ATHLETIC TRAINING EDUCATION JOURNAL
© National Athletic Trainers' Association
www.natajournals.org
ISSN: 1947-380X
DOI: 10.4085/1104194

ORIGINAL RESEARCH

Prediction Modeling for Academic Success in Professional Master's Athletic Training Programs

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Context: A common goal of professional education programs is to recruit the students best suited for the professional career. Selection of students can be a difficult process, especially if the number of qualified candidates exceeds the number of available positions. The ability to predict academic success in any profession has been a challenging proposition. No studies to date have examined admission predictors of professional master's athletic training programs (PMATP).

Objective: The purpose of this study was to identify program applicant characteristics that are most likely to predict academic success within a PMATP.

Design: Cohort-based.

Setting: University professional PMATP.

Patients or Other Participants: A cohort of 119 students who attended a PMATP for at least 1 year.

Intervention(s): Common application data from subjects' applications to the university and the PMATP were gathered and used to create the prediction models.

Main Outcome Measure(s): Sensitivity, specificity, odds ratio, and relative frequency of success were used to determine the strongest set of predictors.

Results: Multiple logistic regression analyses yielded a 3-factor model for prediction of success in the PMATP (undergraduate grade point average $\geq$ 3.18; Graduate Record Examination quantitative [percentile rank] $\geq$ 141.5 [$\geq$12]; taking calculus as an undergraduate). A student with $\geq$2 predictors had an odds ratio of 17.94 and a relative frequency of success of 2.13 for being successful in the PMATP. This model correctly predicted 90.5% of PMATP success.

Conclusions: It is possible to predict academic success in a PMATP based on common application data.

Key Words: Odds ratio, relative frequency of success, athletic training education, academic program admissions

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Full Citation:
Bruce SL, Crawford E, Wilkerson GB, Rausch D, Dale RB, Harris M. Prediction modeling for academic success in professional master's athletic training programs. *Athl Train Educ J*. 2016;11(4):194–207.

Prediction Modeling for Academic Success in Professional Master's Athletic Training Programs

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A common goal of professional education programs is to recruit and select the best students from a pool of candidates. Making and defending these admission decisions is difficult. The more objective the selection process, the easier it can be to identify qualified candidates and to defend against legal actions or other potential problems related to the candidates who were not accepted into the program.

Multiple health education program administrators have examined potential predictors for assisting in more objective methods for the selection or rejection of students. A literature search on programs from clinical psychology, nursing, occupational therapy, physician assistant, physical therapy, and medical schools revealed all have attempted to refine their selection processes.[1–4] Several different approaches have been used in an effort to try and isolate which variable or group of variables are best at predicting those candidates who should be selected for their programs. Predictor variables such as the Graduate Record Examination (GRE), undergraduate grade point average (uGPA), Medical College Admission Tests, past clinical experience, age, race, gender, and ethnicity have all been employed.[5–15] A number of variables were used to identify candidates likely to be successful in their program, including written essays, interviews, subjective inventories, references, and personal characteristics. The outcome variables that have been used include admission into the professional master's athletic training programs (PMATP), graduate grade point average (gGPA), academic performance, clinical rotation success, and graduation from the program.[5,6,8–12,14–27]

In the frequentist's world, the data are generated by repeating the experiment on a random sample (providing the frequency of an event). The basic limitations remain the same during the application of the repeatable experiment; therefore, the parameters are constant. In the Bayesian's world, the data are gathered from an observed cohort. The parameters are unspecified and are described in terms of the likelihood of an event occurring or not occurring; therefore, the data are fixed.[28] A Bayesian approach entails observing the association between subjects and variables, and subjectively determining the probability and "its associated confidence interval."[29(p561)]

No studies to date have examined admittance decisions for PMATPs. One study[21] did examine prediction variables for a postprofessional National Athletic Trainers' Association-approved PMATP using stepwise multiple regression analysis. The authors found that uGPA was the only significant predictor of gGPA.[21] Our purpose for this study was to identify program applicant characteristics (the exposures) that are most likely to predict academic success within the PMATP (the outcome).

METHODS

A cohort study design using students admitted to a PMATP from 2004 to 2012. The cohort's institution was a public, medium, 4-year, primarily residential, metropolitan university with a Carnegie classification as a doctoral science-technology-engineering-mathematics–dominate research university.[30] Of the 371 total applicants, 181 students were offered positions in the PMATP. There were 31 students offered a position in the PMATP that rejected the offer to attend another PMATP. Of this remaining 150 students, 19 either dropped out of the PMATP or were counseled out of the program, leaving 131 students. Records for 12 students were incomplete, which left 119 students who formed the study cohort. There were 30 (25.2%) students classified as in-state, with 9 (7.6%) students earning their undergraduate degree at the university used in this study. The remaining 89 students came from 24 different states. The institutional review board approved this project.

Predictor Variables

A total of 35 variables were initially considered as potential predictors of PMATP success (Table 1). Academic information from students' applications for PMATP admission was used for potential predictors. Based on the students' degree-granting institution, we researched each school's common dataset to obtain their mean or median American College Testing (ACT) and Scholastic Assessment Test (SAT) scores for the most recent academic year's available data.[31] Receiver operating characteristic (ROC) analysis identified the optimum ACT and SAT mean/median scores. Students were then recoded 0 if their score was less than the cutpoint and 1 if the predictor value was greater than or equal to the cutpoint. The cutpoint is the point on the ROC curve which is either closest to the upper left-hand corner or the point furthest away from the diagonal reference line as best determined by Youden's index[32] These recoded variables were then summed and dichotomized (0 if the student had an ACT/SAT score below the mean/median for both tests, 1 if the student had an ACT/SAT score above the mean/median for at least 1 of these standardized tests). The Academic Profile of Undergraduate Institutions (APUI) became a new nominal variable.

The second variable created was whether the student's undergraduate institution was classified as research intensive through the Carnegie classification system.[30] Each school's classification was determined and then dichotomized based on research intensive categorization, and coded: research intensive schools were coded as a 1; all others were coded as 0.

Academic success for this study was operationally defined as gGPA at the end of the first year in the program. Students' gGPA scores at the end of the first year in the PMATP were derived from faculty-accessible, university academic records. First-attempt success (pass or fail) on the Board of Certification (BOC) exam was used as a criterion for outcome dichotomization through ROC analysis to establish the cutpoint for gGPA at the end of the first year in the PMATP.

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Table 1. Potential Predictor Variables Analyzed

Academic Profile of Undergraduate Institution
Undergraduate institution ACT mean/median
Undergraduate institution SAT 75th percentile
Undergraduate institution ACT 75th percentile
Undergraduate institution SAT 80th percentile
Undergraduate institution ACT 80th percentile
Advanced math and science courses
Number of advanced science courses
Any advanced biology
Any advanced chemistry
Biomechanics
Calculus
Pathophysiology
Physics
Advanced math, science, and athletic training courses
Number of advance math courses
Number of advance science courses
Total number of advanced courses
Athletic training courses
Number of athletic training courses
Basic athletic training or care and prevention courses
Advanced athletic training courses
Basic Carnegie classification categories
Bachelor's and master's
Doctorate/research
Research intensive
GRE scores
GRE composite
GRE quantitive
GRE verbal
GRE written
Residency (in-state versus out-of-state)
Total number of advanced science and athletic training courses
Type of institution (public versus private)
Undergraduate grade point average
Undergraduate institution size and setting
Large (10 000+ undergraduates)
Medium (3000–9999 undergraduates)
Small (<1000–2999 undergraduates)
Undergraduate admission acceptance rate

Abbreviations: ACT, American College Testing; GRE, Graduate Record Examination; SAT, Scholastic Assessment Test.

Due to the wide variety of candidates' undergraduate preparation, we categorized advanced math and science classes, number of athletic training classes, and combined these categories to create predictor variables. A student's in-state/out-of-state residency, the type of institution from which they earned their undergraduate degree from, the size of their undergraduate institution, and the admission acceptance rate were all examined (Table 2).

Data Reduction

Univariable examinations of the 35 original potential predictors used ROC analyses to identify cutpoints for dichotomization of potential predictors of academic success. Youden's index (sum of [sensitivity (Sn) + specificity (Sp) − 1]) distinguished the best balance between Sn and Sp to identify each predictor's cutpoint. Predictor data were then coded 0 for less than the cutpoint or 1 if the predictor value was greater than or equal to the cutpoint. To assess each predictor for inclusion in multivariable analysis, 2×2 cross-tabulation analyses were used to compare the Sn, Sp, odds ratio (OR) and relative frequency of success (RFS) among predictors. The RFS is similar to relative risk, but since risk is not an appropriate term for this study, RFS was created. We adapted the relative risk definition by Portney and Watkins[33]; thus, the RFS "indicates the likelihood that someone who has been classified (as meeting the criteria for acceptance will be accepted into the PMATP), as compared with one who has not met the criteria (to be accepted into the PMATP)."[33(p333)] Predictors with a univariable OR of $\geq$1.5 or Fisher's exact test (1-sided) P value of $\leq$.20 were retained for multivariable analyses.[34]

Multicollinearity analyses were performed on the continuous and multilevel discrete variables for those variables advanced from the univariable to the multivariable analysis to examine for potential overlap among predictors resulting in production of the variance inflation factor (VIF) and tolerance values. Originally, the continuous and multilevel discrete variables were assessed for multicollinearity. If the VIF values approximated 10 or above or tolerance values approached 0.1 or less, thus indicating multicollinearity, the variable was eliminated from the multivariable analyses.[35–37] The remaining 7 continuous/multilevel discrete variables were dichotomized based on their cutpoints, were combined with the other 3 nominal variables, and the multicollinearity analysis was repeated.

A backward, stepwise, logistic regression analysis was then used to determine the best set of potential predictors relative to their contributions to the multivariable model. The number of positive factors each student possessed was summed, and ROC analysis was performed to determine the best balance between Sn and Sp for the optimum number of positive factors. A 2×2 cross-tabulations table calculated Sn, Sp, OR, and RFS for the derived prediction model.[35–37]

Interaction effects determine "whether or not the odds ratios are constant, or homogeneous, over the strata."[34(p79)] Interactions between the predictive variables were assessed for PMATP success across the strata for each pair of factors. The combination of predictive variables can have a greater (additively or multiplicatively), or lesser effect than a single variable. Meeuwisse[38] described the additive effect as synergism and the lesser effect as antagonism.

We examined each combination of predictors 3 ways. First by 2×2 cross-tabulation analysis of 2-factor combinations (Sn, Sp, OR, RFS, and Fisher's exact test). A second method was through stratified analysis and graphic representation of the potential interaction. Thirdly, interaction effects were assessed through stratum-specific ORs and were compared to the Mantel-Haenszel (M-H) OR estimate and the Breslow-Day (B-D) χ^2 test to confirm or reject homogeneity of the stratum-specific ORs. The final step was to assess the prediction model variables in a 3-way interaction analysis using the same 3 ways for assessment.[34,38]

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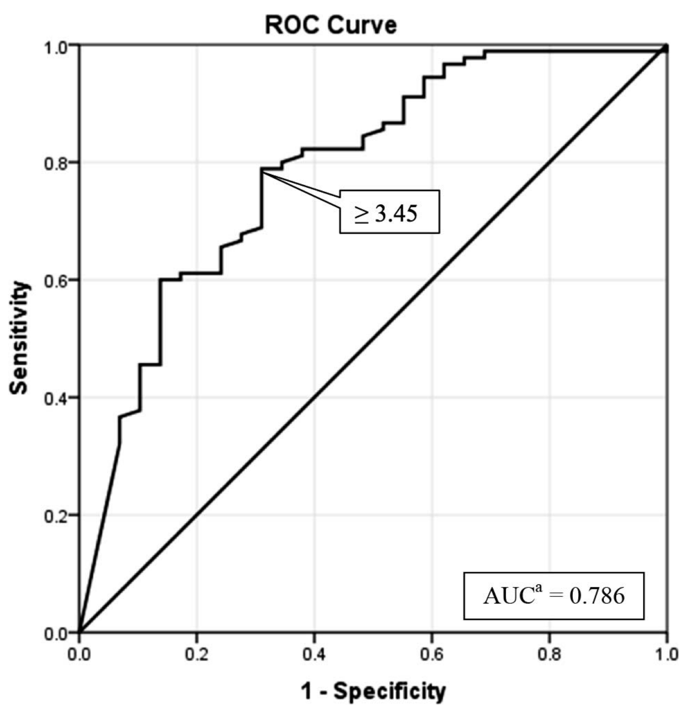
Table 2. Categorization of Coursework Taken as an Undergraduate

Advanced Math	Advanced Science[a]	Athletic Training Courses[b]	Physics	Calculus
Calculus	Biological-chemistry	Advanced athletic training	Physics I	Calculus above precalculus
Differential equations	Cellular biology	Assessment of injuries	Physics II	
Precalculus	Entomology	Basic athletic training		
Trigonometry	Genetics	Care and prevention of injuries		
	Histology	General medical conditions		
	Inorganic chemistry	Human anatomy		
	Marine biology	Human physiology		
	Microbiology	Therapeutic exercise		
	Molecular biology	Therapeutic modalities		
	Neurobiology			
	Organic chemistry			
	Physical chemistry			
	Physics-electricity and magnetism			
	Physics-mechanics and jeat			
	Physics I, II			
	Zoology			

[a] Any other chemistry or biology courses above the chemistry II or biology II.
[b] Athletic training courses a candidate may have taken as an undergraduate, not necessarily as part of an undergraduate professional athletic training program.

A common problem seen when stratifying the data is low cell counts, leading to unstable results and wide confidence intervals (CIs).[34] Because the current stratification was already providing us with this effect, no further higher-order interaction terms were considered.

Figure 1. Receiver operating characteristic (ROC) analysis with identification of the optimum cutpoint for graduate grade point average at end of the first year as a predictor of first-attempt Board of Certification exam success. [a] Area under the curve.



RESULTS

Our priority was to quantify success in the PMATP. The most commonly accepted indicator of academic success is grade point average; therefore, it became the outcome variable for success in the PMATP. We further decided to use the students' gGPA at the end of their first year in the PMATP since students had completed their core athletic training courses and students' final grades would not be posted until after they took the BOC exam, usually in April of the academic year. To determine a cutpoint for academic success, we used first-attempt BOC exam success as an outcome variable. Receiver operating characteristic (ROC) analysis was performed to identify the optimum gGPA at the end of the first year in the PMATP. The cutpoint was $\geq$3.45 and became the outcome variable for academic success in the PMATP (Figure 1). A 2×2 cross-tabulation analysis found an OR of 8.30 (95% CI: 3.26, 21.16) and an RFS of 1.82 (95% CI: 1.49, 2.23; Table 3). These data indicate a student who had a gGPA $\geq$ 3.45 at the end of the first year in the PMATP had 8.30

Table 3. First-Year Graduate Grade Point Average (gGPA) for Prediction of First-Attempt Success on the Board of Certification (BOC) Exam[a]

	First-Attempt Pass on the BOC Exam	
	Yes	No
First-year gGPA $\geq$ 3.45	71	9
First-year gGPA $<$ 3.45	19	20

[a] Fisher's exact test (one-sided) $P < .001$; sensitivity = 0.79 (95% confidence interval [CI]: 0.69, 0.86); specificity = 0.69 (95% CI: 0.51, 0.83); Youden's index = 0.48; odds ratio = 8.30 (95% CI: 3.26, 21.16); relative frequency of success = 1.82 (95% CI: 1.49, 2.23).

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times greater odds of passing the BOC exam on the first attempt than someone who had a gGPA $<$ 3.45 at the end of the first year. The RFS indicates the probability of a student passing the BOC exam on the first attempt with a gGPA $\geq$ 3.45 at the end of the first year in the PMATP is slightly less than twice the possibility of a student with a gGPA $<$ 3.45.

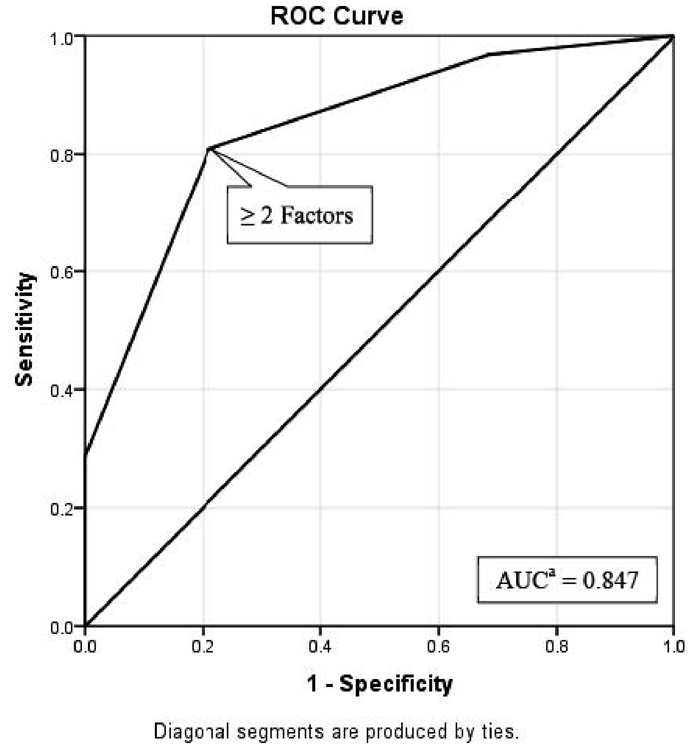
To determine the statistical power of our study, we entered the requested information into the Openepi.com power calculator.[39] The cohort of 119 students who entered the PMATP used for this study were dichotomized based on their gGPA at the end of the first year ($\geq$3.45). For the purpose of calculating statistical power, the exposed group were those students with a gGPA of $\geq$3.45. Those students with a gGPA of $<$3.45 were placed in the nonexposed group. The percentage of students who passed the BOC exam on their first attempt was entered for each group, assuming a 95% CI the calculated power for this study was 99.93%.

We initially identified a variety of 35 different potential predictors of PMATP success. The predictors were identified through those used by other medical professions, and the past experiences, beliefs, and hypotheses of the athletic training faculty members of the PMATP from which the cohort was taken. Univariable analysis reduced the number of variables from 35 to 9 (Table 4). From these remaining 9 variables, 6 were continuous or multilevel discrete variables. These 6 variables were assessed for multicollinearity. No predictors had a VIF value approximating 10 or above or tolerance values approaching $\leq$0.1; therefore, no multicollinearity was indicated.[35–37] These remaining 6 continuous/multilevel discrete variables (APUI, Graduate Record Examination quantitative [GREq], Graduate Record Examination verbal, Graduate Record Examination written, number of advance math and science courses taken, and uGPA) were dichotomized and combined with the 3 other nominal variables, (calculus, physics, graduate from a research intensive institution), and the multicollinearity analysis was repeated (Table 5).

Finding no multicollinearity, these 9 predictors were entered into a backward, stepwise, logistic regression, and a 3-factor model was produced (uGPA $\geq$ 3.18; GREq $\geq$ 145.5; took calculus as an undergraduate student) to predict PMATP success. Steps 1 and 7 of the logistic regression are provided in Table 6. The model of best fit had a Nagelkerke R^2 of 0.493, and the lower limit of the 95% CI for the adjusted ORs $>$ 1.0 for all 3 predictors, indicating an acceptable model. An ROC analysis determined 2 or more predictors were the optimum number of positive factors for the prediction model (Figure 2). A 2 $\times$ 2 cross-tabulations analysis found a student in the PMATP who had any combination of 2 or more of the 3 factors had 20.0 times greater odds of being successful in the PMATP than someone who had $<$2 of the 3 factors. The relative frequency of PMATP success indicates the probability of a student being successful in the PMATP with any 2 or more of the 3 factors was almost 2.75 times greater likelihood of PMATP success compared to a student with $<$2 factors (Table 7).

The success rate for a given number of positive factors is presented in Table 8. Students with 2 or more positive factors demonstrated a 90.91% rate of success in the PMATP, whereas only 30.95% of the students with $<$2 factors were considered successful. Overall, regardless of the number of factors, 69.75% of all students were "successful" with a first-year gGPA $\geq$ 3.45.

Figure 2. Receiver operating characteristic (ROC) curve with identification of the optimum cutpoint for the number of positive factors (out of 3 factors) for prediction of success in the professional master's athletic training program as indicated by graduate grade point average at the end of the first year $\geq$3.45. [a] Area under the curve.



Interaction Effects

The existence of an interaction between uGPA and GREq is suggested by the differences between the univariable OR and the corresponding multivariable adjusted OR, whereas there was relatively little change between the 2 ORs for taking calculus[32] (Table 9). The interaction pairings studied were GREq $\times$ uGPA, uGPA $\times$ calculus, and GREq $\times$ calculus to predict PMATP success.

The interaction between the pairing of high GREq score ($\geq$141.5) $\times$ a high uGPA ($\geq$3.18) for the prediction of PMATP success found students with both of these factors were 93% successful and had almost 35 times greater odds to be successful in the PMATP than someone who had a low GREq and a high GPA. Conversely, students with both a low GREq and a low uGPA had a success rate of only 27%. Students who had a high GREq and a low uGPA had 3.0 times greater odds for PMATP success than one who had a low GREq and a low uGPA (Figure 3A; Table 10).

Controlling for uGPA strata ($\geq$3.18 versus $<$3.18), the relationship between GREq and being successful in the PMATP was examined. The M-H OR estimate was good at 6.5 (2.59–16.52). A statistically significant association between a high GREq score with PMATP success was found through the M-H χ^2 (1) = 18.6 (P $<$ .001). The null hypothesis for the

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Table 4. Summary of Univariable Analysis Results for Final Set of 9 Variables for the Prediction of First-Year Graduate Grade Point Average (gGPA) $\geq$ 3.45

Variable $\geq$ 3.45 gGPA	Cutpoint	Sensitivity	1 − Specificity	Specificity	Youden's Index	AUC	Odds Ratio	Relative Frequency of Success	Fisher's Exact Test (one-sided)
GRE quantitative	141.5	0.90	0.47	0.53	0.430	0.772	10.49	2.66	0.001
Calculus[a]	Yes or No	0.44	0.07	0.93	–	–	10.06	1.62	0.001
GRE verbal	150.5	0.47	0.11	0.90	0.363	0.754	7.48	1.54	0.001
Academic Profile of Undergraduate Institution[b]	American College Testing $\geq$ 25.5 or Scholastic Assessment Test $\geq$ 1132.5	0.56		0.81	–	–	5.39	1.59	0.001
Undergraduate GPA	3.18	0.71	0.33	0.67	0.380	0.715	4.71	1.67	0.001
Number of advanced math and science courses taken	4	0.36	0.14	0.86	0.212	0.632	3.30	1.35	0.009
GRE written	3.75	0.66	0.46	0.54	0.202	0.648	2.30	1.28	0.044
Graduated from a research intensive institution[a]	Yes or No	0.46		0.67	–	–	1.69	1.17	0.121
Physics[a]	Yes or No	0.58		0.52	–	–	1.52	1.14	0.173

Abbreviations: AUC, area under the curve; GRE, Graduate Record Examination.

[a] These are nominal variables; therefore, no receiver operating characteristic analysis was performed.

[b] A subject was considered positive for the Academic Profile of Undergraduate Institution variable if they had an American College Testing score of $\geq$25.5 or a Scholastic Assessment Test score of $\geq$1132.5, thus taking 2 continuous variables and converting them to a nominal variable, and no receiver operating characteristic analysis was performed.

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Table 5. Multicollinearity Analysis Results for a 9-Factor Set of Dichotomized Potential Predictors (Including Graduate Record Examination [GRE] scores) of First-Year Graduate Grade Point Average ≥ 3.45

	Multicollinearity Statistics	
	Tolerance	Variance Inflation Factor
Academic Profile of Undergraduate Institution[a]	0.587	1.703
Calculus[b]	0.575	1.739
Graduated from a research intensive institution[b]	0.783	1.277
GRE quantitative	0.768	1.303
GRE verbal	0.759	1.317
GRE written	0.862	1.160
Number of advanced math and science courses taken	0.767	1.304
Physics[b]	0.672	1.487
Undergraduate grade point average	0.878	1.139

[a] A subject was considered positive for the Academic Profile of Undergraduate Institution variable if they had an American College Testing score of ≥25.5 or a Scholastic Assessment Test score of ≥1132.5, thus taking 2 continuous variables and converting them to a nominal variable.

[b] These are nominal variables.

B-D test assumes that the OR for GREq predicting PMATP success is equivalent for uGPA strata. The B-D test for homogeneity found the ORs to be significantly different for the 2 strata of uGPA (B-D $\chi^2[1] = 6.05$ [$P = .014$]; Table 11).

The interaction between the pairing of taking calculus as an undergraduate × uGPA (≥3.18) for the prediction of PMATP success found a high rate of success regardless of uGPA (uGPA ≥ 3.18 = 96%; uGPA < 3.18 = 88%). A student who took calculus and had a high uGPA (≥3.18) had 5.64 times greater odds for success in the PMATP than someone who did not take calculus but had a high uGPA, but students who took calculus, but had a low uGPA (<3.18) had 14.58 times greater odds for success in the PMATP than someone who did not take calculus but had had a low uGPA (Figure 3B; Table 10).

Table 7. Cross-Tabulations Table for the 2-Factor Model to Predict Success in the Professional Master's Athletic Training Program as Indicated by Graduate Grade Point Average (gGPA) at the End of the First Year ≥ 3.45[a]

	First-year gGPA of ≥3.45	First-year gGPA of <3.45
≥2 Factors	70	7
<2 Factors	14	28

[a] Fisher's exact test (one-sided) $P < .001$; sensitivity = 0.83 (95% confidence interval [CI]: 0.74, 0.90); specificity = 0.80 (95% CI: 0.64, 0.90); Youden's index = 0.630; odds ratio = 20.0 (95% CI: 7.30, 54.78); relative frequency of success = 2.73 (95% CI: 2.23, 3.34).

Controlling for uGPA strata (≥3.18 versus <3.18), the relationship between taking calculus and being successful in the PMATP was examined. The M-H OR estimate was 11.8 (3.71–44.12). A statistically significant association between taking calculus with PMATP success was found through the M-H χ^2 (1) = 16.8 ($P < .001$). The null hypothesis for the B-D test assumes that the OR for taking calculus predicting PMATP success is equivalent for uGPA strata. The B-D test for homogeneity found the ORs to not be significantly

Table 6. Logistic Regression Analyses (Steps 1 and 7 Only) of 9 Variables for Prediction of First-Year Graduate Grade Point Average ≥ 3.45

Predictor Variables with Cutpoints	Adjusted Odds Ratio	95% Confidence Interval Lower	95% Confidence Interval Upper
Step 1			
Academic Profile of Undergraduate Institution: either American College Testing ≥25.5 or Scholastic Assessment Test ≥1132.5	0.703	0.182	2.708
Number of math and science courses: ≥4	1.870	0.314	11.136
Undergraduate grade point average: ≥3.18	7.661	2.303	25.485
GRE verbal (PR): ≥150.5 (≥46.5)	3.137	0.730	13.489
GRE quantitative (PR): ≥141.5 (≥12)	7.041	1.848	26.827
GRE written (PR): ≥3.75 (≥44.5)	1.100	0.370	3.264
Research intensive: yes or no	2.054	0.593	7.121
Physics: yes or no	0.665	0.184	2.407
Calculus: yes or no	13.353	2.060	86.548
Constant	0.081		
Step 7			
Undergraduate grade point average: ≥3.18	7.624	2.627	22.127
GRE quantitative (PR): ≥141.5 (≥12)	7.677	2.481	23.759
Calculus: yes or no	11.767	2.657	52.106
Constant	0.101		

Abbreviation: GRE, Graduate Record Examination.

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Table 8. Percentage of Students with Each of the Specific Number of Factors for a 3-Factor Model for Prediction of Professional Master's Athletic Training Program (PMATP) Success; Relative Frequency of Success: 0.91/0.31 = 2.94

Number of Positive Factors	Success in the PMATP: Graduate Grade Point Average $\geq$ 3.45	Graduate Grade Point Average < 3.45	Total	Percentage	Percentage Above/Below Cutpoint
0	2	11	13	15.38	13/42 = 30.95
1	11	18	29	37.93	
2	45	7	52	86.53	70/77 = 90.91
3	25	0	25	100.00	
Total	83	36	119	69.75	

different from one another (B-D $\chi^2[1] = 0.12$ [$P = .730$]; Table 11).

The interaction between the pairing of a high GREq score ($\geq$141.5) × taking calculus as an undergraduate for the prediction of PMATP success found that students who took calculus tended to be successful regardless of GREq score; 95% if they had a high GREq ($\geq$141.5) versus 75% if they had a low GREq (<141.5). For a candidate who had a high GREq, but did not take calculus, 75% were successful, compared to only 24% who were successful if they had a low GREq and did not take calculus. The OR indicates that a student who had a high GREq and took calculus had 6.33 times greater odds to be successful in the PMATP than someone who had a low GREq and took calculus. A student who had a high GREq and did not take calculus had 9.30 times greater odds to be successful in the PMATP than someone who had a low GREq and did not take calculus (Figure 3C; Table 10).

Controlling for GREq ($\geq$141.5 versus <141.5), the relationship between taking calculus and being successful in the PMATP was examined. The M-H OR estimate was 10.0 (3.29–24.49). A statistically significant association between taking calculus with PMATP success was found through the M-H χ^2 (1) = 18.9 ($P < .001$). The null hypothesis for the B-D test assumes that the OR for taking calculus predicting PMATP success is equivalent for GREq strata. The B-D test for homogeneity found the ORs to not be significantly different from one another (B-D χ^2 [1] = 0.07 [$P = .791$]; Table 11).

Three-Way Interaction

The 3-way interaction indicates that students who had a high GREq score, regardless of whether they took calculus and regardless of uGPA, had a high rate of success (GREq $\geq$ 141.5, uGPA $\geq$ 3.18, and took calculus = 93%; GREg $\geq$ 141.5, uGPA < 3.18, and did not take calculus = 88%). Those students who had a low uGPA, had a high GREq score, and took calculus also had a high rate of success (uGPA < 3.18, GREg $\geq$ 141.5, and took calculus = 85%). Students who had a low GREq score, took calculus, and had a high uGPA ($\geq$3.18), were successful only 54% of the time. Only 25% of the students who had a low GREq (<141.5), and took calculus, but had a low uGPA (<3.18) were successful. Regardless of uGPA, students having a low GREq score who did not take calculus were not successful (uGPA $\geq$ 3.18 = 30%; uGPA < 3.18 = 20%; Figure 4).

A decision tree to assist athletic training faculty in their assessment of candidates related to the specific predictors is provided here (Figure 5). These predictors may or may not be true for other athletic training programs throughout the country.

DISCUSSION

There are 2 main statistical schools of thought: frequentist and probabilistic based on Bayesian methodology. Both methods explore probability, but the theories and the methods are different.[40] The Bayesian approach to probability is to "measure the degree of belief in an event, given the information available."[40(section 2.1)] The focus in on the individual's "state of knowledge" rather than a "sequence of events."[40(section 2.1)] The frequentist approach to probability interprets it as "a long-run frequency of a 'repeatable' event."[40(section 2.2)] With a frequentist's approach, "probability would be a measureable frequency of events determined from repeated experiments."[40(section 2.2)]

We used a Bayesian approach for our study. The resultant quantifiable statistics identified the strength of the association between either a single predictor or a group of predictors through the OR and the RFS. In a frequentist approach, the α level will identify if the independent variable had a statistically significant effect on the dependent variable, but no strength of the association is provided.

Table 9. Comparison of Odds Ratios (ORs) for Predictor Variables

	Univariable OR	Multivariable Adjusted OR
Undergraduate grade point average	4.71 (95% CI: 2.17, 10.23)	7.62 (95% CI: 2.63, 22.13)
Graduate Record Examination quantitative	10.49 (95% CI: 4.11, 26.78)	7.68 (95% CI: 2.48, 23.76)
Calculus	10.06 (95% CI: 2.90, 34.86)	11.77 (95% CI: 2.66, 52.11)

Abbreviation: CI, confidence interval.

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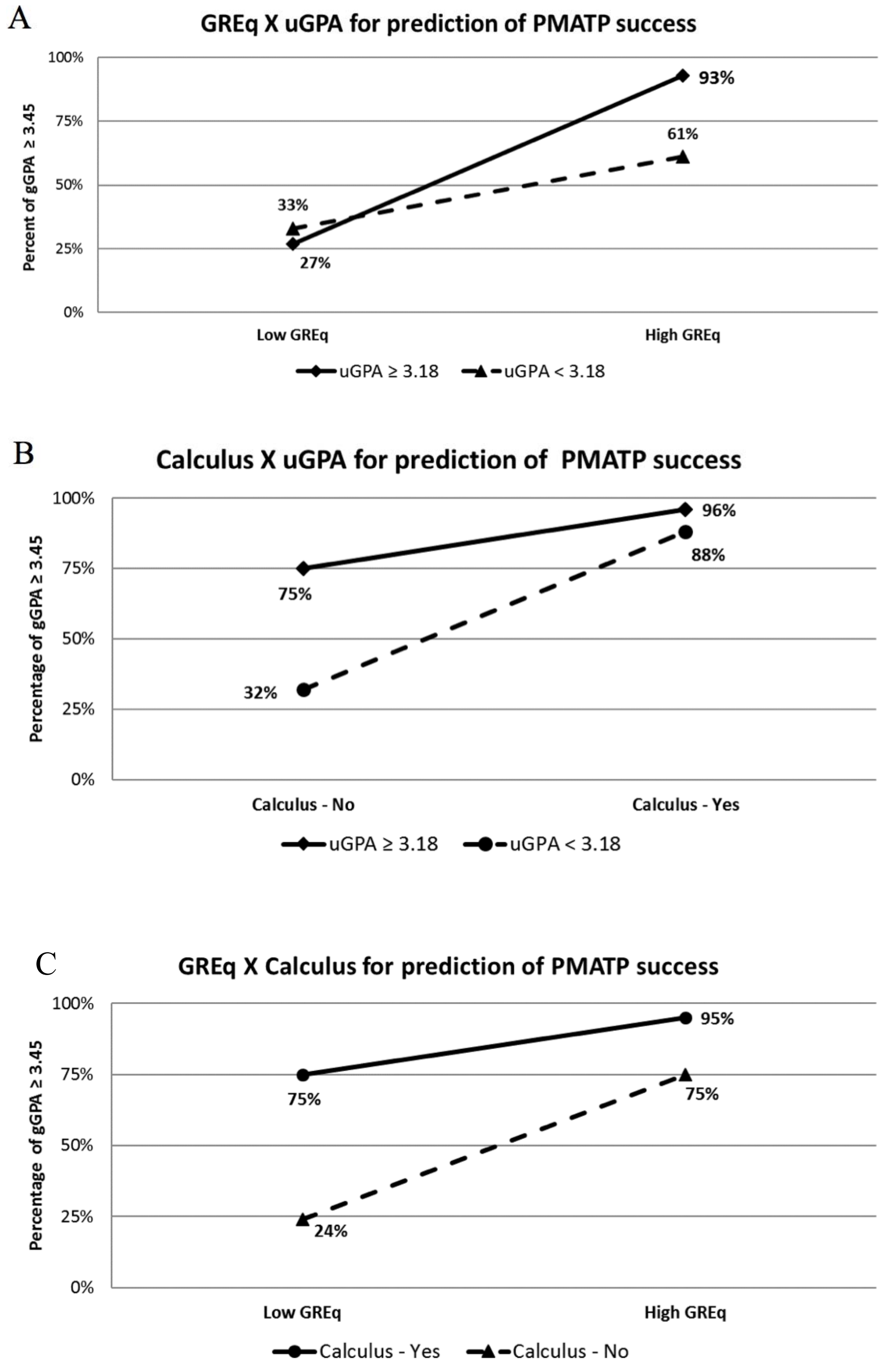
Figure 3. Graphic representation of stratified pairs of dichotomized variables for the prediction of professional master's athletic training program (PMATP) success. A, Interaction between Graduate Record Examination quantitative (GREq) and undergraduate GPA (uGPA) for the prediction of PMATP success. B, Interaction between taking calculus as an undergraduate and uGPA for the prediction of PMATP success. C, Interaction between GREq by taking calculus as an undergraduate for the prediction of PMATP success.



The criteria for this study are similar to the type used for other clinical prediction models related to calculating injury or illness risk or effectiveness of some treatment intervention.[41–45] Several models were cited in the medical professions that attempt to determine criteria for entrance decisions or academic success, but to our knowledge, no studies to date have examined this in athletic training. Of those academic related studies, none had used a model similar to what we have demonstrated with this current study. The purpose of our study was to identify program

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applicant characteristics that are most likely to predict academic success within the PMATP. We identified 3 such characteristics.

Our outcome variable was success in the PMATP and was quantified as having a gGPA at the end of the first year of $\geq$3.45. A second study, to aid in predicting first-attempt BOC exam success, established this cutpoint.[46] The prediction model for this study was created to identify which program applicant characteristics are most likely to predict academic success. A 3-factor model was produced consisting of the student's uGPA, GREq score, and whether or not the student took calculus as an undergraduate. The ROC analysis identified a cutpoint of any combination of 2 or more of the predictor variables as the optimum number of factors, while the 2×2 cross-tabulations table provided the strength of the model with an OR of 20 and a RFS of just over 2.73. A student with 2 or more of the factors has 20 times greater odds of being successful in a PMATP compared to a student who has either 1 or none of the predictors. Stated another way, a student with any combination of 2 or all 3 of the predictors was almost 2.75 times more likely to be successful in the PMATP compared to a student who has 1 or none of the predictors.

Despite concerns over the use of uGPA due to differences in grading methods across instructors, majors, disciplines, and institutions, it is commonly accepted as a measure of academic performance.[47–51] The use of the first year gGPA as a determinate of success was logical since athletic training students are eligible to take the BOC exam in their final semester of academic preparation before graduation and their final grades are known. The GRE has been studied and determined to be useful in making entrance decisions by many professions,[7,9,12,18,22,52–55] including athletic training.[21] We were able to predict graduate level success using standard academic performance, uGPA, and GRE scores, specifically GREq.

When the GREq is examined with uGPA to predict PMATP success, having a high GREq score had much more success regardless of uGPA. When considering 2 students with a similar uGPA for admission to the PMATP, but one with a high GREq and the other with a low GREq, these data suggest that the proper choice would be to select the student with the higher GREq (Figure 3A). The strength of having taken calculus as an undergraduate appears to be even stronger since, regardless of uGPA, those who took calculus were highly successful (Figure 3B). When one examines the relationship between GREq and taking calculus, as long as an applicant has at least 1 of these 2 predictors, they are likely to be successful (Figure 3C). The 3-way interaction confirms that no matter the combination of any 2 predictors, the students demonstrated a high rate of PMATP success, while GREq appears to be the strongest indicator of success because, regardless of the condition of the other 2 predictors, the ORs were all quite robust.

The faculty of the PMATP used for this study believed that many of the independent variables evaluated were predictors of success, but there was no evidence to support these claims. When the prediction model of this study was applied to past students' data, it revealed that 91% of the students who fit our model were successful, while only 35% of the remaining

Table 10. Summary of Interactions by Strata for Professional Master's Athletic Training Program Success

	Undergraduate Grade Point Average $\geq$ 3.18	Odds Ratio (95% Confidence Interval)	Undergraduate Grade Point Average < 3.18	Odds Ratio (95% Confidence Interval)	Took Calculus	Odds Ratio (95% Confidence Interval)	Did not take Calculus	Odds Ratio (95% Confidence Interval)
High Graduate Record Examination quantitative $\geq$ 141.5	93%	34.67 (6.94, 173.21)	61%	3.07 (0.92, 10.25)	95%	6.33 (0.44, 91.71)	75%	9.30 (3.16, 27.36)
Took Calculus	96%	5.64 (0.71, 45.04)	88%	14.58 (2.85, 74.71)	–	–	–	–

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Table 11. Mantel-Haenszel (M-H) and Breslow-Day (B-D) Test Results

Prediction of PMATP Success	M-H Odds Ratio Estimate (95% Confidence Interval)	M-H Test	B-D Test
GREq–PMATP success for undergraduate grade point average strata	6.5 (2.59, 16.52)	M-H $\chi^2(1) = 18.6$ ($P < .001$)	B-D $\chi^2(1) = 6.05$ ($P = .014$)
Calculus–PMATP success for undergraduate grade point average strata	11.8 (3.71, 44.12)	M-H $\chi^2(1) = 16.8$ ($P < .001$)	B-D $\chi^2(1) = 0.12$ ($P = .730$)
Calculus–PMATP success for GREq strata	10.0 (3.29, 24.49)	M-H $\chi^2(1) = 18.9$ ($P < .001$)	B-D $\chi^2(1) = 0.07$ ($P = .791$)

Abbreviations: GREq, Graduate Record Examination quantitative; PMATP, professional master's athletic training program.

students were successful. Overall, 69.8% of the students in the PMATP were successful, indicating the selection committee for the PMATP had made the correct assessment for a large proportion of the students admitted to the program. Another indication is that, when the RFS was calculated, it was 2.94, indicating that those students who fit the prediction model had almost 3 times greater probability of being successful compared to those students who did not fit the prediction model.

Limitations

There were some limitations to our study. The use of the GRE for this study presented 1 challenge. In 2011, Educational Testing Services changed the scoring format.[56] We were using data from applicants 2004 through 2012; consequently, we needed to standardize the scores. Percentile ranks for the scores were provided by Educational Testing Services along with a conversion table for both scoring systems. We used these percentile ranks and, in the end, converted all scores to the new scoring system, which is what is reflected in our study.[57]

The sample used for this research came from 1 specific PMATP. Our statistical power test found that we had a strong model; however, as we began to stratify the data, this led to small cell counts which led to unstable results and large CIs. To further validate our prediction model, the next logical step is to apply it to other PMATPs or combine these data with other like data from multiple PMATPs and repeat the assessment.

A final component of any prediction model is to conduct an impact analysis such as examining the economic effect the model has upon the associated population.[58,59] Future studies could examine the financial impact upon students such as comparing those individuals coming from an undergraduate professional athletic training program versus a PMATP in a variety of outcomes (at least while there are 2 routes to certification eligibility). Despite the numerous variables that would likely have to be accounted for, examining the cost of education regardless of the field of study for the graduate degree between

Figure 4. Three-way interaction of Graduate Record Examination quantitative (GREq) × calculus × undergraduate grade point average (uGPA) for prediction of professional master's athletic training program success.

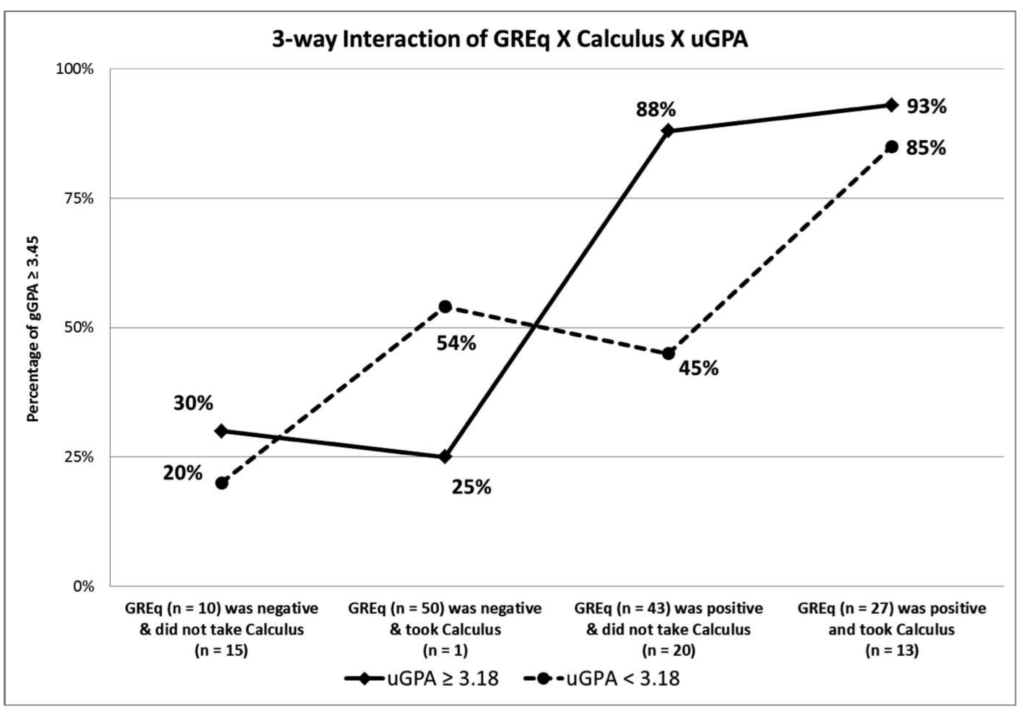

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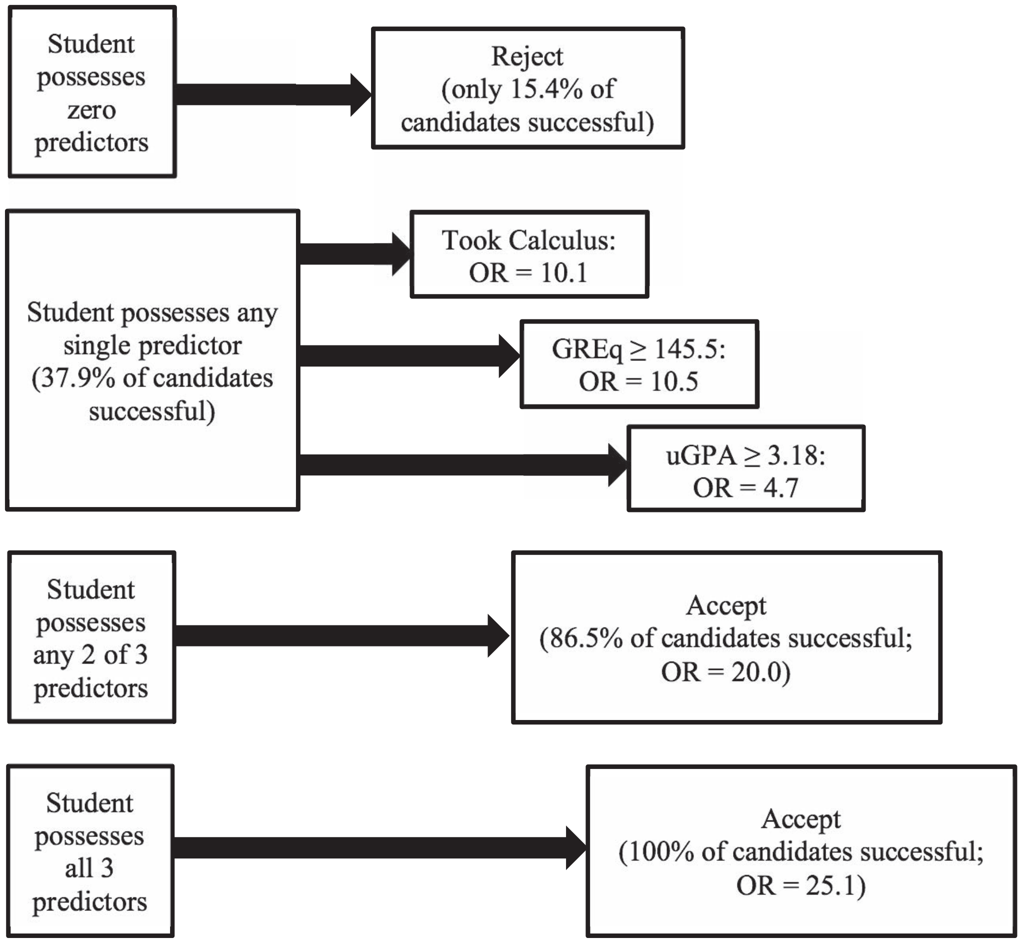
Figure 5. Decision tree: for a candidate possessing 0, 1, 2, or 3 predictor(s) whether to accept the student or reject the student based on the likelihood of the student will be successful in the professional master's athletic training program. Abbreviations: GREq, Graduate Record Examination quantitative; OR, odds ratio for success; uGPA, undergraduate grade point average.



students graduating from an undergraduate professional athletic training program versus students graduating from a PMATP would potentially be an attractive investigation.

Applying the methods for creating prediction models could be used in other health professions such as physical therapy, occupational therapy, or nursing. Bayesian analysis of these data would yield interesting data and results. None of the procedures, methods, or information used to generate this prediction model is exclusive to athletic training. All of the information needed to repeat a similar type of study is available through standard data collection methods from schools' application files. Variables and cutpoints might differ across institutions or professions, but how those associated data and predictors are generated and interpreted would remain consistent.

CLINICAL RELEVANCE

We started this study with the goal of applying the methods used in creating clinical prediction models to an academic setting. We have demonstrated that it can be done, and we believe these methods can be applied across a variety of health-related professions. We have also established an objective process by which PMATP faculty can assess candidates to assist in recruiting high-quality individuals. Recently there have been 2 major changes in athletic training program requirements. The initial change occurred in 2013 when the Commission on Accreditation of Athletic Training Education accreditation standards were modified to require all professional athletic training programs to demonstrate a 3-year aggregate first-time pass rate of 70%.[60] In March 2015, the Athletic Training Strategic Alliance announced that the professional degree in athletic training would change from a bachelor's degree to the master's level.[61] These changes have the potential to increase the need of athletic training programs to identify students who are most capable of learning and are highly likely to succeed in passing the BOC exam on the first attempt and aiding in producing high-quality program outcomes.

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