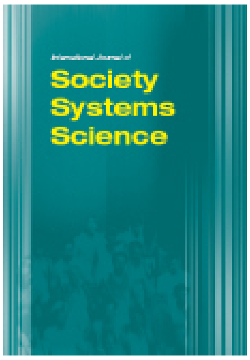

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Predicting student success in an online Master of Business Administration program

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Abstract: Online Master of Business Administration programs have been growing in popularity as an alternative to traditional Master of Business Administration Programs. The literature on academic success has highlighted the use of academic analytics to predict student performance. The purpose of this study is to determine the most significant indicators of student success using student admissions data of an online Master of Business Administration program. Four types of models are constructed in this research including logistic regression, discriminant analysis, classification trees, and neural networks. The best model is selected using classification goodness of fit metrics. The results of this study indicate that applicants' admissions decision and students' academic standing are best predicted using a reduced logistic regression and discriminant analysis models, respectively.

Keywords: machine learning; academic performance; online Master of Business Administration; logistic regression; discriminant analysis; decision trees; neural networks; academic analytics; student success.

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1 Introduction

The emergence of the notion of commerce, as a fragment of business, can be traced back to ancient civilisations with its essence continuing to resonate today beyond the boundaries of time, state, and culture. The 21st-century business thinking focuses primarily on decision-making processes which have been extended to the realm of research. Master of Business Administration (MBA) programs are now being offered by universities in a variety of formats such as one-year and two-year residential MBA programs, specialised Master of Business degrees, as well as online Master of Business Administration (OMBA) programs. Reflection on five consecutive years of student enrolment in MBA programs indicates that the number of applications to traditional two-year MBA programs has declined while there is an increased and sustained interest in OMBA programs due to their convenience (Byrne, 2020; Hazenbush et al., 2019). A meta-analysis by Palvia et al. (2017) confirmed both the growth and acceptance of online graduate business programs in the broader business society.

As the demand for online programs rises, the use of data is becoming increasingly important to drive better decisions about higher education admissions and resource allocation processes. A college can leverage the existing data to determine what portions of an admissions application are most essential to predicting a student's success in an OMBA program. This analysis leads to data-driven decision making in the application process. Beyond improving the admissions process, analysis of demographic, academic, and career factors can allow key institutional decision makers to determine what factors can impede student success. By identifying these factors, the college could provide targeted resources designed to improve their OMBA program for students who most need support. To this end, two predictive models are developed in this study to determine what factors can most frequently impact admission into the program and what attributes may act as key indicators of not being in good academic standing.

The aim of the current study is to examine holistic performance prediction methods in higher education using diverse machine learning models such as logistic regression, discriminant analysis, classification trees, and neural networks for identifying which factors lead to student success.

This paper has been organised into five sections. The background section establishes the context of the research. In the following section, the proposed methodology and the description of the approach are described. The results section discusses the findings of the study. Finally, implications and conclusions are presented in the last two sections.

2 Background

There is scientific debate with widely differing viewpoints concerning how to define student success and which parameters to use for measuring students' academic outcomes. There are several metrics suggested in the literature for tracking student success over time. Some of universal quantitative measures such as number of publications, attrition rate, persistence in major or program, academic self-efficacy, time to completion, exam scores such as Scholastic Aptitude Test (SAT) and American College Test (ACT), course scores, and cumulative Grade Point Average (GPA) can reflect the academic strength of students (Kreiser et al., 2021; Weatherton and Schussler, 2021; Walck-Shannon et al., 2019; Gregg-Jolly et al., 2016). Also, measurements pertaining to career progression of students including seeking and securing employment in a field related to their study program can be used to determine student success (Martinez et al., 2018).

Scientists in the field of academic analytics have been calling for research concentrating on learning analytic models that adopt a holistic approach to the use of data as opposed to envisioning a single outcome for predicting academic excellence. Currently, the utilisation of student data in higher education focuses primarily on a single classroom's data from a learning management system and demographic characteristics of students (Al-Sudani and Palaniappan, 2019). This data is then typically included in single classifier models (Hlosta et al., 2017; Pandey and Taruna, 2016). The holistic and student-centric evaluation of students' academic outcomes is of paramount importance specifically when it comes to assessing the performance of underrepresented population such as first-generation to attend college, students from low- socioeconomic status, and students of colour (O'Shea and Delahunty, 2018). Gašević et al. (2016) examined the effect of different instructional methods and fields of study on predicting student success. They found support for their hypothesis that diverse instructors influence student success differently and argued that a holistic approach to learning analytics is necessary to explain disparities in student performance. Shahiri et al. (2015) conducted a literature review on how educational data mining is used to predict student success. Through examining 30 articles, cumulative GPA was the most frequently used factor for determining student performance, followed by internal course assessment data and demographic data. Similarly, Papamitsiou and Economides (2014) undertook a systematic literature review to determine the future direction of academic analytics and educational data mining. These authors identified four directions of research: pedagogy-oriented issues, contextualisation of learning, networked learning, and educational research handling (Papamitsiou and Economides, 2014).

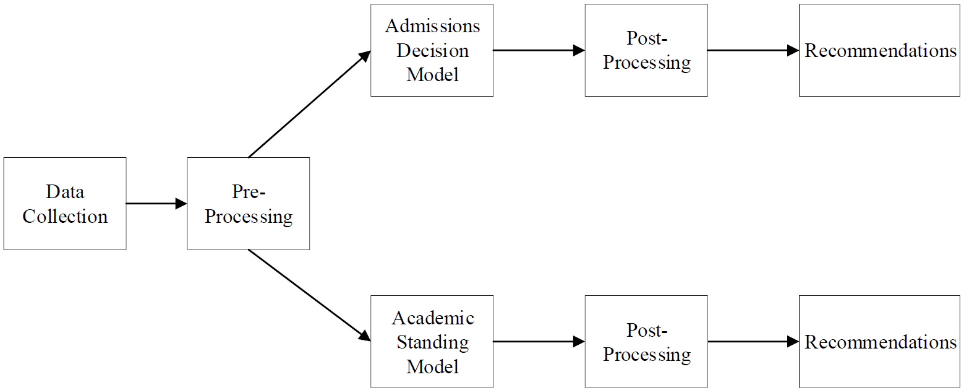
To date several studies have investigated the use of machine learning techniques such as neural networks, deep learning, k-nearest neighbours, k-means clustering, naïve Bayes, support vector machine, logistic regression, decision tree and random forest algorithms to predict student performance and detect who are at-risk (Zeineddine et al., 2021; Kim et al., 2018; Miguéis et al., 2018; Costa et al., 2017; Hoffait and Schyns, 2017; Huang and Fang, 2013). While acknowledging the power of machine learning models such as naive Bayes classifier in identifying the at-risk students, Marbouti et al. (2016) assert that the variation in student behaviour throughout the semester can complicate the task of predicting the academic outcomes of students. Moreover, researchers call for using ensemble-based learning models such as decision tree in early detection of students who are not in good academic standing through forecasting their outcomes with greater accuracy (Kaur et al., 2021). Pandey and Taruna (2016) outlined a framework to combine multiple single-classifiers into a single multiple-classifier for improving the accuracy of the models. Hlosta et al. (2017) created a 'self-learning' model that used data from a specific course for training and testing the predictive model. This novel framework model was able to identify at-risk students by considering students' behaviour who submitted their assignments early. Al-Sudani and Palaniappan (2019) used extended profile data including information about academic, demographic, institutional, psychological, and economic domain measurements to predict student achievement in three types of neural network models. Also, Bainbridge et al. (2015) used logistic regression to identify which factors were most likely to predict an at-risk student. Their study findings showed that the model correctly predicted 80.45% of at-risk cases.

The Okubo et al.'s study (2017) of 108 students in an information systems course indicated that the recurrent neural network can produce results with 90% accuracy. Huang and Fang (2013) compared how different combinations of mathematical models and variables can better predict student success in an individual course using multiple linear regression, multilayer perceptron (neural) network, radial basis function network, and support vector machine. They claimed that individual student performance was best predicted by the combination of GPA, course prerequisites, and the first exam in the course in a support vector machine model. In another study, Chui et al. (2020) proposed the use of reduced training vector-based support vector machines (RTV-SVM) in virtual learning environments to better automate the prediction of at- risk students. These authors argued that the application of RTV-SVM could reduce the time required to process large learning analytics datasets through automation. Taken together, these studies support the notion that adopting a holistic approach to performance prediction merits particular attention which this study aims to accomplish.

3 Methodology

The purpose of the proposed methodology in this research is to construct two separate predictive models exploring traits that influence student success in the OMBA program using admissions records and university registrar enrolment data. The outputs of the first and second models are the admissions decision and students' academic standing, respectively. Following performing data pre-processing on the dataset, both models are tested with four classification algorithms: logistic regression, discriminant analysis, decision tree, and neural networks using goodness-of-fit metrics. Figure 1 presents the methodology process flow of this research.

Figure 1 Methodology process flow



3.1 Data summary

Ohio University is a large research university located in the midwestern USA. The university's Athens campus had a total enrolment of 22,706 students in fall 2019. Primarily an undergraduate campus, the university had 3,171 online graduate students in 2019 (Ohio University Office of Institutional Research & Effectiveness, 2019). There are 1,019 students in Ohio University's online business graduate programs, representing 4.48% of total university enrolment and 31.23% of total online graduate program enrolment. There are 12 graduate programs housed in the College of Business. These include three face-to-face master's programs, six pure online programs, and three programs that are a hybrid of both online and in-person instructions. The most popular online program is the OMBA program, which began in the fall of 2013. As the Ohio University OMBA program grows, it finds itself in an increasingly competitive space with other OMBA programs targeted toward professionals looking to advance their careers.

The data pre-processing phase of this study includes combining datasets, verifying input values, detecting outliers, deriving output data values, matching student records, removing records with missing information, encoding categorical values, and splitting the data into train and test subsets. In the first step, all admission records of students from the OMBA program were entered manually and combined to create a singular dataset. Next, the input data were checked for identifying spelling errors and possible inconsistencies between encoded categorical variables recorded by different staff. Moreover, the existence of outliers was checked, and none were found. Also, the output data provided by the university registrar was matched with the input data. Student records with missing information were removed from the dataset to improve model accuracy. Additionally, each categorical value was encoded into binary values. Then, 20% of each dataset was set aside for testing data. Finally, since the success class for both the output values had a much higher likelihood than 50%, models were first developed for the standard dataset, then a balanced dataset was created for each output using an equal number of non-success class data records and a random sampling of success class data records.

3.1.1 Input data

Data was collected from the OMBA program and the university registrar repositories. Input data consists of information provided by applicants to the OMBA program between the spring 2013 and the fall 2019 semesters. Since the OMBA staff did not have records of applicants in the summer of 2017, there are 14 semesters included in the analysis, as illustrated in Table 1. Also, note that while some variables were collected in 2013 and 2014, we do not have a complete set of data for those years. As such, the full dataset begins in 2015 as noted in Table 1 for inclusion in our analysis. To determine the inclusion criterion for the second model, a credit hour threshold is developed.

Table 1 Total applicants and number of semesters

Semesters	*Total applicants*	*Number of semesters*
Spring	815	5
Summer	426	4[a]
Fall	1,048	5
Total	2,289	14

Note: [a]Records of applicants in summer 2017 are excluded from the analysis.

Table 2 Number of applicants and admitted students

Term	*Number of applicants*	*% change*	*Number of students admitted*	*% change*
Spring 2015	155	-	114	-
Summer 2015	112	-	100	-
Fall 2015	233	-	184	-
Spring 2016	175	13%	150	32%
Summer 2016	115	3%	92	–8%
Fall 2016	220	–6%	186	1%
Spring 2017	147	–16%	111	–26%
Fall 2017	217	–1%	181	–3%
Spring 2018	155	5%	135	22%
Summer 2018	109	N/A[a]	103	N/A[a]
Fall 2018	178	–18%	168	–7%
Spring 2019	183	18%	174	29%
Summer 2019	90	–17%	90	–13%
Fall 2019	200	12%	189	13%
Average	163.5	–1%	141.2	4%

Note: [a]Records of applicants in summer 2017 are excluded from analysis.

As can be seen from Table 1, the highest and lowest numbers of applications were recorded in the fall and summer semesters, respectively. Table 2 displays the breakdown of the number of applicants and students admitted per semester and their corresponding year-over-year percent change rates. Given a total of 2,289 applicants to the OMBA program, 1,977 students were admitted to the program with an average 86% acceptance rate. It can be seen from the data in Table 2.

Moreover, from the original 48 columns in the dataset, there were 27 unique input values included in the model. Broadly speaking, these inputs fall into several categories that capture information about a candidate's: undergraduate institution, academic background, professional background, and demographic information, as shown in Table 3.

Table 3 Student data input variable categories

Undergraduate institution	*Academic background*	*Professional background*	*Demographic information*
Graduation year	Undergraduate GPA	Post-bachelor years of experience	Gender
Undergraduate format	Undergraduate major category	Letters of recommendation score	USA or international
Number of credits at degree-granting institution	Two majors	Career progression score	Traditional or non-traditional student
Number of undergraduate institutions	Academic preparation score	Essay score	Age
Year of first term	Number of accounting courses	Intended concentration	Race and ethnicity
Quarters or semesters	Number of economic courses	Total years of experience	In-state or out of state
For-profit or non-profit institution	Number of statistics courses		
	Advanced degree and coursework		

3.1.2 Output data

The output data for this study was gathered from admissions records provided by the University Registrar's Office. In the admissions data, staff record if they recommend a candidate, do not recommend a candidate, or recommend a candidate with reservations. Then, the admission committee reviews the applications and the recommendations for making the final decision. The final decision of the admissions committee data is used in the predictive models. The data encompasses the GPA of OMBA students and the number of credit hours they earned at Ohio University. It is worthwhile to mention that the number of credit hours completed by the students and the GPA of OMBA students are used to determine whether the records should be kept in the predictive models and whether they are in good academic standing, respectively as shown in Table 4. Students in the OMBA program must maintain above a 3.0 GPA to be considered in good academic standing. Furthermore, to matriculate in the OMBA program, students are expected to complete 35 semester credit hours.

Additional analysis was conducted on output data to determine the best credit-hour threshold for the analysis. In fact, as the credit hour threshold increased, the number of records that could be included in the model decreased. A higher credit hour threshold would remove records of many students who left the program. Consequently, a lower credit hour threshold is better aligned with the objectives of this study, as the model better captures students not in good standing and could yield better insights into potential retention strategies. Data was collected on all students in the program over the course of five years regardless if they had completed the necessary 35 credit hours to graduate. A six-credit hour threshold was considered in the second predictive model to determine if student records would be included in the model. The underlying reason for using a six-credit hour threshold is because with this threshold, up to 83% of the registrar data can be included in the model, allowing for a higher amount of records and historical data to be represented. At the same time, the six-credit hour threshold can help to identify students in need of academic intervention, as 12% of students included in the model are considered to not be in good academic standing.

The number of students in good academic standing and who were admitted to the program, or success class, was significantly higher than the number of students who had a GPA below a 3.0 and who were not admitted, respectively. Since the number of observations in one class is disproportionately higher than the other class, the data was balanced to prevent naïve and poor results, as well as bias towards predicting the variable with more observations. The process for balancing the data entails two steps. First, the data was split into train and test sets (80:20) and the test set is held out to ensure that it reflects the real variation in the data. Next, the random undersampling technique is employed on the train set; selecting a random subset of the majority class that equals to the number of minority class examples (Mohammed et al., 2020; Young et al., 2010).

Table 4 Academic standing model

Credit hours	*Students' records not included in the model*	*Students' records included in the model*	*Students in good academic standing*	*Students not in good standing*
0	0 (0%)	2,223 (100%)	1,749 (79%)	474 (21%)
3	277 (12%)	1,946 (88%)	1,749 (90%)	197 (10%)
6	380 (17%)	1,843 (83%)	1,697 (92%)	146 (8%)
9	552 (25%)	1,671 (75%)	1,567 (94%)	104 (6%)
12	620 (28%)	1,603 (72%)	1,512 (94%)	91 (6%)
15	716 (32%)	1,507 (68%)	1,433 (95%)	74 (5%)
18	728 (33%)	1,495 (67%)	1,423 (95%)	72 (5%)
21	841 (38%)	1,382 (62%)	1,317 (95%)	65 (5%)
24	848 (38%)	1,375 (62%)	1,312 (95%)	63 (5%)
27	963 (43%)	1,260 (57%)	1,200 (95%)	60 (5%)
30	975 (44%)	1,248 (56%)	1,192 (96%)	56 (4%)
33	1,047 (47%)	1,176 (53%)	1,127 (96%)	49 (4%)
35	1,053 (47%)	1,170 (53%)	1,123 (96%)	47 (4%)

3.2 Classification modelling

In this study, a combination of deterministic and stochastic models is created to predict student success. Deterministic models such as logistic regression and discriminant analysis use statistical approaches without introducing randomness to the system. In contrast, stochastic models and well-known machine learning models including neural network and decision tree algorithms use a variation of inputs for training the data which is a stochastic process. Given the different nature of these models, it is imperative to adopt different approaches in reducing the number of input variables. Logistic regression models can be reduced using stepwise feature selection in order to eliminate statistically insignificant attributes. On the other hand, stochastic models use heuristic approaches such as genetic algorithms in their training methods for enhancing the performance of the algorithm through reducing the number of input attributes.

In fact, two separate classification models were constructed to explore student success in the OMBA program, admissions decision and academic standing models. The admissions decision model predicts if a student would be successfully admitted into the OMBA program. The academic standing model determines if a student would be in good standing with the OMBA program. Both the admissions decision and the academic standing models were built using full and reduced logistic regression, discriminant analysis, classification decision trees, and neural networks. Logistic regression models were reduced using step-wise feature selection with a 3.84 F-statistic in and a 2.71 F-statistic out. For the classification decision trees, the maximum number of levels, the maximum number of splits, and the maximum number of nodes were set at 10, 50, and 20, respectively. The neural networks were generated automatically and the network with the highest validation testing accuracy was selected as the neural network model for training and testing. Moreover, the neural networks were developed using a hyperbolic tangent activation function and a random learning order, a maximum number of 30 epochs, a maximum number of 5 epochs without improvement, and a learning rate of 0.1 as shown in the Appendix. To test the models' accuracy, a random sample of 20% of the dataset was set aside to compare each model's prediction. Notably, all models were tested using the same random sample to improve the validity of the comparison.

4 Results

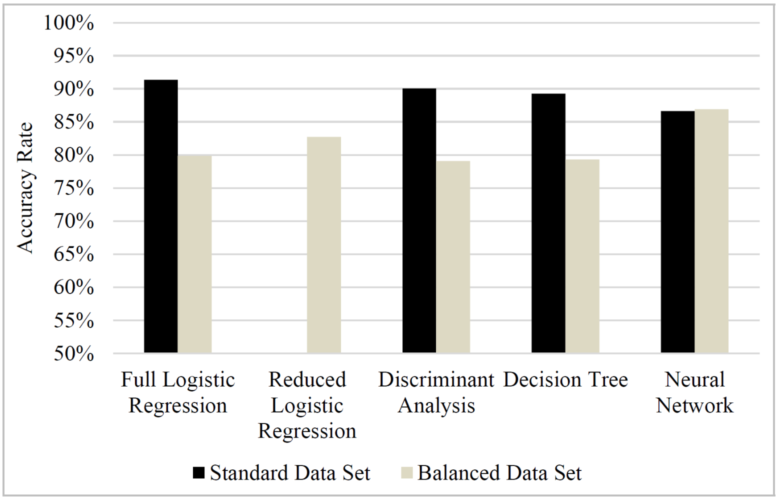
To assess the performance of the models, the admissions decision models are compared with emphasis on accuracy, false negative rate (FNR), and false positive rate (FPR). Similarly, the academic standing models' metrics comparison focuses on accuracy, FPR, and true negative rate (TNR). Next, the best model is selected for each student's success output and a sensitivity analysis is performed to determine what input variables most influence each model's output. The findings of this numerical analysis are discussed using error metrics developed from each model's results.

4.1 Admissions decision results and best model

The breakdown of accuracy rates among the admissions decision models can be seen in Figure 2. It is apparent from Figure 2 that every model built with the standard dataset had a higher accuracy than those built with balanced datasets. What stands out in Figure 2 is that the logistic regression model constructed using the standard dataset has the highest accuracy. Note that no reduced logistic regression model could be generated, as stepwise selection did not reduce the number of input variables in the model.

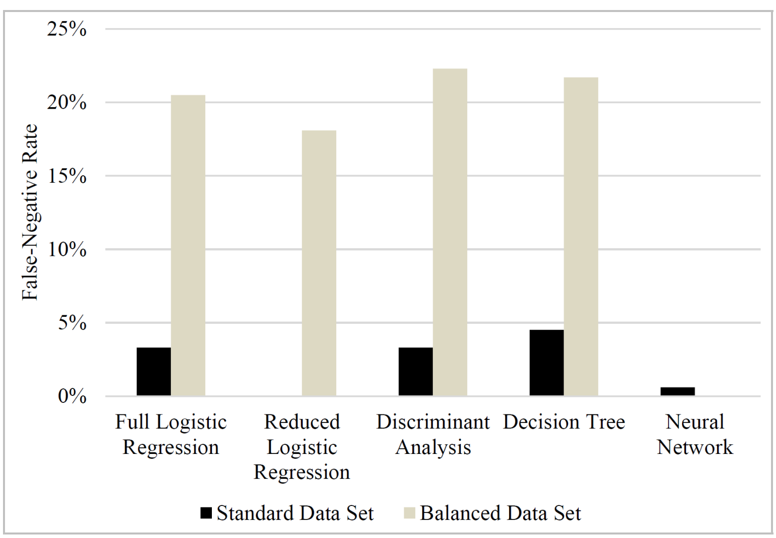
Each model is also compared using the FNR metric since the worst mistake for key administrators to make would be a false-negative error. That is, not admitting a student who would be a good fit for the program. The most striking observation to emerge from the data comparison in Figure 3 is that if the program seeks to reduce this type of error, a neural network could be the best model.

Figure 2 Accuracy rates among admissions decision models (see online version for colours)



Note: The reduced logistic regression model was not developed for the standard dataset.

Figure 3 False-negative rates among admissions decision models (see online version for colours)

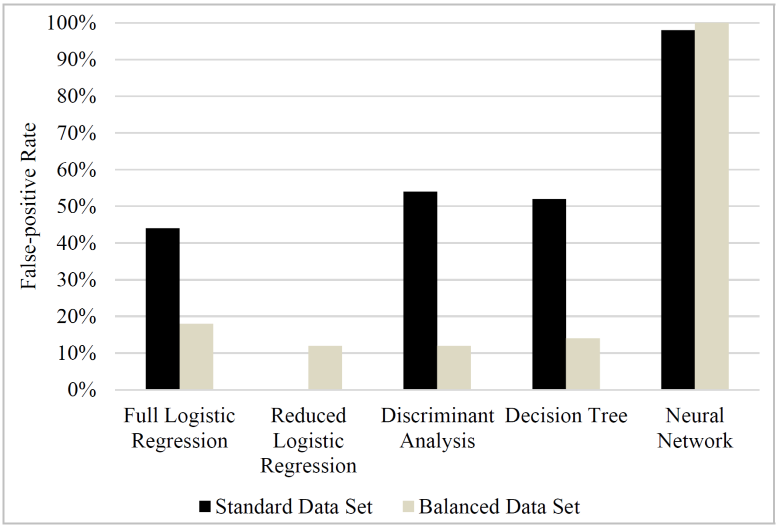


Note: The reduced logistic regression model was not developed for the standard dataset.

Equally important is to consider the FPR metric, since the lower the false-positive rate, the better the model is at predicting students who would not be a good fit for the program. Except for the neural network, a balanced dataset led to lower false-positive rates. Also, the stepwise reduced logistic regression model has the lowest false-positive rate as presented in Figure 4. A full comparison of the best and worst-performing models by metrics can be found in Table 5.

Overall, these results indicate that the best performing admissions model is the balanced reduced logistic regression model while the worst performing model is the balanced neural network.

Figure 4 False-positive rates among admissions decision models (see online version for colours)



Note: The reduced logistic regression model was not developed for the standard dataset.

Table 5 Best and worst performing models by metrics

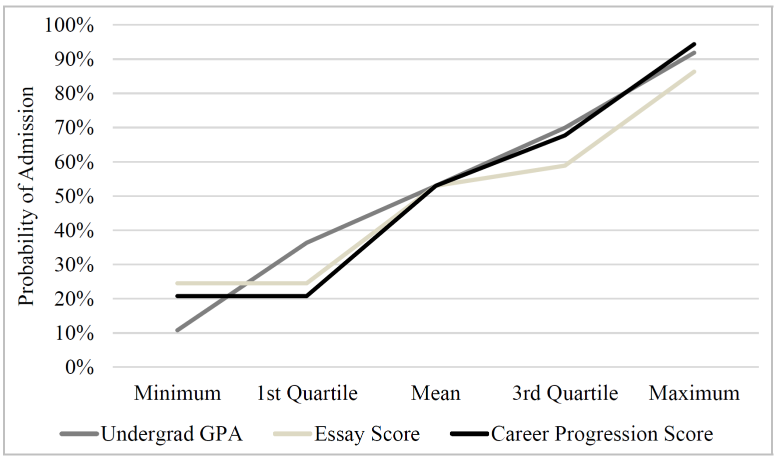
Error metric	*Best model*	*Worst model*
Accuracy	Standard logistic regression	Balanced discriminant analysis
Error	Standard logistic regression	Balanced discriminant analysis
Area under curve	Balanced full logistic regression	Balanced neural network
Sensitivity (TPR)	Balanced neural network	Balanced decision tree
Specificity (TNR)	Balanced reduced logistic regression	Balanced neural network
FPR	Balanced reduced logistic regression	Balanced neural network
FNR	Balanced neural network	Balanced decision tree
Precision	Balanced reduced logistic regression	Balanced neural network

4.2 *Admissions decision sensitivity analysis*

A sensitivity analysis is conducted on the three input variables including undergraduate GPA, essay score, and career progression score collected from the OMBA program to determine which attributes most significantly impact admission to the OMBA program. The sensitivity analysis for the admissions decision output is developed using the minimum, first quartile, mean, third quartile and maximum value for each input in the model. Each value is then individually adjusted, as the value of other inputs remains the same. Also, the standard deviation of the minimum, first quartile, mean, third quartile and the maximum value is calculated for each input.

Indeed, the higher the standard deviation of an input variable, the more that input influences the OMBA program admission decision. Among five machine-learning models tested in this study, the reduced logistic regression model using a balanced dataset is the best performing model with the testing data. The admissions decision is most influenced by a candidate's career progression score, followed by the student's undergraduate GPA, and finally by their essay score as shown in Figure 5.

Figure 5 Probability of admission at each quartile by input variable (see online version for colours)



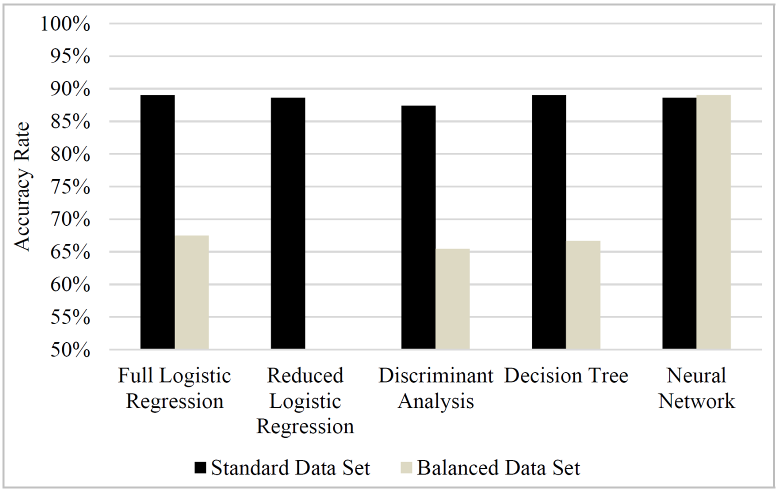
4.3 *Academic standing results and best model*

The first set of analyses examined the factors that impact admission to the OMBA program. The next aim of this study is to find the attribute that influences students' academic standing. The breakdown of accuracy rates among the academic standing models can be seen in Figure 6. Nearly every model constructed with the standard dataset has higher accuracy than the models built with balanced datasets. It can be seen from the data in Figure 6 that the full logistic regression model built using the standard dataset has the highest accuracy.

Each model was also compared using the FPR metric. The worst-case scenario for the decision makers would be predicting a student was in good academic standing, while they are not. If the program seeks to reduce this type of error, the balanced discriminant analysis would be the best model. All academic standing models are compared in terms of the FPR metric in Figure 7.

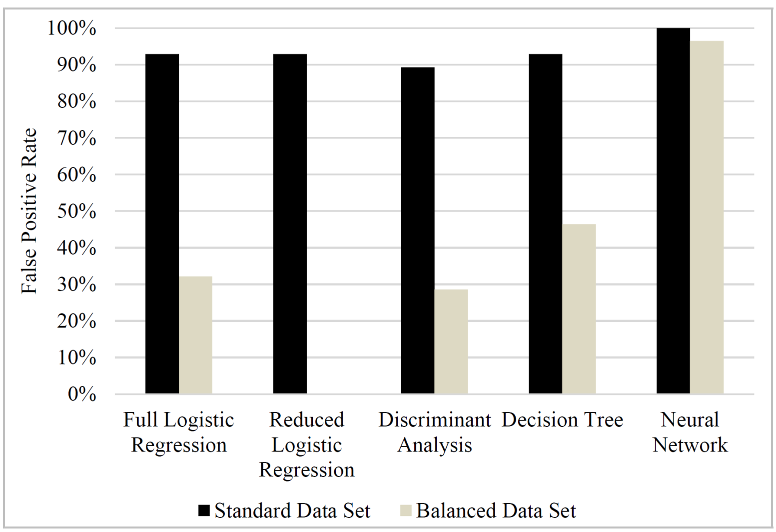
It is interesting to note that a lower FPR is more desirable for the academic standing models because it is important to identify students who are in poor academic standing before they must be dismissed from the program. The balanced dataset has a significantly lower false-positive rate than the standard dataset. The high FPR with both neural network models and among standard datasets indicate that the model predicts every student will be successful in the program, rather than capturing those students who are not.

Figure 6 Accuracy rates among academic standing models (see online version for colours)



Note: The reduced logistic regression model was not developed for the standard dataset.

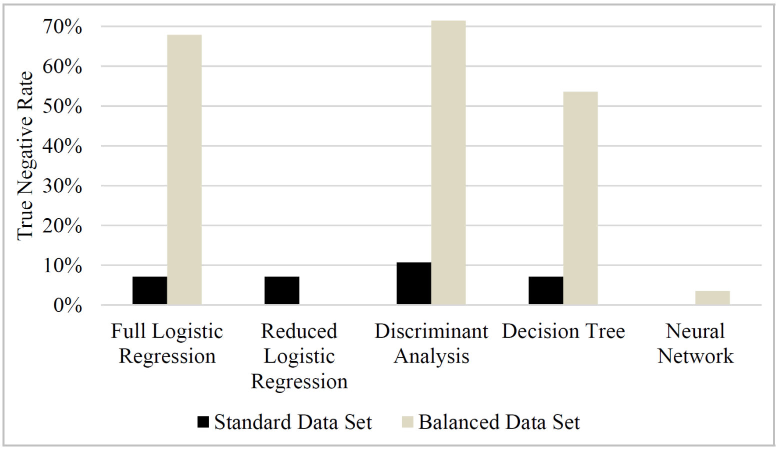
Figure 7 False-positive rates among academic standing models (see online version for colours)



Note: The reduced logistic regression model was not developed for the standard dataset.

A higher TNR metric is more desirable for the academic standing models since it indicates that the model can accurately identify students who are more likely to not be in good academic standing throughout the program. As there is such a high percentage of students in good academic standing, it is more valuable for the model to accurately predict students who are not in the success class. In Figure 8, there is a clear trend that the balanced datasets outperform the standard dataset samples. A comparison of the best and worst-performing models by metric is summarised in Table 6. These results suggest that the best performing admissions model is a balanced discriminant analysis, while the worst performing model is a balanced decision tree.

Figure 8 True-negative rates among academic standing models (see online version for colours)



Note: The reduced logistic regression model was not developed for the standard dataset.

Table 6 Best and worst performing models by metrics

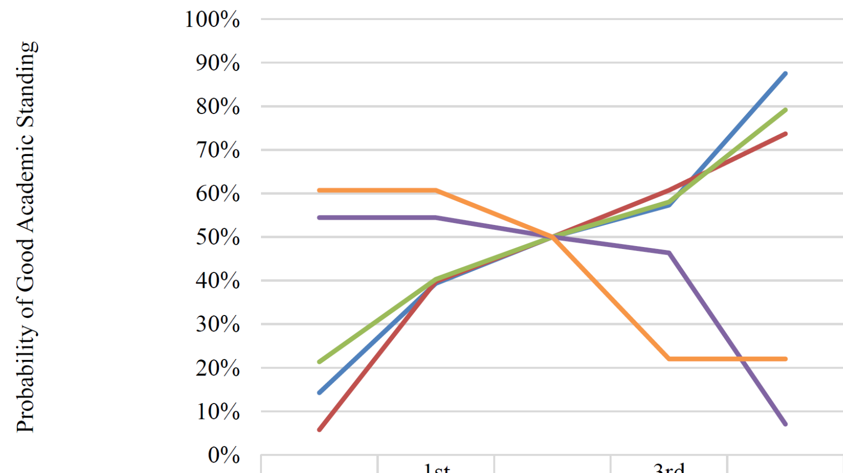
Error metric	*Best model*	*Worst model*
Accuracy	Standard full logistic regression	Balanced decision tree
Error	Standard full logistic regression	Balanced decision tree
Area under curve	Balanced full logistic regression	Balanced neural network
Sensitivity (TPR)	Balanced neural network	Balanced decision tree
Specificity (TNR)	Balanced discriminant analysis	Standard neural network
FPR	Balanced discriminant analysis	Standard neural network
FNR	Balanced neural network	Balanced decision tree
Precision	Balanced discriminant analysis	Balanced neural network

4.4 Academic standing sensitivity analysis

In order to identify which inputs most affect students' academic standing in the OMBA program, a sensitivity analysis is conducted. The results of the analysis show that the discriminant analysis model, utilising a balanced dataset, is the best performing model. This analysis is developed using the minimum, mean, and maximum values for each input in the model. Each input is then individually adjusted, as the value of other inputs remains the same. Also, the standard deviation of the minimum, mean, and maximum is calculated for each input. The higher the standard deviation of an input variable, the more that input influences the likelihood that a student will be in good academic standing within the OMBA program. The top five most sensitive inputs with a standard deviation above 20% are primarily related to a student's academic history and concentration: healthcare variables (Concentration_HC) as shown in Figure 9.

The findings of this section illustrate that a positive correlation is found between the likelihood that a student will be in good academic standing and the following input variables: number of credits at the degree-granting institution, the year of the first term, and the undergraduate GPA. Furthermore, there is a negative correlation between a student's probability of being in good standing and the number of undergraduate institutions and healthcare concentration.

Figure 9 Probability of good academic standing at each quartile by input variable (see online version for colours)



	Min	1st Quartile	Mean	3rd Quartile	Max
# Credits at degree granting institution	14%	39%	50%	57%	88%
Year of 1st term	6%	40%	50%	61%	74%
Undergrad GPA	21%	40%	50%	58%	79%
# UG inst.	54%	54%	50%	46%	7%
Concentration_HC	61%	61%	50%	22%	22%

5 Implications

The main objective of this study is to find the most significant factors for predicting student success in terms of being admitted to the OMBA program and remaining in good academic standing within that program. Several input variables are found to be remarkable in predicting success in both cases. Based on the findings of this research, several recommendations are provided in this section.

5.1 Admissions process recommendations

With regard to admission decisions, three variables are significant in predicting if a student will be admitted to the program: career progression score, undergraduate GPA, and essay score.

Currently, the OMBA program staff spends approximately an hour reviewing each prospective student's application and making a recommendation to the admissions committee. Then, the admissions committee makes a final decision on the application. By focusing primarily on these three inputs, there is potential for time, as reviewers are paid an hourly wage, and cost savings. For instance, reviewers spend a significant amount of time reviewing the letters of recommendation submitted by the applicant and assigning a score based on the quality. This score is not considered in the best-performing model and thus could represent an opportunity to reduce the time spent reviewing each application.

Moreover, reviewers do not know which attributes are most significant in the admissions decision. Identifying these inputs could allow them to make more insightful comments on applications to the admissions committee. In addition, the OMBA program at Ohio University has targeted programming toward applicants who do not have strong quantitative skills. The results of this model can help to identify students who would benefit from these supplemental quantitative courses. There is potential to expand this programming based on the results of the sensitivity analysis and to improve student success outcomes within the OMBA program.

Equally important as the significant inputs, is the performance metrics of the developed model. Specifically, the most accurate neural network developed for the admissions decision model recommends admitting every student, which leads to a 100% FPR. Since the percentage of applicants admitted to the program is high, the neural network has the highest accuracy of prediction that every student would be admitted. These results pose an interesting question to key stakeholders in the program about the number of applicants admitted to the program, which only they can answer. Each application from a student takes an hour for reviewers to analyse and 86% of applicants are admitted to the program. Is there merit in admitting every prospective student automatically to the program? Or perhaps benefits to automating portions of the process? Or do the benefits of being selective justify the additional time it takes to review student applications critically? These findings paint a clear picture for those looking to understand what affects student success in the OMBA program.

5.2 Academic standing recommendations

Among the variables used to develop the discriminant analysis model, the most sensitive is the number of credits a student had obtained at their degree-granting undergraduate university. That is, the more credits a student obtained, the more likely they were to be in good academic standing within the OMBA program. The number of undergraduate institutions is also a sensitive variable meaning that the more institutions a student attended, the less likely they were to be in good standing. Other key indicators of student success are also linked to a student's experience in undergraduate studies. As such, a lower undergraduate GPA indicates a higher likelihood of being dismissed from the program. Additionally, a lower (or less recent) graduation year leads to higher student success, while a lower (or less recent) year of the first undergraduate term relates to lower student success. Also, four out of the five most sensitive variables linked to good academic standing are directly related to students' time spent in undergraduate. For that reason, when identifying students at higher risk of being dismissed from the program, the OMBA program could implement orientations or support services directly targeted to OMBA students who may not have had a traditional, four-year, one-institution undergraduate experience that many undergraduate students at Ohio University have had. Finally, these results demonstrate that students in the healthcare concentration are less likely to be in good academic standing. This requires further analysis, as an immediate explanation is not readily apparent. Given that other concentrations, such as finance and executive management also have high sensitivity, the OMBA program could analyse the sensitivity of these concentrations and provide additional programming and support services to students who may not have a traditional business or analytical background, such as those in the healthcare industry.

5.3 Recommendations

The use of analytical models for predicting student success presents opportunities for other universities to adopt this practice. The first recommendation for other higher education institutions is to implement the use of academic analytics on their own data to inform their student success efforts. All predictive models built for this study had above a 65% accuracy in predicting the student success outcomes of a random set of data. While not every model was as accurate as the two best models selected for further analysis, exploration of the output revealed several significant input variables and actionable recommendations to increase student success both with admissions decisions and academic standing. In fact, this research would not have been possible if the OMBA program had not undergone extensive effort to record student data throughout the admissions process. Moreover, the three inputs found in the admissions decision model including undergraduate GPA, career progression score, and essay score may also be significant in another university's admissions decisions. By identifying what is most essential to a program, key gatekeepers can potentially automate some of their decision processes, especially for admission to less competitive programs. In the same vein, the most significant input variables for the academic standing model yield key recommendations for other graduate programs.

Notably, students' undergraduate experience is the most significant factor in predicting their academic standing. For other professional graduate programs, this presents an opportunity to provide targeted programming to improve student experiences.

6 Conclusions

Academic analytics is an emerging field that allows universities to better predict student outcomes, and thus improve the success of students at their institutions. The purpose of the research was two-fold. The first contribution was to develop a predictive model to understand the most important variables when making administrative decisions related to accepting or not accepting students into an online MBA program. The second contribution of the research was to develop a predictive model in order to understand the most important factors related to a student's academic standing related to the required coursework within the online MBA program. Generating individual models for these two initiatives allowed comparisons to be made in order to determine if there were common characteristics related to admission decisions as well as academic performance. Analysing the performance of students allows administrators to determine what is most important to their ideal outcomes. Using the data collected, actionable recommendations are made in this study to the OMBA program for enhancing the student success outcomes of admissions decision-making processes and being in good academic standing. These include:

- streamline the admissions process by focusing on providing comments and recommendations on undergraduate GPA, career progression score, and essay score
- consider spending less time reviewing applications to the program, either by admitting a wider number of students or spending less time on the essay review process
- target retention strategies toward non-traditional students who have a higher number of undergraduate institutions, lower undergraduate GPAs, or lower number of credit hours at their undergraduate institution.

6.1 Limitations

Together with this growing body of literature, our findings support that the use of academic analytics can enhance predicting student achievement. However, this study is not without limitations. This study considers data from a single university and the online MBA program. For this particular online MBA program, students are required to have at least two to three years of professional experience. Given this requirement, the conclusions of this study might be skewed towards a more experienced demographic than other online MBA programs. In addition, another limitation of this investigation is based on the admissions data that was available at the time this study took place. Based on administrative practices used within the online MBA program, the application information that was used to generate the predictive models was limited to six application cycles. Although hundreds of samples were used in this study, the presence of imbalance datasets also reduced the overall number of samples that were used in the development of the predictive models featured in this investigation. Given that the investigation was based on six application cycles, this reduced the overall time horizon in which academic success could be investigated. In its presented form, a student's academic success was measured after completing six credit hours, which equates to four required courses in the online MBA program. To extend this time horizon, information for additional academic admissions cycles would be needed. In addition, in this study a six-credit hour threshold was considered in the analysis allowing more data points to be captured by the models. Therefore, research to examine different cutoff points would be beneficial for taking into account the time to adjust to new program and educational environment.

Future work can consider data across many universities for comparison of student admissions and student success. Future directions for research might include creating a single classifier framework from the models developed, as well as developing a recurrent neural network to capture the different credit hour thresholds. Moreover, the variables included in this model could also be improved with the addition of more career data analysis, such as position level or field.

Furthermore, the random undersampling approach used in this study has the limitation of reducing the overall sample size of the original dataset. Other sophisticated methods for tackling the data imbalance issue should be tested to capture the real distribution of the data. Finally, in order to enhance the performance of machine learning models, several dimensionality reduction techniques can be used to find the most important features that can decrease the computational complexity of the method while retaining a considerable amount of variance in the data.

References

Al-Sudani, S. and Palaniappan, R. (2019) 'Predicting students' final degree classification using an extended profile', *Education and Information Technologies*, Vol. 24, No. 4, pp.2357–2369.

Bainbridge, J., Melitski, J., Zahradnik, A., Lauría, E.J., Jayaprakash, S. and Baron, J. (2015) 'Using learning analytics to predict at-risk students in online graduate public affairs and administration education', *Journal of Public Affairs Education*, Vol. 21, No. 2, pp.247–262.

Byrne, J.A. (2020) *Eight Big Trends that Shaped Business Education in the Just-Ended Decade*, 8 January, Poets&Quants [online] https://poetsandquants.com/2020/01/08/eight-big-trends-that-shaped-business-education- in-the-just-ended-decade/ (accessed 1 August 2021).

Chui, K.T., Fung, D. and Lytras, M.D. (2020) 'Predicting at-risk university students in a virtual learning environment via a machine learning algorithm', *Computers in Human Behavior*, June, Vol. 107, p.105584, DOI: https://doi.org/10.1016/j.chb.2018.06.032.

Costa, E.B., Fonseca, B., Santana, M.A., de Araújo, F.F. and Rego, J. (2017) 'Evaluating the effectiveness of educational data mining techniques for early prediction of students' academic failure in introductory programming courses', *Computers in Human Behavior*, Vol. 73, pp.247–256, https://doi.org/10.1016/J.CHB.2017.01.047.

Gašević, D., Dawson, S., Rodges, T. and Gasevic, D. (2016) 'Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success', *The Internet and Higher Education*, January, Vol. 28, pp.68–84, DOI: https://doi.org/10.1016/j.iheduc.2015.10.002.

Gregg-Jolly, L., Swartz, J., Iverson, E., Stern, J., Brown, N. and Lopatto, D. (2016) 'Situating second-year success: understanding second-year STEM experiences at a liberal arts college', *CBE Life Sciences Education*, Vol. 15, No. 3, https://doi.org/10.1187/CBE.16-01-0044/ASSET/IMAGES/LARGE/AR43FIG2.JPEG.

Hazenbush, M., Schoenfeld, G., Cebulash, E., Bastan, M., Williams, T., Hernandez-Andersen, T. and Salazar, M. (2019) *Application Trends Survey Report 2019*, Graduate Management Admission Council.

Hlosta, M., Zdrahal, Z. and Zendulka, J. (2017) 'Ouroboros: early identification of at-risk students without models based on legacy data', *LAK '17: Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, pp.6–15.

Hoffait, A.S. and Schyns, M. (2017) 'Early detection of university students with potential difficulties', *Decision Support Systems*, Vol. 101, pp.1–11, https://doi.org/10.1016/J.DSS.2017.05.003.

Huang, S. and Fang, N. (2013) 'Predicting student academic performance in an engineering dynamics course: a comparison of four types of predictive mathematical models', *Computers & Education*, February, Vol. 61, pp.133–145, DOI: https://doi.org/10.1016/j.compedu.2012.08.015.

Kaur, S., Gupta, S., Singh, S., Dahiya, N., Garg, M., Kumar, M., Mehta, G., Nayar, N. and Sharma, A. (2021) 'EMT: ensemble meta-based tree model for predicting student performance in academics', *IOP Conference Series: Materials Science and Engineering*, Vol. 1022, No. 1, p.012062, https://doi.org/10.1088/1757-899X/1022/1/012062.

Kim, B.H., Vizitei, E. and Ganapathi, V. (2018) 'GritNet: student performance prediction with deep learning', *Proceedings of the 11th International Conference on Educational Data Mining, EDM 2018*, https://doi.org/10.48550/arxiv.1804.07405.

Kreiser, R.P., Wright, A.K., McKenzie, T.L., Albright, J.A., Mowles, E.D., Hollows, J.E., Limbocker, S., Eslinger, M., Limbocker, R. and Nguyen, L.T. (2021) 'Utilization of standardized college entrance metrics to predict undergraduate student success in chemistry', *Journal of Chemical Education*, https://doi.org/10.1021/ACS.JCHEMED.1C00719/SUPPL_FILE/ED1C00719_SI_002.D OCX.

Marbouti, F., Diefes-Dux, H.A. and Madhavan, K. (2016) 'Models for early prediction of at-risk students in a course using standards-based grading', *Computers & Education*, Vol. 103, pp.1–15, https://doi.org/10.1016/J.COMPEDU.2016.09.005.

Martinez, L.R., Boucaud, D.W., Casadevall, A. and August, A. (2018) 'Factors contributing to the success of NIH-designated underrepresented minorities in academic and nonacademic research positions', *CBE Life Sciences Education*, Vol. 17, No. 2, https://doi.org/10.1187/CBE.16-09-0287.

Miguéis, V.L., Freitas, A., Garcia, P.J.V. and Silva, A. (2018) 'Early segmentation of students according to their academic performance: a predictive modelling approach', *Decision Support Systems*, Vol. 115, pp.36–51, https://doi.org/10.1016/J.DSS.2018.09.001.

Mohammed, R., Rawashdeh, J. and Abdullah, M. (2020) 'Machine learning with oversampling and undersampling techniques: overview study and experimental results', *11th International Conference on Information and Communication Systems, ICICS 2020*, pp.243–248, https://doi.org/10.1109/ICICS49469.2020.239556.

O'Shea, S. and Delahunty, J. (2018) 'Getting through the day and still having a smile on my face! How do students define success in the university learning environment?', *Higher Education Research & Development*, Vol. 37, No. 5, pp.1062–1075, https://doi.org/10.1080/07294360.2018.1463973.

Ohio University Office of Institutional Research & Effectiveness (2019) *Athens Campus: Fall 2019 Enrollment by College*, Ohio University Office of Institutional Research [online] https://www.ohio.edu/instres/student/collegeenrollment.html (accessed 15 April 2021).

Okubo, F., Yamashita, T., Shimada, A. and Ogata, H. (2017) 'A neural network approach for students' performance prediction', *LAK '17: Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, pp.598–599.

Palvia, S., Kumar, A., Kumar, P. and Verma, S. (2017) 'Exploring themes, trends, frameworks: a meta-analysis of online business education research', *AMCIS 2017 Proceedings*.

Pandey, M. and Taruna, S. (2016) 'Towards the integration of multiple classifier pertaining to the Student's performance prediction', *Perspectives in Science*, September, Vol. 8, pp.364–366, DOI: https://doi.org/10.1016/j.pisc.2016.04.076.

Papamitsiou, Z. and Economides, A. (2014) 'Learning analytics and educational data mining in practice: a systematic literature review of empirical evidence', *Journal of Educational Technology & Society*, October, Vol. 17, No. 4, pp.49–64.

Shahiri, A., Husain, W. and Rashid, N. (2015) 'A review on predicting student's performance using data mining techniques', *Procedia Computer Science*, Vol. 72, No. 2015, pp.414–422, DOI: https://doi.org/10.1016/j.procs.2015.12.157.

Walck-Shannon, E.M., Cahill, M.J., McDaniel, M.A. and Frey, R.F. (2019) 'Participation in voluntary re-quizzing is predictive of increased performance on cumulative assessments in introductory biology', *CBE Life Sciences Education*, Vol. 18, No. 2, https://doi.org/10.1187/CBE.18-08-0163.

Weatherton, M. and Schussler, E.E. (2021) 'Success for all? A call to re-examine how student success is defined in higheeducation', *CBE Life Sciences Education*, Vol. 20, No. 1, pp.1–13, https://doi.org/10.1187/CBE.20-09-0223/ASSET/IMAGES/LARGE/CBE-20-ES3-G002.JPEG.

Young, W., Weckman, G. and Holland, W. (2010) 'A survey of methodologies for the treatment of missing values within datasets: limitations and benefits', *Theoretical Issues in Ergonomics Science (TIES)*, Vol. 12, No. 1, pp. 15-43, https://doi.org/10.1080/14639220903470205.

Zeineddine, H., Braendle, U. and Farah, A. (2021) 'Enhancing prediction of student success: automated machine learning approach', *Computers & Electrical Engineering*, Vol. 89, p.106903, https://doi.org/10.1016/J.COMPELECENG.2020.106903.

Appendix

Neural network settings for all models

Learning rate	0.1
Weight change momentum	0.6
Error tolerance	0.01
Weight decay	0