STRATEGIC ENROLLMENT MANAGEMENT FOR CHIEF ENROLLMENT OFFICERS: PRACTICAL USE OF STATISTICAL AND MATHEMATICAL DATA IN FORECASTING FIRST YEAR AND TRANSFER COLLEGE ENROLLMENT

RANDALL LANGSTON, ROBERT WYANT, AND JAMIE SCHEID

Both an art and a science, enrollment projections have become a major component to effective college and university fiscal planning. With stagnant or declining state budget support for public higher education along with an increasing emphasis on revenue generation, never before has predicting the size of an entering class become more imperative. Too few students and budgets are sure to suffer; too many students and residence halls will be overflowing. This article presents several approaches to manage enrollment data for an entering class and predict enrollment yield. By examining past yield behavior coupled with trend and conversion data, a college or university will be better positioned to provide exceptionally accurate enrollment forecasts to senior administration. The authors provide pragmatic examples to empirically engage and data mine applicant pools for

STRATEGIC ENROLLMENT MANAGEMENT QUARTERLY, Volume 4, Number 2, 2016

View this article online at wileyonlinelibrary.com • DOI:10.1002/sem3.20085

both first year and transfer populations in order to predict yield conversion with a greater level of confidence. Special attention will be placed on describing different statistical and mathematical techniques to predict enrollment.

Today's senior enrollment managers face a litany of issues where they are forced to contend with on a daily basis. Perhaps none of these issues are more important today than that of adequately predicting the enrollment at a particular college or university. However, projecting enrollment is not a simple process. Indeed, Liu (1998) noted that "enrollment projection is very difficult to perform" (p. 598). This is due to a very large number of factors that often impact these projections and equations. With declining state support for higher education, competition from other institutions of higher education and rapid demographic change, colleges are being squeezed from many different directions. Despite affordability being noted as a top legislative priority in 2015 (Weeden, 2015), public colleges and universities nationwide face the prospect of having to operate with fewer fiscal resources from state legislatures. With razor-thin margins for error in developing budgets, colleges and universities face an uncertain future where "the effects of anticipated enrollment shortfalls can be devastating" (Armstrong & Nunley, 1981, p. 295). This is a particularly challenging given that "universities have three basic missions: teaching, research and public service … [but to] survive HE institutions must behave like for-profit organizations, prioritizing revenue creation" (Pucciarelli & Kaplan, in pressin press, p. 2). Given these imperatives and expectations, effective enrollment projection is paramount for institutions of higher education nationwide.

Why We Project Enrollment and the Role of Strategic Enrollment Management

Enrollment on any college campus is significant from both a capacity and revenue perspective. Caruthers and Wentworth (1997) noted that for the vast majority of colleges and universities, the number of students to be enrolled is often the most important variable in developing revenue projections (p. 84). Unplanned smaller student enrollments equate to budget challenges which can lead to painful austerity measures (e.g., freezing positions, cutting budgets, or layoffs). But the premise of simply recruiting students to the college, waiting for them to attend, and counting numbers is both not strategic and a poor way to manage a class. Often, there are numerous factors involved with the yearly recruitment dance that admissions officers engage in. For the enrollment management leader who is typically responding to numerous internal constituencies needs those often need to be addressed in a meaningful and professional way. From the academic side that clamors about academic quality, to the financial side that stresses fiscal sustainability, to boards that seek academically prepared diverse populations, every stakeholder has a legitimate claim on priorities for their student populations. At a time where there are rising expectations from internal and external constituencies such as "higher enrollments, more [degree] completions, [and] deeper learning outcomes [there are also constrained resources such as] budget cuts, declining family ability to pay for college [and space issues such as] limited seat capacity" (Wagner & Hartman, 2013, slide 6). All of these factors are but a few examples of some of the reasons why enrollment projections are so critical.

ENROLLMENT PROJECTION IS CRITICAL

Enrollment projection is a key element for any strategic enrollment management (SEM) planning process. Dolence (1998) noted that any credible SEM plan must have several components, which include being: (a) comprehensive; (b) deliberately designed; (c) one that achieves meaningful goals; (d) strives for optimal enrollment; and (e) involves recruitment and retention activities (pp. 72–73). Statistical and mathematical projections are typically planning activities that are comprehensive and require a great amount of purposeful design to achieve a true representation of what the enrollment landscape is at a particular institution.

To effectively maintain optimal enrollment at any institution, numerous activities related to, and intertwined with, strategic recruitment must occur and these activities should be informed by solid statistical and mathematical analytics.

LEVELING OFF OF PUBLIC SUPPORT FROM STATES

Externally, one of the most critical variables associated with the need to accurately project enrollment in public colleges and universities involves support from state legislatures. While at private colleges and universities, where "between 80 and 90 percent of their revenue comes directly from student tuition" (Hossler, 2006, p. 109), much support for higher education for public colleges and universities originates directly from the state (Doyle, 2012). State appropriations have declined in the recent past, especially during the Great Recession years, and, as a result, there has been a fundamental shift related to how institutions are funded. Public college and university budgets, once subsidized generously by states, have seen their funding drop dramatically (Barr & Turner, 2013; Zumeta, 2010), especially in the years immediately following the Great Recession. However, in 2014 there were signs that states were acquiescing to small budget increases. State support for colleges and universities nationwide increased by $4.72 billion between fiscal year (FY)14 and FY15, but is tempered somewhat due to skewing related to mandated appropriations to State Universities Retirement Systems (SURS) budgets particularly in Wisconsin and California (Grapevine Report, 2016). These positive increases do mask the reality that in 2015, "half of states pent less on higher education than they did in 2010" (Wexler, 2016, para. 9). According to the Center on Budget and Policy Priorities, state funding for higher education still remains far below pre-recession levels in all states except Alaska, Wyoming, and North Dakota (Mitchell & Leachman, 2015, p. 4). Other states such as Arizona, Louisiana, and South Carolina have experienced change in state spending per student between 2008 and 2015 dropping 47%, 42%, and 38% respectfully (Mitchell & Leachman, 2015, p. 4). As state funding has decreased, colleges and universities have transferred a proportion of these costs directly to students and today more than $1.2 trillion in student loan debt is still outstanding (Gale, Harris, Renaud, & Rodihan, 2014).

Since 2010, states have also been cutting support more rapidly than in years past, which have had a dramatic impact on college and university budgets. As a result of these cuts, public colleges have been forced to increase tuition dramatically (Barr & Turner, 2013; Oliff, Palacios, Johnson, & Leachman, 2013), cut spending on infrastructure appropriations (Tandberg & Ness, 2011), and eliminate positions on campuses (Long, Manchir, & Hellmann, 2015; Oliff et al., 2013). However, tuition increases often have a negative impact on enrollment, especially at colleges and universities where tuition discounting is already elevated. Given the continued uncertainty related to external factors or "to reduce vulnerability to environmental forces" (Dolence, 1998, p. 74), it is more important than ever for a skilled SEM leader to both comprehensively understand the political factors impacting enrollment and simultaneously develop mechanisms or procedures (i.e., forecasting models) to more clearly understand and counter enrollment change that could occur.

COMPETITION FOR STUDENTS

Another external factor that impacts enrollment is that of increased competition in the marketplace. With declining demographics in some parts of the nation, colleges and universities that in the past had a reliable pipeline of students attending their schools are finding that as population migration occurs, it invariably impacts the number of students they see at recruitment events. This in turn impacts the number of applications received in the admissions funnel, which cascades down to admits, deposits, and matriculated yield. With increased competition there is the real possibility of colleges and universities succumbing to fiscal realities. While Moody's Investors Service in 2015 moved the higher education sector from "'negative' to 'stable' for the first time since January 2013. … Moody's also announced this year it expects the number of annual closures and mergers among higher education institutions to increase" (Mathewson, 2015, para 9). With increased pressure on enrollment management (EM) leaders to yield students, competition for college bound students is sure to increase over the next several years.

Declining Enrollment at Colleges and Universities

Moody's Investors Services, "which rates more than 500 public and private non-profit colleges and universities, downgraded an average of 28 institutions annually in the five years through 2013, more than double the average of 12 in the prior five-year period" (McDonald, 2014, p. 2). In what is called the *small college death spiral*, colleges that have large operating liabilities coupled with heavy discounting of students' tuition are facing urgent issues of solvency. This death spiral for small colleges has recently started spreading to larger colleges and universities as they face less discounting but significant cuts in state aid. It's clear that in some cases the sustainability model that has governed these institutions in the past has begun to falter.

In the United States, enrollment at colleges has been on the decline since 2011. According to a spring 2015 National Student Clearinghouse (NSC) report, as compared to spring 2014, overall postsecondary enrollment decreased 1.9% with declines most precipitous at for-profit institutions and nearly unchanged among four-year public colleges, which equates to a total decline in student enrollment during this period from 18,948,521 to 18,592,605 (NSC, 2015, p. 2). This loss is on top of the enrollment declines from spring 2013 to spring 2014, equating to a decrease from 19,105,651 students to 18,948,521 (NSC, 2015, p.4). In some parts of the United States the declines are much more precipitous. In the Midwest for example, 11 out of 12 states have experienced enrollment decreases over the past several years (Bidwell, 2013). When considering a state-by-state analysis of enrollment, some states are doing better than others. States such as New Hampshire (+19%), Utah (+4.8%) have experienced increases in enrollment and are doing well in spring 2015 as compared to Spring 2014 enrollment at post-secondary institutions, where states such as New Mexico (–8.3%), Oklahoma (–5.5%) and Missouri (–5%) are struggling to maintain persistence at their colleges (NSC, 2015, pp. 9–12). However, there has been some evidence, including projections by the U.S. Department of Education, that enrollment in U.S. degree-granting institutions is expected to rise to 23.8 million in 2022, which would equate to a 13.9% jump in enrollment (Hussar & Bailey, 2014) but does not control for a factor such as the cost of a college education.

Reasons for past and current weakening in enrollment at colleges and universities include reductions in family income (Long, 2014), increases in tuition costs (Long, 2014), lack of financial aid (Lovenheim & Owens, 2014), decreases in housing wealth (Lovenheim, 2011), cuts to higher education by states that are leading to less support for students to attend college (Mitchell & Leachman, 2015), and a decline in public faith in higher education (Thorson, 2014). Given these issues, there exists an imperative for EM leaders to accurately and successfully predict the probable enrollments for both entering and continuing students on their campuses.

Creating Forecasting Models

Given the current difficult state of funding issues, competition for students, and internal pressures to achieve enrollment growth, colleges and universities have been turning to EM professionals to forecast enrollment effectively and precisely (Ward, 2007). Brinkman and McIntyre (1997) noted that "enrollment forecasts are fundamental elements of planning and budgeting at any higher education institution that depends on student enrollments or at any agency or organization that has responsibilities for supporting those institutions" (p. 67).

FACTORS THAT PLAY A ROLE IN PROJECTION MODELS

In understanding the factors that lead to successful enrollment at colleges and universities numerous influencers impact the number of students who will ultimately settle on a particular institution. Brinkman and McIntyre (1997) referred to these influencers as *manageable* and *unmanageable*. Manageable factors typically refer to those issues that a college or university can influence. These include the tuition that the school sets, housing and dining costs, admissions standards (selectivity), scholarships or grants awarded, and engaging in marketing and communication. Internal communication between EM and other offices and how in concert senior administration is with the EM efforts are other manageable influencers. As an EM leader and steward, some questions to consider when developing a projection model include: Is your school primed to view EM as a department-wide effort (i.e., Admissions) or campus-wide (recruiting is shared between academics and EM)? Is EM promoted from the top down? Is EM a culture at the college?

Unmanageable factors include such issues as demography, economics, high school graduation rates, ability to pay for school, competitors in the marketplace, and state funding for higher education. In many parts of the nation, demographic challenges are especially acute. As population moves out of one state (outflow migration), it adversely impacts competition as more schools are vying for a much smaller pool of students. This is especially more challenging when a college or university is attempting to keep steady or increase its selectivity.

METHODOLOGIES FOR ENROLLMENT FORECASTING

Statistical prediction methodologies for projecting an entering class typically takes on two forms: curve-fitting techniques (trend analyses) and causal (explanatory, structural, econometric). Within curve-fitting statistical data analysis, historical data is used to identify patterns. Rudimentary techniques for curve fitting include simple and moving averages, whereas more complex methods employ exponential smoothing or giving weight to more recent values. Other approaches to using curve-fitting techniques include the Holt-Winters method, the Box-Jenkins technique, and fuzzy-time series.

In causal modeling for enrollment, "attention shifts to the underlying factors that directly or indirectly influence enrollment levels" (Brinkman & McIntyre, 1997, p. 71). One factor might be that students are more likely to enroll if they are closer to campus. Faherty (1997) described this as a belief that "if 'A' almost always causes 'B' to exist, then whenever 'A' appears in a particular context, it can be forecast with a high degree of accuracy that 'B' also exists" (p. 407). Also called time series analysis, the assumption here in "forecasting is that the future depends upon the present while the present depends on the past" (Chen, 2008, p. 4).

While there is certainly an urgency and institutional imperative for forecasting, the ways and means to achieve this goal are varied and nuanced. Keep in mind that when you are predicting longitudinally, final prognostications are subject to statistical error and human behavior (this year's class did not act the same as last year's class) and issues of homogeneity may arise (sample equally reliable and alike over time). If you are utilizing a statistician, there could be validation issues that could occur due to this individual not knowing why numbers have changed or acted differently over time.

REGRESSION

Regression analysis is another approach college and universities can readily use to better predict student enrollment. Regression analysis "has three goals: predicting, modeling, and characterization" (Arsham, 2006, n.p.). Here, the SEM leader is utilizing statistical methods to provide a better understanding of enrollment behaviors of students. This can include enrollment or financial aid leveraging. An example of this would be to use new, first-time enrollment (i.e., the number of new, first-time students in a given year) as the unit of analysis for the dependent variable and then define explanatory predictor variables such as average student aid, average distance from campus, and competitor tuition pricing. In this case, the SEM manager utilizes ordinary least squares regression (i.e., linear regression) to develop an aggregate enrollment projection model. Another example of utilizing statistical methods to provide a better understanding of enrollment behavior is to use logistic regression, where the unit of analysis for the dependent variable is categorical (i.e., the enrollment outcome of each individual student). Both methods are described in more detail below.

Linear Regression

Linear regression utilizes a system of determinants. Lins (1960) noted that the determinants (independent variables) are sequenced so that X_1 is a variable most closely associated to the greatest degree with Y (dependent variable being the number of enrolled students). X_2 then is a variable with a high degree of association with Y, but not as significant as X_1. "Regression analysis helps us to understand how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed" (Goyal & Vohra, 2012, p. 116). Regression coefficients are utilized to determine if the relationship between X and Y is rectilinear or curvilinear and a regression equation emerges that takes the form of the following equation:

$$Y = a + b_1X_1 + b_2X_2 + \cdots + b_nX_n. \tag{1}$$

Logistic Regression/Logit Transformation

Logistic regression is a statistical technique that utilizes the binomial distribution in order to predict the outcome of a binary dependent variable. Unlike ordinary least squares regression where the dependent variable is continuous, logistic regression estimates the odds ratio that an outcome is a success (y = 1) or failure (y = 0). Typically, when projecting enrollment, the dependent variable (i.e., enrollment equals yes or no) is a dichotomous variable, and the independent variables are either continuous or dichotomous (e.g., GPA, SAT/ACT, major, filed a FAFSA [Y/N], visited campus [Y/N], etc.). The relationship between the dependent variable and an independent variable can be expressed mathematically through the logistic response function in the following way:

$$\pi = \frac{e\,(\beta_0 + \beta_1X_1 + \beta_2X_2 + \ldots + \beta_nX_n)}{1 + e\,(\beta_0 + \beta_1X_1 + \beta_2X_2 + \ldots + \beta_nX_n)}\,. \tag{2}$$

This function can then be transformed using a nonlinear transformation called the logit transformation, which linearizes the equation:

$$\log_e\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1X_1 + \beta_2X_2 + \ldots + \beta_nX_n\,. \tag{3}$$

It is important to note that if an institution restricts enrollment for programs, then the demand model may not be the most appropriate model to use because these models tend to do best when all students are subjected to the same effect (i.e., all admitted under the same criteria). Thus, predicting graduate school enrollment where departments accept students under different criteria would not work well with a standard demand model. When the enrollment behavior varies significantly among certain subpopulations in the data (e.g., first-time students vs. transfer students, in-state vs. out-of-state, main campus vs. subcampus, different racial/ethnic groups) or when a policy differs significantly among certain subpopulations (e.g., different admissions criteria based on academic school or department, different financial aid policy), it may make sense to segment data into smaller groups as long as those groups are not too small. Separate regression analyses could then be performed on each individual group.

Practical Examples of Approaches to Predicting Enrollment

As the senior enrollment manager, one of the main tasks will be to present to senior leadership or administrators is to determine the ultimate enrollment of an entering class and continuing student body at the college or university. A skilled enrollment manager can effectively blend best practices in mathematics or statistics along with informed judgement in developing very accurate forecasts (Chen, 2008; Lawrence, Goodwin, O'Connor, & Önkal, 2006). Simply using judgment alone without the benefit of statistical or mathematical analysis is a risky proposition for any EM manager. In fact, Hogarth and Makridakis (1981) noted that in reviewing 175 scholarly research papers that implicated statistical forecasting, in every case "quantitative models outperform judgmental forecasts" (p. 126). Current literature connects contemporary statistical data analysis with "big-data analysis," and this is discussed in general terms below. This section will also examine more traditional statistical data analytics that are also very useful in prediction modeling including the role of trend estimation, population components, curve-fitting techniques, and causal (flow) models. Each of these approaches have their positives and negatives and each requires a skilled EM leader to evaluate which methodology works best at their institution.

BIG-DATA ANALYTICS

One of the more recent advents in mathematical computation involves big data analytics. In the past, a statistical analyst would work with several data points and determine a dependent variable and numerous independent variables. The information could be readily analyzed and synthesized in a way that there could be clearly defined outcomes or conclusions. However, today business professionals and some in higher educations are utilizing what is called advanced analytics. Advanced analytics can be thought of as a "collection of related techniques and tool types, usually including predictive analytics, data mining, statistical analysis, and complex SQL … [and] data visualization" (Russom, 2011, p. 5). Another way to consider this is through the lens of *Business Intelligence and Analytics* or BI&A. In this case big data is "used to describe the data sets and analytical techniques in applications that are so large (from terabytes to exabytes) and complex … that they require advanced and unique data storage, management, analysis, and visualization technologies (Chen, Chiang, & Storey, 2012, p. 1166). Big data is fundamentally different than traditional data analysis based on three central "components: variety, velocity, and volume" (Sagiroglu & Sinanc, 2013, p. 42). Variety refers to the scope of the data such as structure, unstructured, or semistructured, where volume refers to the size of the data, and velocity relates to the streams of data and data speed (which permits real-time or near-real-time analysis) that are being fed into the model (Sagiroglu & Sinanc, 2013). The higher education industry has also been rapidly implementing big data into analytics. Managing all of the data and analyzing the information can be managed by a skilled statistician using such applications as SPSS, SAS, or R, for example (Ozgur, Kleckner, & Li, 2015).

Big data analytics can certainly be a "game changer" in determining new breakthroughs that allow the SEM manager the opportunity to act upon virtually on the fly. Instead of week old reports where the experienced EM leader would have to wait and then act on a prescribed day of the week, now data can be fed electronically or automatically through systems and interpreted virtually real time. Data visualization tools permit the EM leader the opportunity to quickly digest large amounts of data and make strategic decisions quickly and efficiently. But big data has some obstacles that an EM leader will need to overcome. This includes such issues as (a) clear knowledge of software and hardware packages that are being employed, (b) familiarity with the data, (c) goals and objectives being clearly defined prior to data mining, and (d) the need to wade through the analysis to determine what is useful and what is not as helpful in determining EM strategy. Hayward et al. (2014) noted that "successful analytics require a solid foundation comprised of firm organizational strategy and values, clean and reliable data, and a strong sense of the questions to be explored and the actions that will result" (p. 2).

CURVE FITTING

Curve-fitting enrollment projections are best described as an approach where "enrollment growth during a specified period of time can be described by some type of mathematical function and that enrollment growth will continue, in the future, to follow the path it has followed in the past" (Armstrong & Nunley, 1981, p. 297). Lins (1960) described this as a linear relationship between enrollment and time. In this scenario, projection techniques take the form of the equation $Y = a + bX$, where Y is the estimated enrollment, X is the deviation in years for the year chosen as the base, a is the enrollment of the base, and b is the estimated annual increase or decrease in enrollment (Lins, 1960, p. 8). The benefit of this type of projection is that it allows the individual projecting the enrollment the ability to look at data empirically and make an educated guess based on empirical evidence. Also called an extrapolation model, this approach assumes that past and present events will influence future events when statistically modeling (Faherty, 1997; Kahn & Weiner, 1967). The drawback to this approach is that it is subject to a human behavioral component. In other words, this method is predicated completely upon the confidence of the researcher that behavior of students (i.e., enrollment patterns) will not change dramatically from one recruitment cycle to the next.

POPULATION COMPONENTS

While a major disadvantage associated with curve-fitting projection modeling is behavior, another approach to predicting enrollment that involves a more holistic approach is called population-component modeling. Armstrong and Nunley (1981) noted that this type of modeling looks at specific segments of the student population. By examining enrollment by subpopulations rather than aggregately, the EM leader is able to get a much better understanding of what the true yield will be for any given year. For example, within any large population of students applying to any given college, there are a number of subpopulations. These could include transfer students, adult students, military populations, and first-generation students. It should be clear from data to any EM leader that each population acts differently. So a veteran student typically has a different path to ultimate enrollment (e.g., stop-out for military service, submission of a DD-214 transcript, military credit, GI benefits) than a first-time student. Such is also the case with how territories yield in any given market. The yield for market A, which is local, will perform much differently than market B, which could be 500 miles from campus. So it stands to reason that yield conversions for markets are much different. Predicting the class on a macro scale (all students) ignores the inherent nuances associated with differing yield conversions within markets.

SHORT-RANGE ENROLLMENT ESTIMATES

Short-range enrollment projections serve the institution as a way to provide accurate data to senior administrators to better develop an annual budget for sustainability. When developing a short-range enrollment model, separate projections are usually developed for the following groups of students:

- *New direct from high school students (NDHS).* These are students who have typically never enrolled at any college or university in the past. These students tend to be traditional-aged (18–22 years old) and have completed little to no college coursework. You may also want to consider grouping these students into two categories: NDHS with college coursework and NDHS without college coursework as there are differences (timing and behavior) that make grouping these populations not appropriate.
- *Transfer students.* These are students who have attended another institution of higher education and are actively transferring in coursework. Careful attention should be placed on those students who are attending a high school, attain many college level credits, and enter in advanced standing.
- *Reentry students.* These are students who have attended the college or university in the past and either left, stopped-out, or were academically dismissed in the past and are seeking reenrollment.
- *Continuing students.* These are students who are currently enrolled at the institution and are making satisfactory progress toward degree attainment.

LOU'S MODEL

One example of a rudimentary curve-fitting model, which we will call "Lou's Model," for new undergraduate (UG) and graduate (GR) students involves . The first step in this process involves guessing how many new full-time (FT) and part-time (PT) undergraduate students, as well as how many graduate students, the school will have in any given year. This is typically carried out by examining trends in enrollment and assigning likelihood for enrollment based on historical 3- to 5-year trends. FT continuing and returning students are projected by examining:

- Prior five first-time, FT fall cohorts times the appropriate retention rate.
- Prior four FT fall transfer cohorts times the appropriate retention rate.
- Prior four FT spring transfer cohorts times the previous years published half-year retention rate.

Once this is achieved, step 2 in the process involves examining the first-time FT enrollment multiplied by the yearly retention rate. This is represented mathematically in Equation 4 for first-time and continuing/returning cohorts. Here, first-time student data can be substituted with transfer data as well. Transfer students can also be included in this model by substituting TR (transfer students) for FR (first time students).

Fall 2014 FT Continuing/Returning
= (Fall 2013 first-time, FT x 1st year retention rate)
+ (Fall 2012 first-time, FT x 2nd year retention rate)
+ (Fall 2011 first-time, FT x 3rd year retention rate)
+ (Fall 2010 first-time, FT x 4th year retention rate)
+ (Fall 2009 first-time, FT x 5th year retention rate). (4)

BENEFITS AND SHORTCOMINGS OF THIS APPROACH

With every model there are some benefits and some negatives and this curve-fitting approach is no exception. Some benefits of using this approach include: a simple formula for continuing/returning students, easy to make long-range forecasts, works well for tying revenue to enrollment projections, and quite accurate projections for FT continuing/returning students. Some shortcoming of this approach include: "guesstimates" are often inaccurate, it assumes that students starting as FT will return as FT in the spring, and forecasts are not often updated through the cycle. This is a significant issue as the model does not take full advantage of information that is available. If, for example you experience population drop in first year retention, you will need to adjust the second, third and fourth year retention rates to account for this scenario. Again, this is a simplistic curve-fitting model that, with some monitoring and adjusting, can assist you in predicting enrollment.

TREND ANALYSIS (PART I)

Trend analysis utilizes historical data to predict future behavior. This approach is more complex than basic curve-fitting techniques and allows the EM manager the opportunity to more readily utilize mathematical analysis in predicting future enrollment patterns. Typically, by November of any recruitment year, the EM leader is beginning to pore over data and determine trends to better inform them of where enrollment will end at the conclusion of the recruitment cycle. One important caveat is that the further out that you go with projections before the start of a new session at the school, the less reliable projections will be. However, this approach eliminates any guess work and allows the enrollment manager to present to administrators a more quantifiable projection months before students start in the fall. Another important caveat for this process relates to one's own institutional context. It would be worthwhile to consider determining how many groups (populations and sub-populations) to think about when engaging in this type of analysis. Some possible "buckets" that may be useful for analysis could include (a) FR versus TR students, (b) resident versus nonresident, (c) local versus regional location in relation to where the student applied from, and (d) religious affiliation if applicable.

As part of the trend analysis we utilize a four-step process as follows:

1. Assess the number of new applications received at one point of the year (e.g., November 1) and the end of the year by looking at past years' application performances from the same point in time.
2. Examine application-to-accepted yield conversions over past years.
3. Examine accepted-to-deposited yield conversions over past years.
4. Examine deposit-to-matriculated yield conversions over past years.

Step 1: Determine Actual Applications Expected

In this first step, the enrollment manager determines the number of new applications received between the beginning and the end of the recruitment cycle based upon historical data going back two years. By adding the number of historical applications received from one point in time (e.g., last year from November 1 to the end of the recruitment cycle) to the current number of applications received to date in the current year, you can get a better idea on where you will end at the end of the year.

Step 2: Application-to-Admit Yield Conversion

The second step in this process involves evaluating the application-to-accepted yield conversion for the entire pool of students for the previous two years. For example, if you had 8,648 applications in 2014 and accepted 4,028, then the conversion would be 46.58%. But in 2015 you determine that you have a 48.2% applied-to-accepted yield conversion. This means that the conversion actually increased 1.62% year over year. At this point you are faced with a dilemma: does the enrollment manager accept some risk and add an extra 1.62% conversion to the prediction model for admits (effectively adding more admits), or does she/he choose to be more conservative and go with the year where the conversion was 46.58%? This is a choice that the enrollment manager will need to make before progressing to the third step.

Step 3: Admit-to-Deposit Yield Conversion

The third step in this process is determining what actual deposit yield will transpire based on the projections in steps 1 and 2. The first part in this process will be to calculate previous years' actual accepted-to-deposited conversions. In this case, the EM manager would again refer to 2014 data, which indicated that you accepted 4,028 students and deposited 1,113, or a 27.61% yield. For example, in 2015 the EM manager understood that their conversion increased and this equated to 4,155 applications and 1,159 deposits, or a 27.89% yield.

You can then utilize this data to project deposits by multiplying .2789 (27.89%) by the projected number of acceptances. The enrollment manager can use a conservative number or utilize the 1.62% increased admit conversion number to arrive at this year's projected deposit number.

Step 4: Deposit to Matriculation Conversion

While the enrollment manager may now have a satisfactory projected deposit number that they are comfortable with, this does not end the projection process. "Melt" must be accounted for in the projections. This is accomplished by examining at least three years of admissions data and dividing the number of deposited students by the actual number of enrolled. As an example, an institution could have received 1,159 deposits in 2015 but only 1,050 enrolled. This would equate to a melt percentage of 6.56%. But what if the previous year the institution received 1,113 deposits and 1,050 enrolled? This would mean the melt was 5.67%. This is nearly a percentage point divergence and represents a significant difference in actual enrollment, especially if the college or university is affixing its budget to a projection. Perhaps the enrollment manager may want to consider the average between the melt in 2014 and 2015 (6.115%) and use this to drive projections. So if the deposit projection number for 2015 is 1,138 on the conservative side, multiply .06115 by 1,138 to arrive at a melt of 69.58 students. Finally, by subtracting the 69 students from the 1,138 number, one can then see that the actual enrollment of the first-year class would be around 1,069.

This approach to conversion and prediction can be also used for transfer students as well as for different entry terms (e.g., fall, spring, or summer). In a perfect world, you could present senior administration with a TR projection in April and of course the transfer student projection will inherently be more accurate simply because the recruitment and application season for transfer (TR) students is shorter and allows you to make projections much later in the cycle. But in enrollment projections, we as EM leaders are asked to make TR projections much earlier in the funnel. By following a path that is similar for FR students, you can, in fact, project a transfer enrollment number early in the recruitment year but with a larger margin of error. Regardless of when you choose to assess TR students, by using the same conversion premises that the above steps outlined, you can just as readily predict a TR entering class.

TREND ANALYSIS (PART II)

Trend analysis can be taken one step further with the use of historical data beyond the previous recruitment year. This method mirrors Part I in principle. However, extended historical data can allow the projections to inform a trend rather than a direct comparison to the previous year. This method is useful to offset statistical anomalies that could be present.

Figure 1a uses sample data to demonstrate an institution that is currently in week 30 of its 2016 recruitment cycle. The institution currently has 8,988 freshman applications, behind 2015 and 2014, but well ahead of 2011–2013. Step 1 of the trend analysis model requires an accurate projection of expected applications. To determine this, Figure 1a examines the application difference between each week over a five-year period. Each year is then averaged together and applied to the current year's (2016) data. In Figure 1a, the average application difference between weeks 30 and 31 is 42 over a five-year period, yielding a projected 9,030 applications for week 31. This process is continued through week 52, giving the projected census application number and allowing the rest of the projection to continue. For this example, the projected number of applications for 2016 is 9,221. Figure 1b provides a graphical representation of the application projection using the numbers in Figure 1a.

Step 2 of the trend analysis model requires the enrollment manager to determine the number of admitted students the institution can expect through the recruitment cycle. Figure 2a uses the same sample data from the example institution to project this number. As of week 30, the sample institution has 4,732 admitted students, representing a 52.7% application-to-admit yield rate (4,732 ÷ 8,988). Much like step one, the EM manager must project the week 52 admitted number by using trend analysis from an historical perspective. In this case, application-to-admit yield rates are calculated and averaged over a five-year period to determine the week-to-week change. This change is then added or subtracted from the previous week and then applied to the projected application number.

Figure 1. Trend Analysis—Application Data

(a)

Wk	2016	2015	2014	2013	2012	2011	Week-to-week Application Change					
							Avg	2015	2014	2013	2012	2011
30	8988	9266	9589	8656	8429	8514	43	37	56	51	30	39
31	9030	9324	9632	8704	8467	8539	42	58	43	48	38	25
32	9069	9381	9668	8751	8501	8557	38	57	36	47	34	18
33	9100	9419	9710	8785	8529	8571	31	38	42	34	28	14
34	9124	9450	9744	8808	8544	8586	24	31	34	23	15	15
35	9136	9468	9758	8821	8554	8594	13	18	14	13	10	8
36	9147	9492	9767	8833	8557	8601	11	24	9	12	3	7
37	9159	9510	9784	8841	8566	8610	12	18	17	8	9	9
38	9168	9527	9794	8850	8571	8614	9	17	10	9	5	4
39	9181	9543	9812	8863	8580	8620	12	16	18	13	9	6
40	9189	9549	9825	8868	8587	8628	7.8	6	13	5	7	8
41	9197	9563	9832	8877	8594	8631	8	14	7	9	7	3
42	9205	9575	9842	8888	8597	8639	8.8	12	10	11	3	8
43	9210	9580	9844	8891	8603	8644	4.2	5	2	3	6	5
44	9214	9584	9852	8896	8606	8647	4.6	4	8	5	3	3
45	9218	9588	9853	8900	8611	8650	3.4	4	1	4	5	3
46	9220	9592	9853	8903	8614	8652	2.4	4	0	3	3	2
47	9221	9596	9854	8903	8617	8650	1.2	4	1	0	3	-2
48	9221	9597	9854	8903	8618	8648	0	1	0	0	1	-2
49	9221	9597	9854	8903	8618	8648	0	0	0	0	0	0
50	9221	9594	9854	8903	8618	8648	0	-3	0	0	0	0
51	9221	9593	9854	8903	8618	8648	0	-1	0	0	0	0
52	9221	9593	9854	8903	8619	8648	0	0	0	0	1	0

(b)

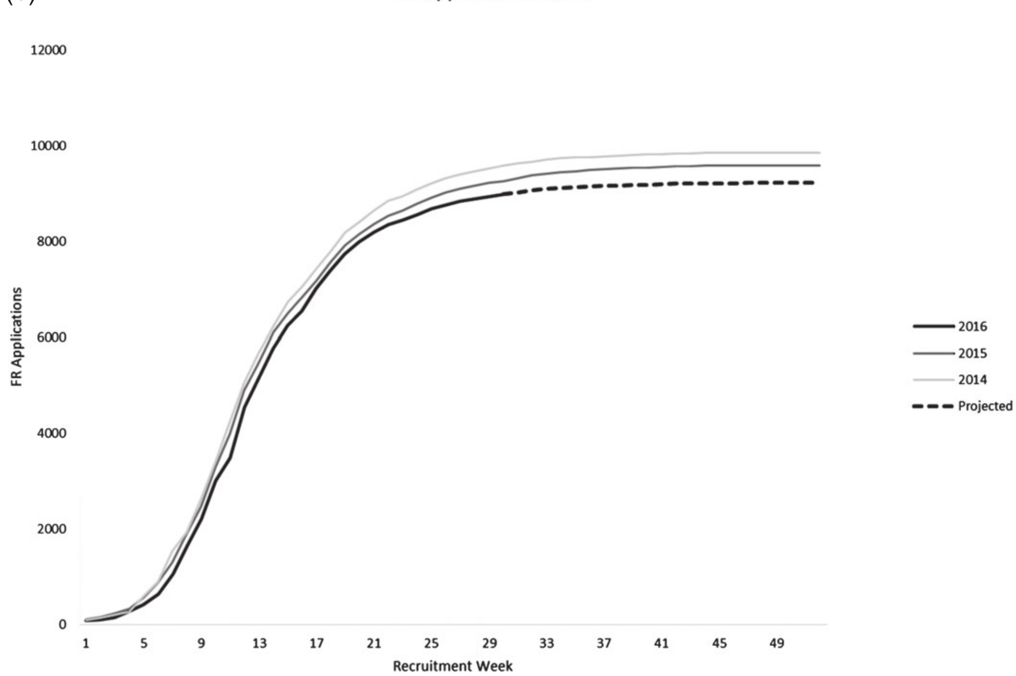
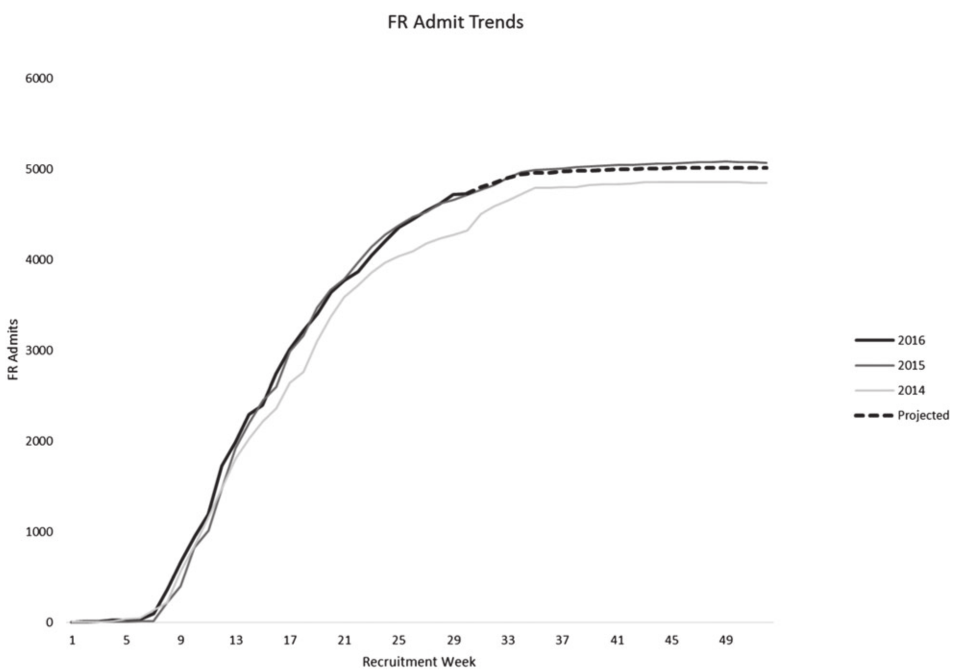


Figure 2. Trend Analysis - Admit Data

(a)

							Projected	Week-to-week Application-to-Admit Yield Difference							
Wk	2016	2015	2014	2013	2012	2011	Apps	2016	Change	Avg	2015	2014	2013	2012	2011
30	4732	4718	4324	4104	3998	3905	8988	52.70%	0.27%	47.34%	50.9%	45.1%	47.4%	47.4%	45.9%
31	4801	4772	4501	4146	4033	3937	9030	53.17%	0.51%	47.86%	51.2%	46.7%	47.6%	47.6%	46.1%
32	4854	4827	4590	4187	4090	3955	9069	53.53%	0.37%	48.22%	51.5%	47.5%	47.8%	48.1%	46.2%
33	4906	4906	4655	4224	4126	3988	9100	53.91%	0.38%	48.60%	52.1%	47.9%	48.1%	48.4%	46.5%
34	4943	4967	4725	4264	4137	3990	9124	54.17%	0.27%	48.87%	52.6%	48.5%	48.4%	48.4%	46.5%
35	4960	4989	4798	4257	4131	3995	9136	54.28%	0.11%	48.98%	52.7%	49.2%	48.3%	48.3%	46.5%
36	4963	4997	4799	4261	4129	3997	9147	54.25%	-0.03%	48.95%	52.6%	49.1%	48.2%	48.3%	46.5%
37	4973	5006	4805	4270	4133	4015	9159	54.29%	0.04%	48.99%	52.6%	49.1%	48.3%	48.2%	46.6%
38	4980	5027	4807	4275	4138	4019	9168	54.32%	0.03%	49.02%	52.8%	49.1%	48.3%	48.3%	46.7%
39	4987	5032	4827	4279	4139	4020	9181	54.32%	0.00%	49.02%	52.7%	49.2%	48.3%	48.2%	46.6%
40	4994	5043	4835	4289	4141	4024	9189	54.35%	0.03%	49.05%	52.8%	49.2%	48.4%	48.2%	46.6%
41	4998	5048	4837	4291	4145	4027	9197	54.35%	-0.01%	49.04%	52.8%	49.2%	48.3%	48.2%	46.7%
42	5003	5051	4845	4297	4147	4029	9205	54.34%	0.00%	49.04%	52.8%	49.2%	48.3%	48.2%	46.6%
43	5008	5057	4855	4300	4151	4032	9210	54.38%	0.03%	49.07%	52.8%	49.3%	48.4%	48.3%	46.6%
44	5010	5060	4857	4301	4152	4034	9214	54.37%	0.00%	49.07%	52.8%	49.3%	48.3%	48.2%	46.7%
45	5013	5066	4858	4301	4156	4036	9218	54.38%	0.01%	49.08%	52.8%	49.3%	48.3%	48.3%	46.7%
46	5015	5069	4860	4305	4157	4037	9220	54.39%	0.01%	49.09%	52.8%	49.3%	48.4%	48.3%	46.7%
47	5017	5078	4861	4307	4157	4037	9221	54.41%	0.02%	49.11%	52.9%	49.3%	48.4%	48.2%	46.7%
48	5018	5081	4861	4308	4157	4037	9221	54.42%	0.01%	49.12%	52.9%	49.3%	48.4%	48.2%	46.7%
49	5018	5083	4859	4308	4157	4035	9221	54.42%	0.00%	49.11%	53.0%	49.3%	48.4%	48.2%	46.7%
50	5015	5082	4855	4302	4156	4034	9221	54.39%	-0.03%	49.09%	53.0%	49.3%	48.3%	48.2%	46.6%
51	5013	5075	4854	4302	4155	4031	9221	54.37%	-0.02%	49.06%	52.9%	49.3%	48.3%	48.2%	46.6%
52	5013	5072	4852	4305	4155	4028	9221	54.35%	-0.01%	49.05%	52.9%	49.2%	48.4%	48.2%	46.6%

(b)



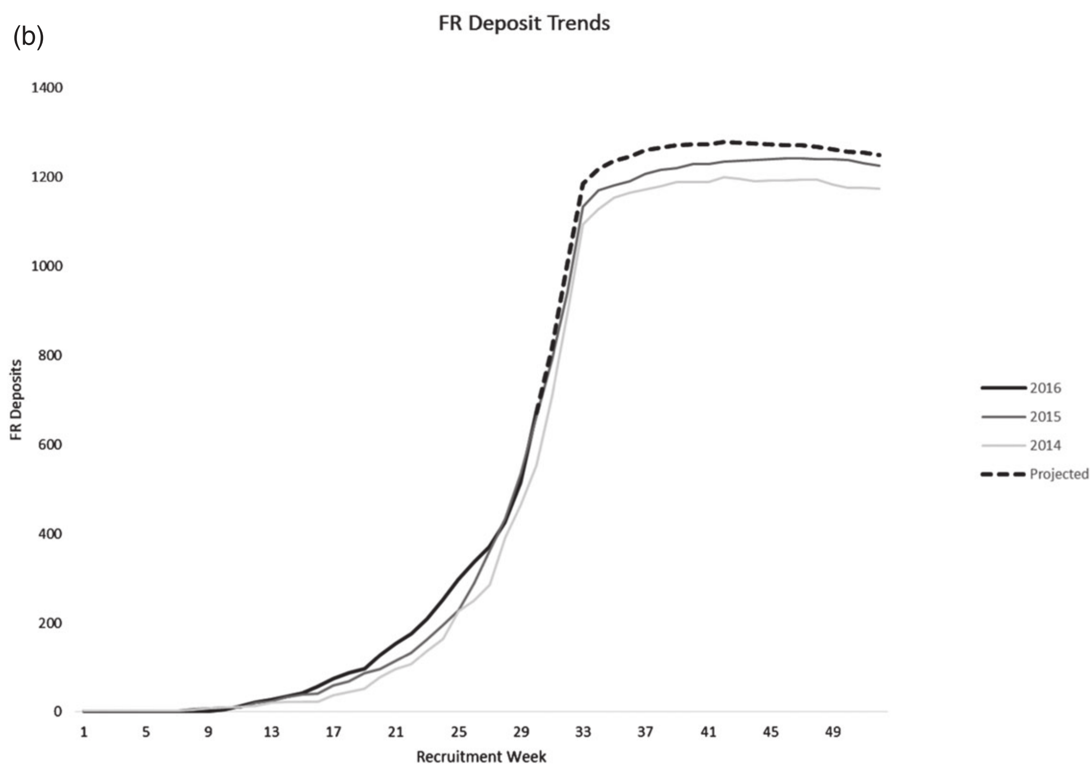
In the example above, week 31's average application-to-admit yield from 2011 to 2015 is 47.86%. That number is then subtracted from the week 30 average to obtain the 0.51% projected increase from week 30 to 31 (47.86% – 47.34%). The 0.51% number is then added to the 2016 actual application-to-admit yield of 52.65% to obtain the projected week 31 application-to-admit yield of 53.17%. Finally, this rate is then applied to the projected number of applicants for week 31 in Figure 1a (9,030) to obtain the projected admitted number of 4,801 for week 31. This process is continued through week 52 to determine that the sample institution is projecting 5,013 admitted students as of week 30. Figure 2b provides a graphical representation of the admitted student projection using the numbers in Figure 2a.

Figure 3. Trend Analysis—Deposit Data

(a)

Wk	2016	2015	2014	2013	Projected Admits	2016	Change	Avg	2015	2014	2013
						Week-to-week Deposit Yield Rate Difference					
30	671	663	554	655	4732	14.18%		14.27%	14.1%	12.8%	16.0%
31	817	790	707	791	4801	17.02%	2.84%	17.11%	16.6%	15.7%	19.1%
32	1005	941	894	981	4854	20.71%	3.69%	20.80%	19.5%	19.5%	23.4%
33	1186	1134	1093	1108	4906	24.18%	3.47%	24.28%	23.1%	23.5%	26.2%
34	1219	1170	1128	1145	4943	24.67%	0.49%	24.76%	23.6%	23.9%	26.9%
35	1236	1182	1155	1160	4960	24.91%	0.24%	25.00%	23.7%	24.1%	27.3%
36	1246	1191	1166	1171	4963	25.11%	0.20%	25.20%	23.8%	24.3%	27.5%
37	1260	1208	1173	1186	4973	25.35%	0.24%	25.44%	24.1%	24.4%	27.8%
38	1267	1216	1180	1191	4980	25.44%	0.09%	25.53%	24.2%	24.6%	27.9%
39	1272	1221	1189	1194	4987	25.51%	0.07%	25.60%	24.3%	24.6%	27.9%
40	1274	1229	1189	1194	4994	25.51%	0.00%	25.60%	24.4%	24.6%	27.8%
41	1274	1230	1190	1192	4998	25.49%	-0.02%	25.58%	24.4%	24.6%	27.8%
42	1280	1235	1200	1195	5003	25.58%	0.09%	25.68%	24.5%	24.8%	27.8%
43	1278	1236	1196	1195	5008	25.53%	-0.05%	25.62%	24.4%	24.6%	27.8%
44	1275	1239	1191	1187	5010	25.44%	-0.09%	25.54%	24.5%	24.5%	27.6%
45	1273	1241	1193	1178	5013	25.39%	-0.05%	25.48%	24.5%	24.6%	27.4%
46	1271	1243	1192	1172	5015	25.33%	-0.06%	25.42%	24.5%	24.5%	27.2%
47	1271	1243	1195	1172	5017	25.33%	0.00%	25.42%	24.5%	24.6%	27.2%
48	1269	1241	1195	1169	5018	25.29%	-0.04%	25.38%	24.4%	24.6%	27.1%
49	1263	1240	1183	1164	5018	25.16%	-0.13%	25.25%	24.4%	24.4%	27.0%
50	1258	1238	1177	1157	5015	25.07%	-0.09%	25.17%	24.4%	24.2%	26.9%
51	1255	1231	1176	1156	5013	25.02%	-0.05%	25.12%	24.3%	24.2%	26.9%
52	1250	1226	1174	1150	5013	24.93%	-0.09%	25.03%	24.2%	24.2%	26.7%

(b)



The third step of the trend analysis model is very similar to the second, but this time the EM manager is calculating an admit-to-deposit yield through week 52. Figure 3a shows how the sample institution calculates its projected number of deposits through the census date. Unlike the previous two examples, deposit yield average is taken over a three-year period rather than over five years. This type of change can be made at the enrollment manager's discretion in the case of a statistical anomaly. In this example, the institution may have embarked on a yield initiative back in 2012 that is skewing the historical yield data, thus throwing the projected data off.

Much like the previous example, average yield rates are calculated and subtracted from the current week's number to establish the historical week-to-week change. That change is then applied to the actual yield rate to determine the projected admit-to-deposit yield through the duration of the recruitment cycle. The projected yield is then applied to the projected number of admits given in Figure 2a. Figure 3b provides a graphical representation of the deposit projection using the numbers in Figure 3a.

The fourth and final step is to apply a deposit-to-matriculation conversion based on historical data. For this example, let's assume the sample institution has a 6.56% historical melt over a three-year period and the 2016 week 52 deposit projection is 1,250. The final projection would be 1 minus melt (0.0656) or 93.44% of 1,250 which would equal 1,168. The enrollment manager can further project FTE of this population by deriving the historical breakdown of full-time and part-time registrations over the same period of time.

In summary, this model projects FR students at the application, admit, and deposit stages through the use of mathematical analysis on a week-by-week trend line. As opposed to the previous trend analysis that was presented, this type of analysis permits the EM leader to assess the admissions funnel weekly. This approach offers the benefit of predicting weekly enrollment progress on a weekly basis rather than at one specific moment in time.

Recommendations

While the processes of predicting the size of an entering class have become much more complex, there are many practical ways that an EM leader can effectively implement successful enrollment projection modeling at an institution. Prior to engaging in the process of enrollment projection, institutions should consider the following:

- There needs to be an early determination of who the "players" will be at the table when developing statistical forecasting models. This should include individuals who are comfortable with, but not limited to, statistical regression, receiver operating characteristic curves, classification tables, and logit transformations.
- An enrollment manager needs to clearly define the goals of forecasting efforts (Lawrence et al., 2006).
- An enrollment manager must make a judgement related to the type of data that will be included in any forecasting model.
- An enrollment manager or the statistical analysis team should have a comprehensive understanding of how to interpret the data and readily apply it to practice.

In conclusion, with increased completion for students, declining demographics in some parts of the nation coupled with declining or flat state appropriations for higher education, today's SEM leaders need to have a keen awareness in how to effectively predict enrollment on their college campus. With overall fiscal operation of any college or university tied directly into tuition revenue, forecasting accurately is essential for accurate budgeting. With rapidly changing student behaviors and greater institutional accountability from both internal and external stakeholders, it is incumbent upon the EM leader to have the skills to shift seamlessly with trends in the marketplace to ensure institutional viability.

References

Armstrong, D. F., & Nunley, C. W. (1981). Enrollment projection within a decision-making framework. *Journal of Higher Education, 52*(3), 295–309.

Arsham, H. (2006). Time-critical decision making for business administration. Retrieved from http://home.ubalt.edu/ntsbarsh/business-stat/statdata/forecast.htm#rcomputeodel

Barr, A., & Turner, S. E. (2013). Expanding enrollments and contracting state budgets: The effect of the great recession on higher education. *Annals of the American Academy of Political and Social Science, 650*(1), 168–193.

Bidwell, A. (2013, December 12). College enrollment falls for second year in a row. *US News & World Report*. Retrieved from http://www.usnews.com/news/articles/2013/12/12/college-enrollment-falls-for-second-year-in-a-row

Brinkman, P. T., & McIntyre, C. (1997). Methods and techniques of enrollment forecasting. *New Directions for Institutional Research, 1997*(93), 67–80.

Caruthers, J. K., & Wentworth, C. L. (1997). Methods and techniques of revenue forecasting. *New Directions for Institutional Research, 1997*(93), 81–93.

Chen, C. K. (2008). An integrated enrollment forecast model. IR Applications: Using Advanced Tools, Techniques, and Methodologies, 15, 1–18.

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly, 36*(4), 1165–1188.

Dolence, M. G. (1998). Strategic enrollment management. In C. Swann & S. E., Henderson (Eds.), *Handbook for the college admissions profession* (pp. 71–91). Washington, DC: Greenwood Press.

Doyle, W. R. (2012). The politics of public college tuition and state financial aid. *Journal of Higher Education, 83*(5), 617–647.

Faherty, V. E. (1997). Using forecasting models to plan for social work education in the next century. *Journal of Social Work Education, 33*(2), 403–411.

Gale, W. G., Harris, B. H., Renaud, B., & Rodihan, K. (2014). Student loans rising. An overview of causes, consequences, and policy options. Washington, DC: Urban Brookings Tax Policy Center.

Goyal, M., & Vohra, R. (2012). Applications of data mining in higher education. *International Journal of Computer Science, 9*(2), 113–120.

Grapevine Report (2016). Table 1: State fiscal support for higher education, by state, fiscal years 2010–11, 2013–14, 2014–15, and 2015–16. In cooperation with the Illinois State University's Center for the Study of Education Policy and the State Higher Education Executive Officers (SHEEO) Retrieved from http://education.illinoisstate.edu/grapevine/Table1_GPV16_Rev_Jan29.pdf

Hayward, C., Hetts, J., Kisker, C. B., Newell, M., Nguyen, A., Nguyen, K … Zentner, A. (2014). Possibilities for improving student success using predictive analytics: Findings from an environmental scan of predictive analytics. (pp. 1–36). Sacramento, CA: The Research and Planning Group for California Community Colleges. Retrieved from http://rpgroup.org/system/files/Predictive%20Analytics%20Environmental%20Scan_FINAL.pdf

Hogarth, R. M., & Makridakis, S. (1981). Forecasting and planning: An evaluation. *Management Science, 27*(2), 115–138.

Hossler, D. (2006). Students and families as revenue: The impact on institutional behaviors. In D. M. Priest & E. P. St. John (Eds.), *Privatization and public universities* (pp. 109–128). Bloomington: Indiana University Press.

Hussar, W. J. & Bailey, T. M (2014). *Projections of education statistics to 2022 (41st Ed.)*. National Center for Educational Statistics. Washington, DC: U. S. Department of Education. Retrieved from http://nces.ed.gov/pubs2014/2014051.pdf

Kahn, H., & Weiner, A. (1967). *The year 2000*. New York, NY: Macmillan.

Lawrence, M., Goodwin, P., O'Connor, M., & Önkal, D. (2006). Judgmental forecasting: A review of progress over the last 25 years. *International Journal of Forecasting, 22*(3), 493–518.

Lins, L. J. (1960). *Methodology of enrollment projections for colleges and universities*. Washington, DC: American Council on Education.

Liu, R. (1998). Short-term enrollment projection: An example at state level. *Education, 118*(4), 597.

Long, B. T. (2014). The financial crisis and college enrollment: How have students and their families responded? In J. R. Brown & C. M. Hoxby (Eds.), *How the financial crisis and Great Recession affected higher education* (pp.175–207). Chicago, IL: University of Chicago Press.

Long, R., Manchir, M., & Hellmann, J. (2015, February 19). U of I; other universities brace for Rauner funding cuts. *Chicago Tribune.* Retrieved from http://www.chicagotribune.com/news/local/politics/ct-rauner-budget-higher-education-met-0220-20150219-story.html

Lovenheim, M. F. (2011). The effect of liquid housing wealth on college enrollment. *Journal of Labor Economics, 29*(4), 741–771.

Lovenheim, M. F., & Owens, E. G. (2014). Does federal financial aid affect college enrollment? Evidence from drug offenders and the Higher Education Act of 1998. *Journal of Urban Economics, 81*(0), 1–13.

Mathewson, T. G. (2015, December 30). *5 higher ed trends to watch in 2016*. [Web log post] Education Dive. Retrieved from: http://www.educationdive.com/news/5-higher-ed-trends-to-watch-in-2016/411362/

McDonald, M. (2014, April 14). Small U.S. colleges battle death spiral as enrollment drops. *Bloomberg*. Retrieved from http://www.bloomberg.com/news/articles/2014-04-14/small-u-s-colleges-battle-death-spiral-as-enrollment-drops

Mitchell, M., & Leachman, M. (2015). *Years of cuts threaten to put college out of reach for more students.* Washington, DC: Center on Budget and Policy Priorities. Retrieved from http://www.cbpp.org/sites/default/files/atoms/files/5-13-sfp.pdf

National Student Clearinghouse Research Center. (2015). *REPORT: Current term enrollment estimates—Spring 2015* [Data file]. Retrieved from https://nscresearchcenter.org/wp-content/uploads/CurrentTermEnrollment-Spring2015.pdf

Oliff, P., Palacios, V., Johnson, I., & Leachman, M. (2013). Recent deep state higher education cuts may harm students and the economy for years to come [White Paper]. Washington, DC: Center on Budget and Policy Priorities. Retrieved from http://www.cbpp.org/files/3-19-13sfp.pdf

Ozgur, C., Kleckner M., & Li, Y. (2015). Selection of statistical software for solving big data problems. *SAGE Open, 5*(2), 1–12.

Pucciarelli, F., & Kaplan, A. (in press). Competition and strategy in higher education: Managing complexity and uncertainty. *Business Horizons*.

Russom, P. (2011). *Big data analytics*. TDWI Best Practices report, 4th Quarter.

Sagiroglu, S. & Sinanc, D. (2013, May). Big data: A review. In *Collaboration Technologies and Systems (CTS'13)*, 2013 International Conference on Collaboration Technologies and Systems (pp. 42–47). San Diego, CA:IEEE.

Tandberg, D. A., & Ness, E. C. (2011). State Capital Expenditures for Higher Education: "Where the real politics happens". *Journal of Education Finance, 36*(4), 394–423.

Thorson, G. R. (2014). *Why have Americans lost faith in their schools? Declining public support for the American educational system and its policy implications*. Paper presented at the 2014 Annual Meeting of the American Political Science Association, Washington, D. C.

Wagner, E. & Hartman, J. (2013). *Welcome to the era of big data and predictive analytics in higher education* [PowerPoint Slides]. Retrieved from http://www.sheeo.org/sites/default/files/0808-1430-plen.pdf

Ward, J. (2007). Forecasting enrollment to achieve institutional goals. *College and University, 83*(3), 41.

Weeden, D. (2015, January 4). *2015 higher education legislation review* [Web log post]. Retrieved from: http://www.ncsl.org/blog/2016/01/04/2015-higher-education-legislation-review.aspx

Wexler, E. (2016, January 25). State support on the rise. Inside Higher Education [Web Periodical]. Retrieved from: https://www.insidehighered.com/news/2016/01/25/state-support-higher-education-rises-41-percent-2016

Zumeta, W. (2010). The great recession: Implications for higher education. In *NEA 2010 almanac of higher education* (pp. 29–42). Washington, DC: National Education Association.

Randall Langston serves as the Assistant Vice President for Enrollment Management at the College of Brockport – State University of New York where he provides leadership to the Admissions, Financial Aid, Registration & Records, and the Academic Advisement areas within the Enrollment Management and Student Affairs division. In his role at Brockport, Randall is responsible for initiating strategic high level discussion surrounding campus wide enrollment management issues, preparing enrollment and revenue projections collaboratively with other departments on campus, interpreting predictive modeling, and collaborating on institutional financial aid leveraging strategy for new and continuing students. Randall earned a bachelor's degree in 1994 from Sam Houston State University (TX) and a master's degree from Texas Tech University in 1995.

Robert Wyant is an Associate Director of Admissions in the Office of Undergraduate Admissions at The College at Brockport–State University of New York. He is a member of the Undergraduate Admissions senior leadership team and provides forecasting data and other weekly enrollment reports to campus administration. He earned a bachelor's degree in Business from the University of Pittsburgh in 2006 and a master's degree in higher education and enrollment management from Walden University in 2014.

Jamie Scheid is an Enrollment Analyst in the Office of Research, Analysis and Planning at The College at Brockport – State University of New York. He is involved with analyzing data related to recruitment and retention and has extensive experience with financial aid leveraging and predictive modeling. He earned a bachelor's degree in mathematics from Cedarville University in 2001 and a master's degree in applied statistics from Rochester Institute of Technology in 2005.