academicresearchJournals

Vol. 3(2), pp. 35-44, February 2015
DOI: 10.14662/IJARER2015.006

ISSN: 2360-7866
http://www.academicresearchjournals.org/IJARER/Index.htm

International Journal of Academic Research in Education and Review

Full Length Research

Predicting Post-Baccalaureate Student's GPA from cumulative Undergraduate GPA using Logistic Regression Analysis: *A Test of Hypothesis*

Oscar Wambuguh, M.Sc., Ph.D.

Associate Professor, Health Sciences, Department of Nursing & Health Sciences, California State University, East Bay
Telephone: (510) 885-3252; E-mail: oscar.wambuguh@csueastbay.edu

Accepted 16 February 2015

Post-baccalaureate (postbac) students are non-traditional students returning to school after completing their bachelor's degrees in either science or non-science majors. As a result, they are deemed to be more conscientious individuals who are not only better self-disciplined and high in self-achievement, but also more hardworking, highly motivated, well organized and ambitious in nature. Using a sample of 372 students accepted into our postbac program from fall 2011 to winter 2014, data regarding their graduating institution and its geographical location, and students' academic achievement as measured by cumulative grade point average, was analyzed. Results indicate that: 1) most postbac students applying to our program come from California and a small percentage from international locations. 2) Students' cumulative undergraduate GPAs weakly correlate with their postbac cumulative GPAs; but they significantly differ from postbac cumulative GPAs after at least one full year of coursework in our program. 3) Logistic regression analysis showed that students entering the postbac program with overall undergraduate GPAs close to 3.0perform better than those with lower undergraduate GPAs. 4) Logistic regression analysis also showed that students entering the program with at least a 3.0 GPA had a higher probability of attaining a cumulative postbac GPA of at least 3.7, than those with lower than a 3.0 GPA. Postbac students bring a multiplicity of important personal traits like the ability to overcome adversity, tenacity, work and varied life experiences, and a relatively high level of maturity and responsibility compared to undergraduate student pools. Factors other than academic aptitude are becoming a critical part of the admissions process for many advanced programs worldwide. Many studies focusing on student achievement and admissions applaud and reiterate the importance of such a broad-based and holistic approach to student admissions particularly in graduate and health professional programs.

Keywords*:* undergraduate, post-baccalaureate, postbac, academic performance, biomedical school, GPA, logistic regression.

INTRODUCTION

Student academic performance has been the subject of intense research in higher education institutions for the last two decades. Academic achievement has generally been described as behavior resulting into two academic outcomes: success or failure. Academic failure is a central issue in higher education worldwide wasting time and financial resources in addition to straining the students' mental, family and social environments (Jannati et al., 2012). Amongst educators and biomedical school admissions offices, there is an almost universally accepted notion that among other factors, students who perform well in foundation (lower division) and advanced (upper division) science courses; and score above the national average in the required entrance tests (for example, the Medical College Admission Test or the Dental Admission Test in the United States) have increased chances of getting accepted for graduate biomedical training. Post-baccalaureate students are often more mature and more experienced, and deemed to possess better organization skills, are better motivated, seek assistance when needed, utilize available resources optimally, and are able to adapt their study habits to suit their academic needs (Zimmerman, 1998; Dooden, 2008; Wambuguh & Yonn-Brown, 2013).

A review of the literature on human learning indicates that learning is a complex human activity that cannot easily be mapped by any one universal model. Academic success is usually associated with personality factors (that might include age, cognitive abilities, and student learning styles) and contextual factors (like family and social environment, course assessment procedures, and learning activities). While some authors cite intelligence as one of the major determinants of academic success (for example, Ackerman & Heggestad, 1997; Sternberg & Kaufman, 1998; and Akomolafe, 2013); others have explored the relationship between personality variables (like neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness) and academic success (for instance, Farsides & Woodfield, 2003; Chamorro-Premuzic & Furnham, 2005; O'Connor & Paunonen, 2007; Conrad & Party, 2012). Citing previous studies (particularly those of Chamorro-Premuzic & Furnham, 2008 and Conrad & Patry, 2012), Akomolafe's research (2013) further finds that one personality variable (conscientiousness) as the single most important predictor of academic success. According to Akamolafe, conscientious individuals are not only better self-disciplined and high in self-achievement, but are also known to be more hardworking, well organized and ambitious in nature (2013). Other studies have focused on academic and social integration particularly for non-resident students (Rienties et al., 2012); supportive counselling programs (Jannati et al., 2012); and family support (Cheng et al., 2012). Additional studies suggest other factors to be important including student work involvement both inside and outside campus (Alfano & Eduljee, 2013); quality of students, teachers and the institution (Ahmed et al., 2012); student motivational levels (Goodman et al., 2011); student academic ability, effort and persistence (Meltzer et al., 2001; Fraser & Killen, 2005); lecture attendance (Thatcher, 2007); and the role of socio-psychological factors (Malefo, 2000). The role of student acquisition of specific skill sets that emphasize self-assessment, monitoring, adjustment, self-control, and motivation; the courage and ability to adopt efficient learning strategies; and resiliency in case of academic difficulties has previously been described in Wambuguh and Yonn-Brown's study (2013).

Building on this body of research, the current study focuses on academic performance of students who have completed their undergraduate degrees but: a) are lacking the required foundations science courses required by biomedical school doctoral programs (primarily medicine, dentistry, pharmacy, optometry, and veterinary medicine); b) have competed the foundation sciences coursework but have a low Grade Point Average (GPA) which makes them uncompetitive in the biomedical school application process. Such students are accepted into a variety of post-baccalaureate programs like the one at our university which helps them complete the required foundation science coursework; and/or provide a set of enhancement upper division course work which improves their competitiveness for biomedical school programs application. Using logistic regression, the study uses student cumulative undergraduate GPA to predict academic performance at the post-baccalaureate level.

Study Hypothesis and Objectives

We used academic data from our formal post-baccalaureate (hereafter referred to as postbac) students accepted at our campus after completing their undergraduate education. Our postbac program accepts two categories of students: those who have earned a bachelor's degree in a science field (ADV); and also those who have earned it in a non-science field (career changers or CCs). We hypothesized that a student's cumulative undergraduate GPA of at least 2.80 increases the likelihood of the same student attaining a high postbac GPA of 3.7 and above, to more than 50% after one continuous year of coursework. Our specific objectives were to:

i) map out the "source" of our students by geographical location: in-state, out-of-state or International.
ii) find out whether there was a correlation between students' undergraduate and postbac cumulative GPAs.
iii) determine how cumulative GPAs varied in:

a) for both undergraduate CC and ADV students.
b) for both CC and ADV postbac students.

Table 1. Numbers of students applying from US states and from countries outside the US

State	Number of Applicants
California	1197
New York	22
Texas	9
Maryland	9
Illinois	9
Arizona	7
New Jersey	7
Massachusetts	6
Michigan	6
Vermont	6
Pennsylvanian	5
Washington	5
Other States (<5 applicants each)	41
International Applicants	22
Total	**1351**

c) and how cumulative undergraduate GPA predicted the probability of attaining a cumulative postbac GPA of 3.7 and above.

METHOD

Data for the geographical location of each postbac student accepted was obtained from our university's admissions records. We used academic data from our formal postbac students from the past four years (fall 2011 to fall 2014). Both geographical and academic data were amalgamated from the individual cohorts to increase the total sample size to 372 students. Academic data for each student was recorded in two columns in a *Microsoft Excel* spreadsheet: student cumulative undergraduate GPA and postbac cumulative GPA.

Statistical analysis

Data from undergraduate and postbac levels was tested using Spearman's Rank correlation coefficient to assess the nature and strength of the relationship between the two sets. The Student's t-test was next used to determine the difference between mean GPAs at both undergraduate and postbac levels for NSDs alone, ADVs alone and for all students. Lastly, a logistic regression model was used to test how well: a) earning a graduating GPA of between 2.80-2.99 predicted student postbac academic performance (measured by an overall postbac GPA of 3.7 and above); and b) earning a graduating GPA of 3.0 and above predicted student postbac academic performance (measured by an overall postbac GPA of 3.7 and above).

RESULTS AND DISCUSSION

Postbac students applying to our program come from all parts of the world, but most primarily come from universities in the United States (98.4%) with a small, but significant international student population (1.6%). Not unexpected, the state of California, home to our university, accounts for the lion's share with 88.6% of the total number of applicants (Table 1). Partly due to the short duration of the program (average:1-2 years), travel distance, out-of-state tuition considerations, recommendations from peers in person and through social media, plus the level of support provided and quality of our program, many students often choose schools in their home state before applying to other postbac programs in the country. Our small pool of international students usually comes from Canada, China, Korea, Africa, and Central America.

Of the 88.6% of students applying from universities in California, about 82% graduated from the University of California (UC) system of 9 campuses (Figure 1a), 15% graduated from California State University (CSU) system of 23 campuses (Figure 1b), and the rest (18%) graduated from other California institutions. It is notable that two campuses in the University of California system (Berkeley and Davis) contribute nearly 50% of students applying to our postbac program. Not surprisingly, the two campuses are very close to our Hayward campus (Berkeley is about 22 miles away and Davis about 84 miles away) making distance, familiarity with area, our program's reach-out efforts in our catchment area, and word-of-mouth from peers, important factors in student

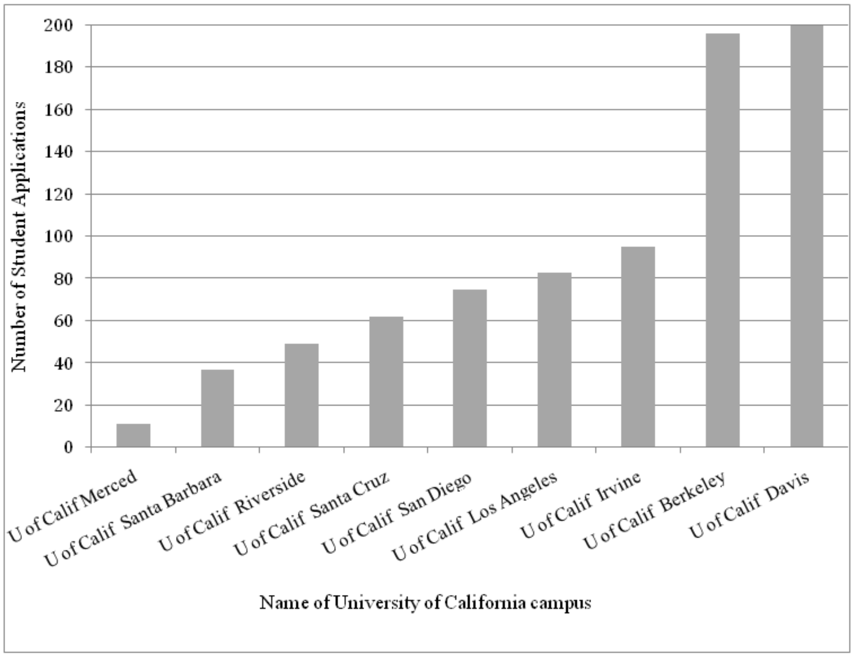

Figure 1a. Number of students applying from University of California campuses

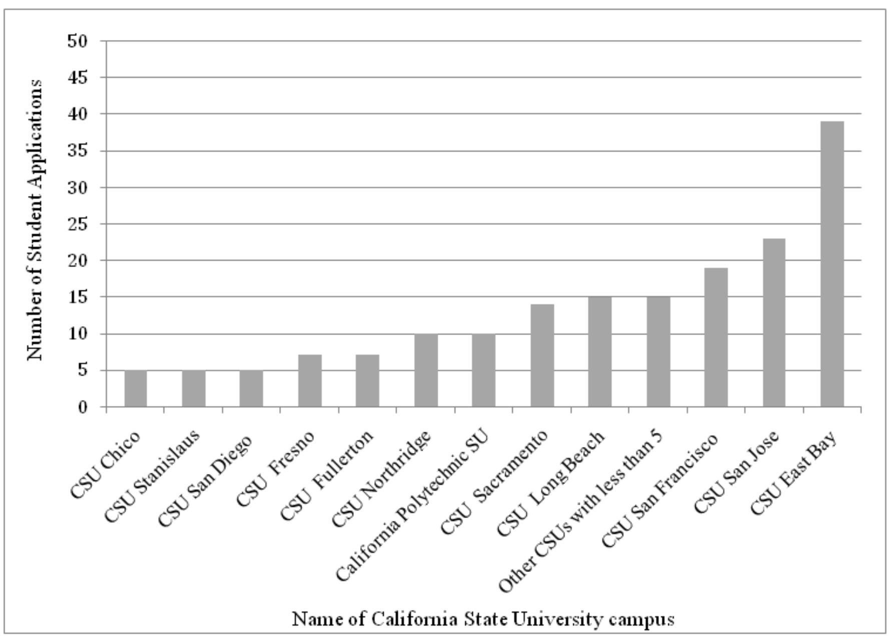

Figure 1b. Number of students applying from California State University campuses

choices. Past studies on student college choice have highlighted selection factors like academic reputation of the institution, campus resources, program size and quality, tuition, availability of financial aid, geographic location, and students' academic ability and achievement characteristics (Kallio, 1995; Poock & Love, 2001; Moring, 2007; Lei & Chuang, 2010). Other important factors mentioned include availability of information about

Table 2. Spearman’s Rank Correlation analysis of undergraduate and postbac GPA data in both CC (n=138) and ADV (n=234) cohort students.

Scenario	***Correlation Coefficient***	***Probability***
Correlation between *undergraduate* and *postbac GPAs* in all students? (n=372)	0.31	P<<0.001
Correlation between *undergraduate* and *postbac GPAs* in career changer cohort students? (n=138)	0.38	P<<0.001
Correlation between *undergraduate* and *postbac GPAs* in advanced cohort students? (n=234)	0.31	P<<0.001

college, admission requirements, student academic aspirations, parental and peer encouragement, and saliency of potential institutions (Cabrera & La Nasa, 2000).

The observation that there are more students (8 of every 10 California graduating students) from the UC system than from CSUs and/or other California colleges is interesting, but not at all surprising for several reasons. One, students who join the UC system from high school often had higher GPA and SAT scores than those applying to other state colleges. Two, UC schools are often large campuses with a campus student population of 30-40,000 students on average. This means that average class sizes are larger than the US college average with up to 700 students typical in foundation science classes like biology, chemistry and physics. Student academic and counseling support to cater for such large student populations is often inadequate or far-stretched. In many science courses, most instructor support and instruction comes from current graduate student instructors (often called TAs or teaching assistants) rather than regular faculty. Inevitably, this means that most science students are not as well prepared to pursue graduate school programs as would be the case. Three, mainly due to inadequate counseling, students often do not fully comprehend (early enough) the rigor and competitiveness of graduate biomedical science programs; and the concomitant requirement for academic excellence through all college years. Four, is the availability of postbac programs in the vicinity. Through outreach efforts and peer word-of-mouth, many graduating students, understanding that applying to biomedical school programs requires a solid academic foundation, already know they have a second chance in a postbac program - as long as they “prove” their academic aptitude in such programs and continue an upward academic trend.

Career changers (CCs) are postbacs who graduate as non-science majors and advanced students (ADV) are those graduating as science majors. There is a weak but positive correlation between undergraduate and postbac GPAs for: a) all students (r=0.31, p<< 0.001, n=372); b) CC students (r=0.38, p<<0.001, n=138); and, c) ADV students (r=0.31, p<<0.001, n=234). (Table 2). There were also significant differences between the mean overall GPAs between undergraduate and postbac stages of student preparation both CC and ADV cohort students (t=31.71, p<0.0001, n=372, Table 3). Further separation to compare undergraduate and postbac GPAs for *only* CC cohort students and *only* ADV students confirmed the above significant differences in overall results (t=12.62, p=0.0004, n=138 and t=31.19, p<0.0001, n=234 respectively, Table 3).

The weak correlation is perhaps expected since at this stage in their academic preparation, most postbacs are performing at a superior academic level likely promoted by several factors. One, the sense of belonging most postbacs find in our program with like-minded peers (with similar overall objectives of eventually applying to biomedical professional schools). Two, small class sizes (averaging about 25 students) encourage closer peer and instructor interactions. Three, formal tutoring support for every course our program offers fosters teamwork and cooperativity amongst peers. Wong, Waldrep and Smith (2007) found that formal peer-teaching greatly improved medical student academic success as measured by GPA and US Medical Licensing Examination test scores. Four, previous collegiate experience allows postbacs to assimilate into the academic culture of any campus (including ours) more easily. Evidently, they have pursued this road before and thus understand the “drill” better than their undergraduate peers. Five, and perhaps most important, as discussed in the ‘Introduction” section above, are personal factors including student’s level of maturity, perceived risk with this second chance likely fueling individual initiatives, motivation and work ethic.

The average *undergraduate* GPAs for CCs (n=138) and ADV (n=234) cohort students, was significantly different (t=5.11, p<0.0001, Table 4).This may not be at all unusual since many students find foundation science courses with laboratory very challenging. It could be a result of insufficient high school preparation in the sciences; taking science courses too early in their college careers when many students are still adjusting to campus

Table 3. Paired t-test analysis comparing both postbac GPA data for both CC (n=138) and ADV (n=234) cohort students.

Scenario	*Undergraduate Mean*	*Postbac Mean*	*t-test*	*Probability*
Is there a difference between mean undergraduate and mean postbac GPAs for all cohort students? (n=372)	2.95	3.62	31.71	<0.0001
Is there a difference between the mean undergraduate GPAs and mean postbac GPAs in *career changer cohort students*? (n=138)	3.04	3.57	12.62	0.0004
Is there a difference between the mean undergraduate GPAs and mean postbac GPAs in *advanced cohort students*? (n=234)	2.88	3.65	31.19	<0.0001

life and new surroundings; poor student study habits; class sizes that are too large with upwards of 500 students; and not enough academic support services including tutoring, faculty consultation and poor self-advocacy amongst the student population.

The average *postbac* GPAs for CCs (n=138) and ADV (n=234) cohort students were also compared and no significant differences were found between the two means (t=1.97, p>0.05, Table 5).Since both CCs and ADV perform equally well in the program, it appears that undergraduate exposure to science courses may not impact on postbac (science courses) academic performance. The level of motivation, maturity, collegiate experience, good time management, self-testing, adaptability, ability to utilize available support resources fully amongst all postbac students, as noted by Wambuguh and Yonn-Brown (2013), perhaps explains this finding. This elevated academic performance amongst postbacs is not only expected but required for postbacs to ensure continued support from the program. As postbacs, there's an overwhelming need to "prove" their continued upward academic trend to biomedical school admissions committees with excellent postbacs GPAs and better standardized test scores. These tests include the Medical College Admission Test (MCAT) for pre-medical students; the Dental School Admission Test (DAT) for pre-dental students; the Optometry Admission Test for pre-optometry students; the Pharmacy College Admission Test (PCAT) for pre-pharmacy students; and the Veterinary College Admission Test (VCAT) for pre-veterinary students.

Our postbac students take a variety of foundation science (physics, biology, chemistry and mathematics) and upper division biology and biochemistry courses including genetics, biochemistry, immunology, microbiology, neurobiology, molecular/cell biology, anatomy and physiology, and endocrinology. Houglum, Aparasu and Delfinis (2005) report that among the predictors of academic success amongst pharmacy school students, demonstrating academic excellence in science prerequisites is critical. McCall, Allen and Fike (2006) note that advanced biology coursework (especially genetics, cell biology, immunology, biochemistry, and molecular biology) highly predicted academic success in pharmacy school.

Logistic regression analysis data for the various predictive scenarios (Table 6) indicates the following: 1) Students entering the postbac program with overall undergraduate GPAs between 2.80-2.99 are two-and-a-quarter times more likely (Odds Ratio =2.26) to get postbac GPAs of at least 3.7 (χ^2 = 13.61, p=0.0002, n=372) than those with lower undergraduate GPAs. 2) Students entering the postbac program with overall undergraduate GPAs of at least 3.0 are three times (Odds Ratio =2.75) as likely to get postbac GPAs of at least 3.7 (χ^2 = 21.64, p<0.0001, n=372) as those with slightly lower undergraduate GPAs. It is interesting to find that postbacs with GPAs of at least 2.80 are 2.25-3 times as likely to achieve a GPA of 3.7 or above in their postbac studies. Cumulative undergraduate GPAs of at least 2.80 indicate a student who is generally above average in academic performance and who, given a chance, can do much better. This finding supports this proposition.

Wambuguh and Yonn-Brown (2013) used a similar statistical analysis to predict final examination performance from regular quizzes, finding that students who had an average of 90% overall in their total lecture quizzes scores were 3 times more likely to get at least 90% in their final examination. Although this study had a sample size of 372 students, this analysis definitively indicates that many postbac and graduate programs accepting students to prepare for advanced (doctoral) graduate programs, may not discount prospective students with GPAs below (but close to) 3.0. Sack (2004) reports that when the UC system decided to increase

Table 4. Paired t-test analysis of mean GPA data for all students (CC and ADV cohort students, n=372).

Student Category	*Undergraduate Mean GPA*	*t-test*	*Probability*
Career Changer Cohort	3.04	5.11	<0.0001
Advanced Cohort	2.95		

Table 5. Paired t-test analysis comparing both undergraduate GPA data for both CC (n=138) and ADV (n=234) cohort students.

Student Category	*Postbac Mean GPA*	*t-test*	*Probability*
Career Changer Cohort	3.57	1.97	>0.05
Advanced Cohort	3.65		

their freshmen admission overall GPA from 2.8 to 3.0, at least 750 high school students were affected every year. Nationwide, prospective postbac students with GPAs between 2.80-2.99 may number in the thousands and deserve to be given a chance. Such considerations would help ensure a diverse pool of students with a continuum of skills that supersede the regular gateway metrics used by many biomedical school programs. This will also improve the overall experience of students accepted in such programs as a result of differences in state residencies, nationality, socio-economic status and under-represented/minority backgrounds.

The logistic regression model predicts the probability of the occurrence as a function of the independent variable(s), and thus can be used to predict the probability of a hypothetical postbac student accepted successfully getting a cumulative postbac GPA of 3.7 and above. To do this, the y-value obtained from the general equation (y = a + bX) is then converted into a probability between zero and one in an S-shaped curve using the function: $p = e^{a+bX}/1 + e^{a+bX}$. To calculate the probabilities of a hypothetical postbac student entering our postbac program from the cumulative undergraduate GPA using the probability function ($p = e^{a+bX}/1 + e^{a+bX}$), the following results were obtained (Table 7). The results of this study indicate that compared to everyone else's academic performance in the group, a student entering the postbac program with at least a 3.0 cumulative GPA has a 69% chance of attaining a cumulative GPA of at least 3.7 by the end of their first postbac program year (X=1). Those with undergraduate cumulative GPAs of between 2.80-2.99 have 62% chance of attaining a cumulative GPA of at least 3.7 by the end of their first postbac program year (X=1). Students with lower than 2.80 cumulative undergraduate GPA have only a 42% chance of attaining a cumulative GPA of at least 3.7 by the end of their first postbac program year (X=0).

The results of this study have also enabled the development of three probabilistic equations depending on the student cumulative undergraduate GPA. We found this somehow complex analysis (especially for those who are not very conversant with logistic regression analysis) necessary as an academic performance predictor as described below. Thus, a hypothetical student can use his/her cumulative undergraduate GPA to predict excellent academic performance with at least 3.7 cumulative GPA by the end of their first full year in the program. For example, using the derived equation (y = -0.35 + 0.82X) a student with an undergraduate cumulative GPA of say, 3.22, can expect his/her probability of attaining a 3.7 GPA in the program to be at least 69% by substituting the values in this equation using the general probabilistic function ($p = e^{a+bX}/1 + e^{a+bX}$). If the student's GPA was below 2.80 (then, X=0) and using the equation (y = -0.21 + 1.01X), the resulting probability would be lowered to 42%. This may not be as bad and is an optimistic assurance that the student can still do well in the postbac program with better engagement and readiness for *harder* work. As noted by others (for example, Zimmerman, 1997, 1998, 2000; Van Den Hurk, 2006; Wambuguh & Yonn-Brown, 2013) such students will need careful self-monitoring, continuous self-evaluation, timely adjustments to study habits as integral components of self-directed learning. Postbac students like those applying to our program bring a multiplicity of important personal traits like the ability to overcome adversity, tenacity, work and varied life experiences, and a relatively high level of maturity and responsibility compared to our undergraduate student pool.

Table 6. Logistic regression analysis of both undergraduate and postbac GPA data in all students (n=372).

Scenario Prediction	*Chi-square (χ^2)*	*Odds Ratio*	*Coefficient*	*Probability*
How well does earning a graduating cumulative GPA of between 2.80-2.99 predict student postbac academic performance (as measured by an overall postbac GPA of 3.7 and above)?	13.61	2.26	0.82	0.0002
How well does earning a graduating GPA of 3.0 and above predict student postbac academic performance (as measured by an overall postbac GPA of 3.70 and above)?	21.64	2.75	1.01	<<0.0001

Table 7. Probabilistic equation and function results of logistic regression analysis data for the three undergraduate cumulative GPA scenarios[1] (n=372).

Scenario	*Equation* y = a+bX	*Probability* $e^{a+bX}/1 + e^{a+bX}$
Undergraduate Cumulative GPA 3.0 and above	y = -0.35 + 0.82X [X=1]	0.69
Undergraduate Cumulative GPA 2.80-2.99	y = -0.21 + 1.01X [X=1]	0.62
Undergraduate Cumulative GPA below 2.80	y = -0.21 + 1.01X [X=0]	0.42

[1]*The probabilities in last column are those for achieving a postbac GPA of 3.7 and above given the scenario.*

Although a common trend in the last two decades, increasingly, factors other than academic aptitude (as demonstrated by GPA and standardized test metrics) are becoming a critical part of the admissions process for many advanced graduate and professional programs. Many authors applaud and reiterate the importance of this broad approach to student admissions. Powis (2010) argues in favor of taking into account non-academic personal qualities in the selection of biomedical school students and discusses some problems associated with a selection method based primarily on academic achievement. Kancel and Hezlett (2007) state that while GPAs and standardized tests predict subsequent student performance across disciplines; they note that student motivation and interest (critical for sustained effort in graduate school) must be inferred from various unstandardized measures like personal statements, letters of recommendation and interviews. Turner and Nicholson note that "in this age of decreased variability amongst candidates, and given the importance of being fair, consistent and transparent in our selection practices, it is imperative that additional appropriate selection tools are developed and evaluated. The future success of the selection process will depend on its ability to formulate and develop additional criteria against which to compare candidates." (2011, p.9). This broad admissions approach is clearly validated by the recent 2015 changes to the Medical College Admission Test (MCAT) in the United States and Canada. According to the American Association of Medical Colleges (AAMC, 2014), the concepts tested in the new MCAT are "designed to test the knowledge and skills of tomorrow's doctors" consistent with current "medical advancements, changes to the health care system, and the increasing diversity of the population." (2015).

CONCLUSION

The academic performance of postbac students reported in this study has demonstrated that despite their undergraduate major focus (science or non-science) and/or academic adversity, students entering the program with at least a 2.80 undergraduate GPA improve their odds of attaining a cumulative GPA of at least 3.7 by two-and-a- quarter times (or 62% probability). Those with at least 3.0 GPA improve their odds of achieving a 3.7 by three times (or 69% probability). This is consistent with the study's guiding hypothesis (presented on page 5). Factors that include sustained health career interest, high level of motivation, dedication and strong believe in hard work will produce a very attractive breed of promising candidates ready for biomedical school programs. At a time and age when biomedical school programs are highly competitive and do not have space for all well-qualified candidates, admissions officers will continue to use a variety of ways to evaluate suitable candidates who will translate into the kind of biomedical professionals required in the 21st century. Common metrics like GPA and entrance test scores will continue to provide a solid basis for selecting students with a firm academic foundation in required prerequisite science courses. Postbac students will continue to provide an avenue through which biomedical school programs can recruit talented candidates who have demonstrated sustained upward academic growth as well as bringing on board their exquisite personal traits and a variety of skills/experiences that stretch beyond just good metrics.

ACKNOWLEDGEMENTS

I would like to thank Ms. Amarjit Bath, a premed student at our campus, for assisting in the early stages of data analysis.

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