Predictors of Academic Success for Students at the Michigan College of Optometry

Robert S. Buckingham, OD, PhD
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Optometry school admission committees must choose students based on their predictions of the applicants' success. This study evaluates the predictive value of the Optometry Centralized Application Service (OptomCAS) variables. Each undergraduate course taken by students entering the Michigan College of Optometry at Ferris State University was categorized according to the OptomCAS variables. Linear regression analysis found that the Optometry Admission Test academic average and reading comprehension as well as other undergraduate GPAs are the best predictors for academic success. No academic variables could predict graduation. This study provides optometry admission committees additional tools for improving their selection process.

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Optometry school admission committees must choose students based on their predictions of the applicants' success. This study evaluates the predictive value of the Optometry Centralized Application Service (OptomCAS) variables. Each undergraduate course taken by students entering the Michigan College of Optometry at Ferris State University was categorized according to the OptomCAS variables. Linear regression analysis found that the Optometry Admission Test academic average and reading comprehension as well as other undergraduate GPAs are the best predictors for academic success. No academic variables could predict graduation. This study provides optometry admission committees additional tools for improving their selection process.

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Background

Optometry school admissions are very competitive. With more applicants than available slots,[1,2] the Michigan College of Optometry (MCO) admissions committee members must choose, from a myriad of well qualified applicants, those students who they feel will be successful graduates. However, no research has been published analyzing MCO applicants. In addition, very little research has been published on the predictors of academic success in optometry school as it relates to the Optometry Centralized Application Service (OptomCAS) variables.[3,4] OptomCAS is an application service that all students must use to apply to optometry schools in the United States. The purpose of this study is to determine at MCO whether there is a subset of OptomCAS variables that significantly predicts students' grade point averages (GPAs) for each year of optometry school, as well as graduation from MCO.

Optometry schools decided to use OptomCAS for school year 2009-2010 to get a better understanding of the number of applicants and to streamline the application process. All applicants to optometry schools in the United States must apply using this centralized Web-based system in which they are able to use one application to apply to several schools and colleges of optometry. The database includes each applicant's demographic information, recommendation letters, extracurricular activities, colleges and universities that they attend with course history, work/professional experience, individual essay and awards/honors. It then separates this information into a series of variables to allow comparison between applicants based on the GPAs for different types of course work, GPAs for different years of schooling, and Optometry Admission Test (OAT) score breakdown.[5]

The OAT is a computerized standardized test that is required for application to U.S. optometry schools. It includes sections on biology, general chemistry, organic chemistry, reading comprehension, physics and quantitative reasoning. Each section is scored individually as well as averaged into an academic average of all sections. The raw scores are converted to a standard score that ranges from 200-400 with an average of 300.[6]

To select the appropriate students for admission into an optometry school, admittance committees consider a number of selection criteria such as the OptomCAS variables including undergraduate cumulative GPAs and undergraduate science GPAs, as well as OAT scores.[3,4] For all students entering optometry school in the United States in 2009, the mean GPA was 3.41 on a 4.0 scale. In addition, the OAT academic average score was 334.[7] Because the majority of these students have high GPAs and high OAT scores, the selection committees must choose between applicants who appear very similar.[4]

Since the 2010-2011 cycle, OptomCAS provides optometry schools with 38 different GPA variables.[5] The GPA variables range from freshman to senior cumulative science, non-science, and total GPAs. In addition to the previous, the science, non-science, and total GPA variables include post-baccalaureate cumulative, undergraduate cumulative, graduate cumulative and overall cumulative science, non-science, and total GPAs. Also, included in the GPA variables are the biology/life science GPAs, inorganic chemistry GPAs, organic chemistry GPAs, biochemistry GPAs, physics GPAs, biology/chemistry/physics total GPAs, math GPAs, psychology GPAs, English GPAs, other science GPAs, and other general GPAs. In addition, OptomCAS provides the eight OAT variables: quantitative reasoning, reading comprehension, biology, general chemistry, organic chemistry, physics, total science, and academic average scores.

Even though OptomCAS provides significant information on each applicant, selecting the wrong person can lead to attrition of that student from the program. Attrition has a negative impact not only on the individual but also on the school. Students who enter but do not graduate are encumbered with a large debt without any meaningful skill to pay off that debt.[8,9] As for the schools, revenue from tuition and fees that they would be taking in from the now disenrolled students is lost. Besides the financial loss, there is a significant emotional and psychological toll for the disenrolled students.[8,10,11]

Previous studies in the health profession schools demonstrate that schools have various predictors of academic achievement. Some of the more common predictor variables include pre-admission science GPAs, pre-admission cumulative GPAs, and standardized entrance tests.[10-21]

A retrospective study at the University of Missouri-St. Louis College of Optometry (UMSL) examined the predictors of academic success of optometry students from 1984 through 1992. The study discovered that a grouping of the undergraduate cumulative GPAs, the OCAT (Optometry College Admission Test, the predecessor to the OAT) reading test score, the OCAT biology score, and the personal interview were the best predictors of GPAs at UMSL.[3]

Exploring further into the personal interviews, Spafford investigated the types of interviews performed during the admissions process at optometry schools. In this study, the optometry schools ranked the importance of certain variables in the decision process for admitting students. The schools ranked the undergraduate GPAs as the highest ranked admittance variable followed by the OAT scores, interview and references.[22]

Investigating OAT scores, Kramer and Johnston examined the relationship between OAT scores, undergraduate GPAs and first- and second-year GPAs in seven optometry schools. The study revealed that the best predictor of optometry school GPA was a combination of undergraduate GPAs and OAT scores.[23]

In 2007, researchers at Pacific University College of Optometry evaluated 175 student records for academic success. This study found that the 1) undergraduate science GPAs, 2) GPAs of the last 45 undergraduate credits, 3) undergraduate cumulative GPAs, 4) OAT academic average score, 5) OAT quantitative reasoning score, 6) OAT general chemistry score, 7) OAT organic chemistry score, and 8) OAT total science score demonstrated a statistically significant difference between students who failed a course and students who did not fail a course.[4]

In the admissions process in the past, MCO used the following variables for the selection process: the OAT academic average score, the overall undergraduate GPA, and the overall prerequisite GPA as well as knowledge of the profession, optometric experience, employment, extracurricular activities, personal essay, letters of recommendation, and honors/awards. With the advent of OptomCAS, no research has been accomplished on the predictors of success as it relates to the OptomCAS variables. Therefore, the authors evaluated the predictors of academic success at MCO using the OptomCAS variables. To this end, the purpose of this study is to determine whether there is a subset of OptomCAS variables that significantly predicts the students' GPAs for each year at MCO, as well as graduation from MCO. A study of this nature provides the MCO optometry admissions committee the tools to make wiser decisions when enrolling students.

There are three research questions. The first research question evaluated the ability of the OptomCAS variables to predict first-year, second-year, third-year and fourth-year cumulative GPAs at MCO. The second research question assessed the ability of the variables to predict graduation from MCO. The third research question evaluated whether the OAT data provide meaningful information above and beyond the GPA data in predicting end of the year GPA and graduation from MCO. This provides information on the value of a standardized entrance test.

Methods

The research design employed in this study was non-experimental, ex post facto because the data variables were evaluated after their normal occurrence.[24] The data were collected from archival data of student records from MCO. The population for this study included all students who started optometry school at MCO from 1995 through 2004 and who graduated or should have graduated from MCO in the years 1999 through 2008. During this time period, the entering class size ranged from 32 to 34 students. These years were selected because the OAT scores were recalibrated in May 2009. In addition, the curriculum at MCO underwent a major change beginning with the Class of 2009. Students who were still enrolled in the optometry program were not included nor were students who were disenrolled due to non-academic reasons.

Of the nearly 3,000 applicants from 1995 through 2004, 327 students were admitted to MCO. Of those students, 4 were disenrolled due to non-academic issues and another was eliminated due to a lack of the normal prerequisites. For MCO, the normal prerequisites were 1) one year of general biology with lab, 2) one year of general chemistry with lab, 3) one year of organic chemistry with lab, 4) one year of physics with lab, 5) one year of English, 6) a microbiology course with lab, 7) a calculus course, 8) a statistics course, 9) an introductory psychology course, and 10) a speech/communications course.

The 322 students in the study took a total of 13,203 courses before entering MCO. Based on the classification in the students' transcripts, all 13,203 courses were categorized into freshman, sophomore, junior, senior, post baccalaureate, or graduate courses. In addition, the 13,203 courses were classified into biological/life science, inorganic chemistry, organic chemistry, biochemistry, physics, math, English, psychology, other science, or other general courses. The previous two years of OptomCAS data entry was used as a guide in the classification of the courses.

GPAs were computed for each student for each of the above OptomCAS variables. The GPAs were computed by summing the points earned for each course and dividing this number by the credit hours attempted. To ensure equity between educational institutions, if the college was on a quarter hour system, the total number of credit hours was converted from quarter hours to semester hours when appropriate. For example, a 3-credit course in quarter hours is equivalent to a 2-credit course in semester hours.

SPSS for Windows was employed to analyze the data. When data were found to be missing, multiple imputation was employed.[25-30] The authors employed descriptive and inferential statistics to portray and analyze the data on the variables.[24,27,31-34] The probability level was set at .05 for rejecting the null hypotheses.

The dependent variables were graduation, first-year cumulative GPA, second-year cumulative GPA, third-year cumulative GPA, and fourth-year cumulative GPA. The dependent variable, graduation, was nominal, categorical and was coded as graduate or non-graduate.

For research question 1, we used linear regression analysis for evaluation of the GPAs. To minimize collinearity, the predictor variables were narrowed down using the forward stepwise regression model. The forward stepwise regression adds predictor variables with the highest partial correlation as long as the variable is statistically significant. It continues to add predictor variables based on the partial correlation until none of the predictor variables is statistically significant.[32,35-39] For research question 2, binary logistic regression tests were used to predict graduates vs. non-graduates based on the independent variables. For the logistic regression, a forward elimination likelihood ratio regression model was employed to produce the odds ratio. The odds ratio is defined as the increase in the dependent variable for a unit increase in the independent variable. The forward elimination uses the likelihood-ratio test to enter or remove variables from the model.[33-36,40,41] For research question 3, we employed both linear regression and binary logistic regression analyses. In this scenario, the data were partitioned into two segments. One segment was the coursework GPAs and the other segment was the OAT data. A stepwise regression was then performed on the coursework GPAs and not on the OAT information. Next, a two-block enter method linear regression was done with the first block being the variables identified in the previous regression equation and the second block being the OAT academic average score. We then compared the change in the adjusted R square values and the change in the Nagelkerke R square values for the first block compared to the second block. This provided the effect of adding the OAT variables into the predictor model.

Results

From 1995 through 2004, there were 327 students who entered MCO. Of those students, 4 were disenrolled due to non-academic issues and another was eliminated due to a lack of normal prerequisites. Therefore, the total number of students in this study was 322. Of the 322 students, 12 students did not graduate and 310 graduated.

Of the 322 students, no students had any graduate classes prior to entering MCO. Thus, the 3 graduate GPA variables and the 3 overall GPA variables (which included the graduate GPAs) were eliminated from analysis.

Further analysis revealed that very few students had post baccalaureate GPAs. In addition, the listwise analysis revealed that only three students had data for each of the independent variables. A listwise analysis excludes an entire record if any single value pertaining to that record is missing, significantly reducing our eligible sample size. Due to the low frequency, the 3 post baccalaureate GPA variables were eliminated from the analysis. This left 37 independent variables for analysis.

Research question 1

Research question 1 asks to what extent the independent variables are predictive in determining the GPAs for each year of optometry school. We evaluated if we should use a stepwise or backward data entry method for the linear regression. Due to the excessive multicollinearity with the backward stepwise model, we employed the stepwise model.[38,39] In addition, missing values were evaluated in the data using the multiple imputation method.[42-45] After utilizing multiple imputation, the authors performed some exploratory forward and backward stepwise linear regression on the imputed data and the original data. The authors then compared the adjusted R square values for the imputed data vs. the original data. The authors found that the original data had higher adjusted R square values than the multiple imputation data. The lower adjusted R square values of the imputed data may be due to variance induced by the estimations employed when performing multiple imputation. Based on this information, the authors decided to use only the original data.

Next, the authors evaluated whether a forward stepwise linear regression or a backward stepwise linear regression would be a better predictor model of the cumulative optometry GPAs. To accomplish this, the authors evaluated the multi-collinearity of the two models. Of the two models, the forward stepwise model had significantly less multi-collinearity than the backward stepwise model. Due to the excessive multi-collinearity with the backward stepwise model, the authors employed the forward stepwise model.

For the linear regression using the forward stepwise method, **Table 1** compares the variables of the regression equation for the original data for the first, second, third, and fourth-year cumulative GPAs. For the original data, the regression equation is First Year GPA = -0.131 + [0.009 (OAT Academic Average)] + [0.166 (GPA Math)]. For the second-year data, the regression equation is Second Year GPA = -0.705 + [0.008 (OAT Academic Average)] + [0.225 (GPA Biology)] + [0.410 (GPA Undergraduate Non-Science)] + [-0.187 (GPA Sophomore Non-Science)]. For the third-year data, the forward stepwise linear regression equation is Third Year Grade Point Average = -0.134 + [0.006 (OAT Academic Average)] + [(0.314 (GPA Biology)] + [0.577 (GPA Undergraduate Non-Science)] + [-0.258 (GPA Sophomore Total)] + [-0.172 (GPA Junior Non-Science)]. For the fourth-year data, the regression equation is Fourth Year GPA = 0.270 + [.005 (OAT Academic Average)] + [0.336 (GPA Biology)] + [0.002 (OAT Reading Comprehension)].

Table 1 reveals that the OAT academic average is a significant predictor for academic performance for all four years and the undergraduate biology GPA is a significant predictor for second to fourth years in optometry school. In addition, undergraduate math GPA is related to academic success in first-year optometry, while undergraduate non-science GPA is related to second- and third-year optometry school GPA. The linear regression equations also include undergraduate sophomore non-science GPA for predicting second-year optometry school GPA, undergraduate sophomore total GPA for predicting third-year optometry school GPA, undergraduate junior non-science GPA for predicting third-year optometry school GPA, and the OAT reading comprehension score for predicting fourth-year optometry school GPA.

Table 1
Comparison of Regression Variables and Coefficients for GPAs

Variables with Coefficients	1st Year	2nd Year	3rd Year	4th Year
(Constant)	-.131	-.705	-.134	.270
OAT Academic Average Score	.009	.008	.006	.005
Math GPA	.166			
Biology GPA		.225	.314	.336
UG Non-Science GPA		.410	.577	
Sophomore Non-Science GPA		-.187		
Sophomore Total GPA			-.258	
Junior Non-Science GPA			-.172	
OAT Reading Comprehension Score				.002

Table 2
Model Comparison of Cumulative GPA Data

Year Data	R	R Square	Adjusted R Square	Std. Error of the Estimate
First Year	.585	.342	.329	.33653
Second Year	.721	.520	.501	.26011
Third Year	.729	.531	.507	.23179
Fourth Year	.736	.541	.528	.22371

Table 2 shows a comparison of the original data adjusted R square value for the dependent variables. The adjusted R square value increases as the student advances from first year to fourth year. By the time the student is in the fourth year of optometry school, the linear regression equation accounts for about 52.8% of the variance in the cumulative GPAs. Thus for the regression models, it is harder to predict first-year optometry school GPA than the subsequent second- through fourth-year optometry school GPAs.

Research question 2

Research question 2 asks to what extent the independent variables are predictive in determining those students who are academically disenrolled (non-graduate) and students who graduate. The analysis revealed that 109 records were included in the analysis and 213 records were excluded from the analysis. The Nagelkerke R square was .177. The Nagelkerke R square is a pseudo R square and is not equivalent to the R square in linear regression. Nagelkerke R square is used to compare models to see which one explains more of the variance.[33,36]

For the logistic regression, only one variable, sophomore science GPA, was statistically significant. The logistic regression equation was the log-odds of Graduation = -3.267 + [2.37 (sophomore science GPA)]. When applying a 50% cutoff for the 315 students with a sophomore science GPA, the equation predicts that all students will graduate. Using this 50% cut off, the logistic regression equation sensitivity is 96.3% and the specificity is 0%. This reveals that the logistic regression equation is a poor predictor of selecting individuals who will not graduate from MCO.

Research question 3

The third area the researchers investigated related to the importance of the OAT scores in determining graduation of students from the optometry college (graduate vs. non-graduate) and end of the year GPAs after each year of school. For first- through fourth-year GPAs, a linear regression was performed on the data which did not contain the OAT information. In the second step in the analysis, a two-block enter method linear regression was performed with the first block being the variables identified in the previous regression equations and the second block being the OAT academic average score. This provided the effect of adding the OAT variables into the predictor model.

Table 3 compares the adjusted R square for the block one data without the OAT information and the block two data where the OAT academic average score was added. For the first, second, third and fourth-year GPAs, the data with the OAT academic average score information have a higher adjusted R square value. In fact, the OAT academic average score accounts for about 10% of the variance in the dependent variables. In addition, **Table 4** reveals that the F change is statistically significant for all of the cumulative GPAs, which indicates that there is a statistically significant difference in the R value and the adjusted R square value when adding the OAT academic average score.[46]

Because the OAT data account for a statistically significant amount of additional variance and because the F change is statistically significant by adding the OAT, the OAT academic average score is important in the predictability of the first, second, third and fourth-year optometry cumulative GPA.

For graduation vs. non-graduation, binary logistic regression revealed that the sophomore science GPA was the only variable in the logistic regression. With adding the OAT academic average score to the logistic regression equation, the Nagelkerke R square increased from 0.133 to 0.154. This means that by adding the OAT academic average score to the model, there was more variance explained than using the data with the sophomore science GPA only. Sophomore science GPAs were found to be statistically significant with a p value of .002, but the OAT academic average score was not statistically significant with a p value of .176. This means that OAT academic average score should be removed from the logistic regression equation and the sophomore science GPA should remain in the equation.

Table 3
Comparison of Dependent Variable Adjusted R Square

Dependent Variable	Non-OAT Data Adjusted R Square	OAT Data Adjusted R Square
First Year	.274	.358
Second Year	.358	.459
Third Year	.354	.453
Fourth Year	.398	.498

Table 4
Model Summary and Change Statistics for Cumulative GPA

Year	Model	R Square	Adjusted R Square	Change Statistics				
				R Square Change	F Change	df1	df2	Sig. F Change
Cum. First Year GPA	1	0.281	0.274	0.281	43.524	2	223	0.000
	2	0.366	0.358	0.086	29.977	1	222	0.000
Cum. Second Year GPA	1	0.364	0.358	0.364	62.029	2	217	0.000
	2	0.467	0.459	0.103	41.621	1	216	0.000
Cum. Third Year GPA	1	0.36	0.354	0.360	60.584	2	215	0.000
	2	0.461	0.453	0.100	39.874	1	214	0.000
Cum. Fourth Year GPA	1	0.403	0.398	0.403	72.367	2	214	0.000
	2	0.505	0.498	0.102	43.872	1	213	0.000

Discussion

The purpose of this study was to evaluate the ability of the OptomCAS variables to predict the GPA and/or graduation of students in MCO. Research question 1 asked to what extent the independent variables are predictive in determining end of the year GPAs for first year, second year, third year and fourth-year optometry students. **Table 2** compared the original data adjusted R square value for the dependent variables, displaying an increased adjusted R square from first-year GPAs to fourth-year GPAs. Looking at the predicted fourth-year GPAs, 52.8% of the variation in the GPA is accounted for by the variables in the regression equation. This adjusted R square is very high, meaning the variables in **Table 1** are excellent predictors of first-year through fourth-year optometry GPAs.

Looking at the variables and the coefficients of those variables in **Table 2**, the OAT academic average score is important in predicting all cumulative GPAs; however, the coefficients reveal that the importance of the OAT decreases from first-year GPAs (.009) to fourth-year GPAs (.005). The math GPAs are a good predictor of success in the first year, whereas biology GPAs are a good predictor in the second through fourth years of optometry school. This is reasonable because optics, which employs intensive math skills, is taught in the first year of optometry school at MCO. In the second through fourth year of optometry school, general biology skills are more important as these years are more focused on pathology, pharmacology, ocular disease and other science courses. Beyond this, the pre-optometry non-science GPAs, which include English, math, other general, and psychology GPAs, as well as the OAT reading comprehension scores, are predictor variables. Perhaps this relates to the graduate level reading material encountered during these years. In short, the better the student comprehends information while reading, the higher GPA the student will achieve.

When comparing this study to other similar research studies, this study supported Wingert's findings that undergraduate course GPAs and certain OAT scores are predictors for first- and second-year GPA.[3] This study also supported the findings of Kramer and Johnston that both the undergraduate course GPAs and OAT scores are predictors for first- and second-year GPA.[23] Finally, this study supported the findings of Goodwin that both the undergraduate course GPAs and OAT scores are predictors for first- and second-year GPA.[4]

Research question 2 asked to what extent the independent variables are predictive in determining those students who are academically disenrolled (non-graduate) vs. students who graduate. The logistic regression revealed that only one variable, sophomore science GPA, was found to be statistically significant in being able to differentiate between graduation and non-graduation of students. The 36 other independent variables were found to be not statistically significant in their ability to differentiate between students who graduate and students who do not graduate.

An excellent logistic regression equation should be able to predict the probability that a subject will graduate or not graduate from MCO. Of the 315 students with a sophomore science GPA, the logistic regression equation predicted all would graduate. Using a 50% cut off, the logistic regression equation sensitivity is 96.3% and the specificity is 0%. Therefore, the binary logistic regression equation is a very poor predictor of identifying individuals who will not graduate from MCO. This poor performance of the logistic equation could be caused by the small number of non-graduates in this study. Another possibility for the poor predictability of the logistic regression equation could be due to the fact that the 37 academic-based variables may not be the main cause for disenrollment from optometry school. There may be non-academic issues affecting the students' academic success and these non-academic reasons are causing these students to not graduate. Even though the logistic equation could not predict non-graduation, the results could be accurate. For example, if a student fails due to non-academic issues such as working 40 hours a week or a death in the family, no academic variables would stand out as predictors for non-graduation.

When comparing this study to other similar research studies, this study added to Goodwin's findings that undergraduate science GPA and total science OAT scores are predictors for failing a course.[4] In addition, this study takes the knowledge base one step further by evaluating graduation of optometry students. Most of the other optometry achievement studies evaluated GPA in optometry school.

Research question 3 evaluated the importance of the OAT scores as predictors for academic achievement for students at MCO. In other words, should the standardized OAT be significant to an optometry school's selection process? In the linear regression analysis, improvement was found in the adjusted R square values when adding the OAT academic average score. **Table 3** compares the adjusted R square for the undergraduate course variables without the OAT variables and the adjusted R square for the undergraduate course variables with the OAT academic average score added. For the first, second, third and fourth-year cumulative GPAs, the data with the OAT academic average score information has a higher adjusted R square than the data without the OAT information. In fact, by adding the OAT academic average score, the linear regression equation provides about a 10% increase in explaining the variance in the first, second, third and fourth-year cumulative optometry GPAs. The additional amount of variance explained is statistically significant at $p < 0.001$ level for all equations. Because the OAT data account for a statistically significant amount of additional variance above and beyond those explained by the undergraduate course grade point averages, the OAT academic average score is important in the predictability of the first, second, third and fourth-year optometry cumulative grade point average. As for the graduation vs. non-graduation analysis, the results were exactly the same as the results of research question 2.

When comparing this research question 3 to other similar research studies, this study supported the findings of Kramer and Johnston that both the undergraduate course GPAs and OAT scores are better predictors for first- and second-year GPA than undergraduate course GPAs alone.[23] This study also added to the knowledge base by showing that the OAT scores are valuable in predicting optometry GPA throughout the four years in optometry school.

Delimitations and Limitations

A few factors limit this study. Categorization of each course into the OptomCAS categories was a somewhat subjective process and could have potential researcher bias. In addition, the study was only conducted at MCO. Thus, other schools may not be able to extrapolate the results to their applicants. Further, the independent variables used in this study are those provided by OptomCAS. There may be other unknown variables that could be predictors of first, second, third and fourth-year cumulative GPAs. In addition, course grades for clinical performance at MCO are credit/no credit. These courses are not included in the overall GPAs of the students. Thus, this study does not directly evaluate the clinical performance of the students. Another issue is that faculty members at different institutions may employ different grading criteria, which in turn would affect an applicant's undergraduate GPA. Another limitation of the study was the low number of students who did not graduate from MCO. This low number could skew the results of the logistic regression. Finally, the current process of selecting students may influence the statistical analysis. Results may be skewed because students with low OAT scores and low GPAs are not generally admitted into MCO due to the competitiveness of the admissions process and the challenging nature of the program.

Recommendations for Future Research

In this study, the researchers found that 30% of the data was missing due to students not having a senior non-science GPA, senior science GPA, and senior total GPA. Historically, approximately 25% of each entering class consists of applicants who do not have a bachelor's degree. A follow-up study should evaluate if the students entering MCO without a bachelor's degree differ from students entering MCO with a bachelor's degree. Looking beyond the OptomCAS variables, there may be other variables that might be indicators of optometry school GPA, such as repeating undergraduate courses, withdrawing from undergraduate courses, failing undergraduate courses, etc. In addition, the number of undergraduate credit hours achieved and possibly the number of undergraduate colleges the individual attended could be evaluated as potential predictors of success in optometry school.

Another possible area of research would be to perform the analysis on recent graduates. The data in this study used OAT scores prior to May 2009. In May 2009, the OAT scores were recalibrated. In addition, by adding another semester of classroom instruction, the curriculum at MCO underwent a major change starting with the Class of 2009. A follow-up study should evaluate the predictors under these new conditions.

Conclusions

Optometry school admissions are very competitive. There are more applicants than there are available seats in optometry schools. The optometry admissions committees must choose, from a myriad of well-qualified applicants, those students whom they feel will be successful graduates. The results of this study found that of the 37 variables reviewed, the OptomCAS variables of 1) OAT academic average score, 2) OAT reading comprehension score, 3) math GPA, 4) biology GPA, 5) undergraduate non-science GPA, 6) sophomore non-science GPA, 7) sophomore total GPA, and 8) junior non-science GPA are predictors of academic achievement at the Michigan College of Optometry. These eight variables explain over 50% of the variance in MCO student GPA. Therefore, when evaluating potential applicants for future academic achievement in optometry schools, admissions committees should give careful consideration to these eight variables.

In addition, this study found that the logistic regression equation involving these academic-based 37 variables is a poor predictor of selecting individuals who will not graduate from MCO. The reason may be the small number of non-graduates in this study, or it may be due to the fact that the 37 academic-based variables may not be the main cause for disenrollment from optometry school. There may be other life or non-academic issues that may be causing these students to not graduate. Future study in this area is warranted. Finally, this research found that both undergraduate course variables and OAT variables combined were better predictors than undergraduate course variables alone, which means that the standardized OAT does add value to the selection process.

The authors recommend that the optometry school admissions committees review the above eight variables for applicability to selection of their applicants. In addition, because the reason students do not graduate from optometry school may be related to non-academic issues, optometry schools should consider gathering information to evaluate the non-academic life issues of their students as well.

Overall, this study increases the current knowledge on optometry school selection criteria variables and the importance of the OptomCAS variables. It also provides optometry admissions committees additional tools for improving their selection process.

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