the author(s) described academic success, as well as what metrics were used in academic success in any empirical studies the data categorised into broad categories like "grades," "critical thinking," and "effective outcomes.".

Ajoodha, Jadhav, and Dukhan [4] use the Tintos framework [16] to analyse biographical and enrollment features, considering that the framework lists (1) Background or Family attributes, (2) Individual attributes, and (3) Schooling attributes as input factors to student attrition. Student institution integration is found to be negatively correlated with academic achievement, implying that students with high levels of integration into university are more likely to have low grade averages, contradicting Tinto's concept [15]. Academic success does not always imply retention, and low academic performance does not always imply attrition [15]. The explanation to this finding firstly is that there is a difference between academic success and attrition, and secondly, Tinto's model was created to explain student attrition, and scholars used Tinto's framework to explain academic performance.

### C. Models

Machine learning is used to predict student attrition, it makes use of historical data to train its models. The models used, to predict student attrition, include classification models

like decision trees, Naive Bayes, Logistic regression, etc. The prediction accuracy for each algorithm differs and usually, it depends on the features used. Determining which algorithm to use can be strenuous and other studies use Automated Machine Learning to predict student success to obtain the best accuracy [3]. The algorithms used are the Logistic regression, Artificial Neural Network, Naive Bayes, Decision Tree, Support Vector Machines, and K-Nearest Neighbour. Numerous machine learning classification models such as Naive Bayes, support vector machine, logistic regression, linear and logistic regression are used and the algorithm with the best accuracy is chosen to measures student success [4]. Most of the time five to six different machine learning models are used to predict student success [17].

## 3. METHODOLOGY

In this study, we attempt to predict student success using the student's career choices, their interest factor that leads to the career choice, the learning style they use in university, and their results in the first year. Using the student features we classify success in two classes: (1)*Fail* where the student has obtained less than 50% for their final mark in a course, (2)*Pass* where the student has obtained more or equal to 50% and above for their final course mark. We used various machine learning algorithms to classify the student into one of the two classes. The confusion matrix and the algorithm's accuracy to accurately classify will be used to evaluate each algorithm's performance.

### A. Data Processing and Collection

In this section, we will describe the steps taken in data collection and pre-processing. The data was collected from a South African university from first year students who enrol in a general Biological science degree in 2019. The dataset is a sub-set of a larger dataset that was collected by one of my supervisors. Since the general Biological science degree has a variety of career options available the information about the student career choices, their interest factor that leads them to the career choice, the learning style they use in university, and their results in first year were collected. The dataset used contained 260 rows, and 17 columns (16 predictor variables and 1 target variable). The target variable had 2 classes, Pass and Fail, each with 130 instances. The predictor variables are explained below.

### B. Features

First year students who enrol on a general Biological Sciences degree were asked questions about their learning style, career choice and factors that lead them to choose that career. For each student five learning approaches were collected and grouped in table 1, four career choices were collected and grouped in table 2, and four factors that lead them to choose a career were collected and grouped in table 3.

Table 1: Describe your learning approach that you use at university.

| | Percentage |
|---|---|
| 1. Use my own notes | 36% |
| 2. Focus on my understanding | 18% |
| 3. Prioritising tasks ahead | 11% |
| 4. Unsure | 10% |
| 5. Use resources on the Internet (e.g. YouTube) | 6% |
| 6. Used of lecture slides | 6% |
| 7. Use the prescribed textbook | 6% |
| 8. Practice questions (like Pearson online exercises) | 5% |
| 9. Peer assistance | 1% |

Table 2: What career field would you like pursuit.

| | Percentage |
|---|---|
| Science | 92% |
| Non-Science | 8% |

### C. Classification and Evaluation

To analyse and compare the machine learning models we will use confusion matrices, the accuracy of the model and its classification error. An example of a confusion matrix is shown in table 4. The predicted and actual classification are shown in a confusion matrix of dimension 2x2 connected with a classifier [18]. The meaning of the entries in table 4 are:

TN is True Negative which means the number of correct negative predictions.
FP is False Positives which means the number of incorrect positive predictions.
FN is False Negatives which means the number of incorrect negative predictions.
TP is True Positives which means the number of correct positive predictions.

Table 4: Two-class confusion matrix [18]

| | False Negative | False Positive |
|---|---|---|
| True Negative | TN | FP |
| True Positive | FN | TP |

The accuracy and the classification error of the models will be obtained from the confusion matrix (Table 4) defined as:

$$Accuracy = \frac{TN + TP}{TN + FP + FN + TP} \tag{1}$$

$$Error = \frac{FP + FN}{TN + FP + FN + TP} \tag{2}$$

Table 3: What factor/s triggered your interest in your chosen career pursuit.

| | Percentage |
|---|---|
| 1. Self-interest in the field | 53% |
| 2. To make an impact on the field | 15% |
| 3. Not sure | 9% |
| 4. Personal background | 7% |
| 5. To have a social status | 6% |
| 6. Job opportunities | 6% |
| 7. Consider the career achievable | 4% |

Six machine learning models will be used to predict student success. The following models will be used.

*a) Naïve Bayes model:* The probabilistic algorithm Naive Bayes is commonly used for classification problems. The probability can be expressed mathematically as follows:

$$P(A/B) = \frac{(B/A) * P(A)}{P(B)} \qquad (3)$$

Naive Bayes is a simple, understandable algorithm that performs well in many situations. The approach is intended for use in supervised induction tasks in which the goal is to reliably predict the class of test instances, and the training instances contain class information, the implementation is adopted from [19]. It's a classification method based on Bayes' Theorem and the assumption of predictor independence.

*b) Multi-layer Perceptron model:* Multilayer perceptrons (MLP) are a type of deep artificial neural network that has a hidden layer with a nonlinear activation function. The MLP architecture is made up of three layers, each with nodes, including an input layer that defines the input value, one or more hidden levels that specify the mathematical function, and an output layer [20]. In the MLP used in this paper, all the nodes are sigmoid (Only if the class is numeric, in which case the output nodes are non-thresholded linear units.).

*c) Simple Logistic Regression model:* In a simple logistic regression model, a covariate $X_1$ is associated to a binary response variable $Y$ in a model

$$log(\frac{P}{(1 - P)}) = \beta_0 + \beta_1 X_1 \qquad (4)$$

where $P = probability(Y = 1)$. The null hypothesis $H_0 : \beta_1 = 0$ is being tested against the alternative $H_1 : \beta_1 = \beta^*$, where $\beta^* \neq O$ denotes that the covariate is related to the binary answer variable [21]. The implementation is based on [22], [23].

*d) Support Vector Machine model:* The support vector machine (SVM) is a supervised machine learning model that uses classification techniques to handle two-group classification problems. It uses a multi-dimensional hyper-plane to partition the training data into classes. We used the popular SVM implementation (LibSVM) from [24].

*e) Decision tree model:* Ross Quinlan devised the $C4.5$ technique for generating decision trees. Quinlan's earlier Iterative Dichotomiser 3 (ID3) algorithm is extended in C4.5. The decision trees in C4.5 can be used for classification, which is why it's also known as a statistical classifier. In this paper we implemented the $c4.5$ from [25].

*f) Random Forest model:* During training, the model generates a large number of decision trees and outputs the class that is the mean/average prediction (regression) of the individual trees, or the mode of the classes (classification). The implementation is based on [26].

## 4. ETHICS CLEARANCE

The University's Human Research Ethics Committee has approved the study's ethics application. The ethics application handles important ethical issues such as safeguarding the identity of study participants and data protection. The protocol number for the clearance certificate is CSAM-2021-02W.

## 5. RESULTS

Initially the data contained 22 variables (see Table 5) and for dimensional reduction we used the principle component analysis(PCA). Out of the 22 variables PCA returned 18 new combination features and the first feature had a standard deviation of 1.82, we divided the standard deviation by 2 which gave us 0.91. From the 18 new features we selected 11 features that had a standard deviation greater or equal to 0.91. Finally, the 11 features were used for machine learning classification.

Table 5: Student variables used in classification models.

| Variable name |
| --- |
| 1. Student's gender |
| 2. First career choice |
| 3. Second career choice |
| 4. Third career choice |
| 5. Fourth career choice |
| 6. What career field would you like pursuit. |
| 7. First interest factor that lead to choosing a career |
| 8. Second interest factor that lead to choosing a career |
| 9. Third interest factor that lead to choosing a career |
| 10. Fourth interest factor that lead to choosing a career |
| 11. What factor/s triggered your interest in your chosen career pursuit. |
| 12. Fist Learning style |
| 13. Second Learning style |
| 14. Third Learning style |
| 15. Fourth Learning style |
| 16. Fifth Learning style |
| 17. Describe your learning approach that you use at university. |
| 18. Block 1 exam mark |
| 19. Block 1 final exam mark |
| 20. Block 2 exam marks |
| 21. Block 2 final exam mark |
| 22. Semester final exam mark |

We discuss results from the six machine learning algorithms used for classification. We used the Naïve Bayes, MLP, Simple logistics, SVM, Decision tree and Random forest. Fig. 1 shows the confusion matrices and accuracy, using 10-folds of cross validation, of each model.

The Confusion matrix (a) represent the results from the Naïve Bayes model which achieved an accuracy of 73%. It took the shortest amount of time to complete.

The Confusion matrix (b) represent the results from the Multi-layer perceptron model which achieved the worst accuracy of 71%. It took the longest amount of time to complete.

The Confusion matrix (c) represent the results from the Simple Logistic regression model which achieved the second best accuracy of 73%.

The Confusion matrix (d) represent the results from the Support Vector Machine model which achieved the best accuracy of 74%.

The Confusion matrix (e) represent the results from the Decision tree model which achieved an accuracy of 72%.

The Confusion matrix (f) represent the results from the Random Forest tree model which achieved an accuracy of

72%. The accuracy is the same as the accuracy achieved in the confusion matrix (e).

Using PCA to reduce the number of features, from 23 features to 11 features, improved the accuracy of our models. Fig. 2 shows an accuracy of the Support Vector Machine before the data dimension was reduced. The accuracy of SVM was 53% before PCA. Fig. 2 compared to Fig. 1 only incorrectly classified more students who passed. The classification for students who failed is the same on both confusion matrices. This means each feature has a contribution to student success. Thus considering the combination of all the features enables us to predict student success.

|  |  | Predicted Class | |
| --- | --- | --- | --- |
|  |  | Pass | Fail |
| Actual Risk | Pass | 32 | 98 |
|  | Fail | 23 | 107 |

Figure 2: Confusion matrix of **Support Vector Machine** before PCA was used for dimensionality reduction. The model has an accuracy of 53% and an inaccuracy of 47% from the data set of 270 number of instances

## 6. Discussion and Conclusion

This study contributes to literature by examining whether student motivation and interest are the key factors for academic success, and It can be used to identify at-risk first-year students.

Using machine learning algorithms we predicted if a student will pass or fail and from the high accuracy results we can see that these factors do influence if a student will succeed or not, whether they will pass or fail. The use of PCA improved the accuracy of the models, this shows that student success does not depend on one factor, but a combination of the factors. The importance of providing a clear career direction as a target is related to the student's motivation to pursue a career within the field which they are studying, in this case science or non-science field. Therefore students' need more exposure to different careers so that they can have a clear career direction.

In this study like most recent publications we used machine learning models to predict student success. But to make it a new research we used several machine learning models and we predicted student success using the student career choices, their interest factor that leads to the career choice, the learning style they use in university, and their results in first year.

It is also worth noting the study's limitations. The amount and quality of the collected data determine the predictive accuracy, the data used was collected from one institution and it contains only a small sample(270) of the first year students and so the results can not be generalised for all South African universities. Subsequent research should consider a large sample size and from different institutions.

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|              | Predicted Class | |
|              | Pass | Fail |
|--------------|------|------|
| Actual Risk Pass | 76 | 54 |
| Fail | 18 | 112 |

(a) Confusion matrix of **Naive bayes model**. The model has an accuracy of **72%** and an inaccuracy of 28% from the data set of 270 number of instances

|              | Predicted Class | |
|              | Pass | Fail |
|--------------|------|------|
| Actual Risk Pass | 89 | 41 |
| Fail | 35 | 95 |

(b) Confusion matrix of **Multilayer Perceptron model**. The model has an accuracy of **71%** and an inaccuracy of 29% from the data set of 270 number of instances

|              | Predicted Class | |
|              | Pass | Fail |
|--------------|------|------|
| Actual Risk Pass | 76 | 54 |
| Fail | 15 | 115 |

(c) Confusion matrix of **Simple Logistic model**. The model has an accuracy of **73%** and an inaccuracy of 27% from the data set of 270 number of instances. It has the same results as the Naive Bayes.

|              | Predicted Class | |
|              | Pass | Fail |
|--------------|------|------|
| Actual Risk Pass | 86 | 44 |
| Fail | 23 | 107 |

(d) Confusion matrix of **Support Vector Machine model**. The model has an accuracy of **74%** and an inaccuracy of 26% from the data set of 270 number of instances

|              | Predicted Class | |
|              | Pass | Fail |
|--------------|------|------|
| Actual Risk Pass | 83 | 47 |
| Fail | 26 | 104 |

(e) Confusion matrix of **Decision tree model**. The model has an accuracy of **72%** and an inaccuracy of 28% from the data set of 270 number of instances

|              | Predicted Class | |
|              | Pass | Fail |
|--------------|------|------|
| Actual Risk Pass | 92 | 38 |
| Fail | 35 | 95 |

(f) Confusion matrix of **Random Forest model**. The model has an accuracy of **72%** and an inaccuracy of 28% from the data set of 270 number of instances

Figure 1: Confusion matrices measuring the performance of the 6 classification models. The accuracy of each classification model is shown, as well as the occurrences that have been correctly and inaccurately classified.

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