SEAMLESS INTEGRATION OF PREDICTIVE ANALYTICS AND CRM WITHIN AN UNDERGRADUATE ADMISSIONS RECRUITMENT AND MARKETING PLAN

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The field of strategic enrollment management has become increasingly invested in data-informed practices. In 2015, The College at Brockport, State University of New York implemented a recruitment strategy that incorporated both predictive analytics and customer relationship management (CRM) technology. This effort both reduced budget expenditures and yielded the largest incoming first-year cohort in over 30 years. A step-by-step pragmatic approach is introduced to allow key enrollment management leaders the ability to understand how to seamlessly integrate statistical modeling with constituent relationship marketing platforms. By providing key components related to design, development procedures for statistical model development, and outcomes, SEM managers can utilize the knowledge gained from this primer in their SEM efforts.

Introduction

Today's strategic enrollment management (SEM) leaders face many issues where they are compelled to manage on a daily basis. Perhaps none of these matters are more important than that of recruiting students to their college or university. While recruitment is a key element for any SEM planning process (Hossler, 1990; Hossler & Kalsbeek, 2013), skilled EM leaders are being driven to consider new and innovative ways to cultivate and retain high-academic-achieving and diverse students to their college campuses. But achieving this involves the ability to successfully carry out complicated

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and multifaceted EM plans in an attempt to compete for students in a very competitive marketplace. Modern enrollment management (EM) processes are often described as complex (Di Maria, 2015; Robinson, 2013), quantitative, and empirical (DesJardins, Ahlburg, & McCall, 2006), encompassing strategic initiatives that involve deliberative planning processes (Bejou & Bejou, 2016), and integrating communication mechanisms in order to connect with prospective students (Bontrager, 2004). But, according to a 2013 poll by Noel-Levitz, despite lofty goals that colleges have in implementing strategic multiyear enrollment plans, just one-third of respondents reported that they believed their SEM plan was of high quality. More concerning is that there appear to be substantial gaps in higher education surrounding the use and practice of quantitative analytics among staff. According to Norris and Baer (2013), a "significant analytics capacity gap exists in higher education, encompassing all of the elements of analytics capacity—technology, processes/practices, skilled people, culture/behaviors, and leadership" (p. 43).

Gone are the days where a skilled admissions professional could develop a recruitment plan and implement it effectively with minimal training and expertise. Contemporary enrollment management (EM) leaders thrive in data-driven environments where concepts like econometrics (Brinkman & McIntyre, 1997; Brooks, 1996), elasticity of demand (Curs & Singell, 2010; DesJardins & Bell, 2006), tuition discounting (Hillman, 2012), technology (Dennis, 1998, p. 23; Penn, 1999, p. ix), data mining (Goyal & Vohra, 2012; Kabakchieva, 2013; Linoff & Berry, 2011; Yu, DiGangi, Jannasch-Pennell, & Kaprolet, 2010), constituent relationship marketing, and predictive analytics have replaced old scattershot approaches with rudimentary aims and objectives. Dolence (1998) noted that dependable EM plans must comprise 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). As the College of Brockport embarked on our own complex EM planning, Dolence's lessons assisted as we sought to craft and develop a very strategic SEM approach to customer relationship management (CRM) communication development and integration with predictive modeling. Ultimately, it was Dolence's reasoning that served as a foundation for our planning process and implementation stages. As we developed a plan of action for successful implementation of predictive modeling and CRM, we were especially mindful of the student recruitment life cycle. From prospect to inquiry, to applicant, to admitted, to enrolled, these steps in the process were foremost in our minds. Following the student recruitment life cycle served as the overarching blueprint for our initial steps into this integration process.

This study seeks to inform the reader on backgrounds associated with predictive analytics and CRM and share insights related to how one college set out to integrate these two conceptual pieces into an enrollment management plan. Specific steps for implementation are discussed, and outcomes associated with the execution of this approach are described.

Predictive Modeling

In order to arrive at an ideal state of enrollment (based on institutional goals), the College at Brockport determined that investing in two key areas was essential. These included predictive modeling and a CRM platform. The purpose of placing resources in both of these initiatives was to seamlessly connect these two processes in a way that mutually benefited our recruitment as well as communication goals and statistical planning objectives. Predictive modeling as a practice is typically outsourced to third-party consulting firms most often due to resources, as many colleges do not have the staff with in-depth knowledge of statistical modeling or the time to engage in deep analytical assessment of predictor variables and regression models. However, at Brockport, the assistant vice president for enrollment management (AVP-EM) and an enrollment analyst in institutional research were both skilled in this area and thus eliminated a probable six-figure investment associated with having an outside company develop models for the college.

Predictive modeling, while highly quantitative, is a terrific way to utilize empirical data and mathematical analysis in a way that better encapsulates past and current student behavior. Predictive modeling essentially utilizes statistical methodology to provide a better understanding of enrollment behavior of students. By looking back longitudinally, one is able to more effectively discern those variables or parameters that predict student behavior. Predictive modeling is utilized within enrollment management for a number of reasons, including (a) strategic (enrolling a class, shaping a class, perhaps you want to use population segmentation [geographic, by academic ability]); (b) budget (drive down marketing costs); and (c) to demonstrate mathematically and empirically effective ways to implement a data-driven culture of evidence at your institution. Goenner and Pauls (2006) defined "predictive modeling [as] analyz[ing] past data to make future predictions, or in econometric terms, data is analyzed to estimate a model which is used to make out of sample predictions" (p. 936). Deloitte (2010) describes this as predictive modeling, which can be defined as the analysis of "large data sets to make inferences or identify meaningful relationships, and the use of these relationships to better predict future events" (p. 4). Typical variables that colleges and universities use for predictive modeling include but are not limited to (a) campus visit, (b) geography, (c) major interest, (d) SAT/ACT scores, and (e) student contact.

One way to make sense of complex, multilayered data (that often encompasses multiple cohorts) was through a predictive modeling process. For this effort, Brockport utilized a wide array of data points and examined past-year cohorts to determine the effectiveness of the model that was implemented in any particular given year. By examining data in the past (i.e., past-year enrollment data) the researcher now had the luxury of already knowing who had deposited and matriculated those years at the college. Therefore, we were able to successfully test numerous factors we believed may have been influential on student enrollment (i.e., GPA, SAT/ACT score, major interest, campus visit, and distance from campus), where we could learn immediately if these were predictor-independent variables for the dependent variable, enrollment. Once we were able to ascertain the statistical validity of these variables, we then applied variables for the current class of students and ascertained a predictive likelihood score for each student. In the case of this model development, we held off on implementing full-scale development until after January to fully access financial aid data because early modeling demonstrated that financial aid was a significant moderating variable that predicts enrollment. For the entering classes of 2015 and 2016 financial aid data were not available until after January, and we recognized that utilizing the data that we had minus financial aid data would significantly weaken our initial model. Therefore, we held on implementing the model until after December to incorporate these integral data.

When discussing predictive modeling, often statistical terminology and application surrounding a concept called regression is considered. There are different types of regression, but our research and work involved logistic regression. To better make meaning quantitatively of the data we were receiving, we chose to implement a logistic regression model. Logistic regression is a commonly utilized statistical approach that "provides a method for modeling a binary response variable, which takes values 1 and 0" (Bewick, Cheek, & Ball, 2005, p. 112). Logistic regression is "best suited for describing and testing hypotheses about relationships between a categorical outcome variable and one or more categorical or continuous predictor variables" (Peng, Lee, & Ingersoll, 2002, p. 4). In the case of our research, we examined linear relationships between a dependent variable (enrollment) with numerous independent variables (Harrell, 2015). Least squares regression was also utilized in an attempt to minimize errors due to the possibility of independent parameters not fitting into the equation. By utilizing least squares calculation, the value of a dependent variable Y based on the value of independent variable X can occur. This then permitted the ability to determine a coefficient of determination, commonly referred to as an R-squared (R^2). Coefficient of determination is defined as the "proportion of the variance in the dependent variable that is predictable from the independent variable" (Nassif, Capretz, & Ho, 2012, p. 2). R^2 is also delineated as "that proportion of the total variability in the dependent variable that is accounted for by the regression equation in the independent variable(s)" (Hahn, 1973, p. 609). R^2 ranges from 0 to 1 ($0 \leq R^2 \leq 1$). An R^2 of 0 means that the dependent variable cannot be predicted from the independent variable, whereas an R^2 of 1 means the dependent variable can be predicted without error from the independent variable. An R^2

between 0 and 1 indicates the extent to which the dependent variable is predictable. An R^2 of 0.10 means that 10% of the variance in Y is predictable from X; an R^2 of 0.20 means that 20% is predictable; and so on. This type of statistical analysis was invaluable to us as we started to understand and make meaning of the data.

Relationship Management and Marketing

Before one can speak about CRM, one must consider the concept of relationship marketing. The modern concept of CRM is thought to have evolved from relationship marketing (Hung, Hung, Tsai, & Jiang, 2010; Rababah, Mohd, & Ibrahim, 2011; Wu & Wu, 2005). The concepts surrounding constituent relationship management and marketing in higher education were adapted first from the business and information technology vendor community in the mid-1990s (Payne & Frow, 2005). Relationship marketing postulates that some customers are more profitable than others (Berry, 1995). Berry (1995) noted that there are cost investments associated with relationship marketing and that there are phases associated with the recruitment of individuals to a particular brand, which includes an "attracting phase" and a "maintaining and enhancing phase" (p. 239). By targeting customers that benefit from your product, the seller of a good or service is able to more readily identify customers who would are likely to be loyal to a particular brand (Berry, 1995, p. 239). Attracting loyal customers is a process by which a company attempts to determine ways to attract and retain those individuals who are particularly attracted to the brand and simultaneously develop other approaches to create value-oriented statements that mitigate losses of those customers who are apt to consider other brands.

While relationship marketing is easily applied to business and industry, its core assumptions are equally important and applicable to higher education and enrollment management. Just as customers are to business, students are to colleges and universities. Ackerman and Schibrowsky (2008) note that relationship marketing is applicable in higher education just as in business as the fundamental tenets of a "relationship" between school and student are based on trust and commitment (pp. 320–321). After students are enrolled at a college, the school's commitment to them as well as an intrinsic trust helps facilitate student retention and loyalty. In fact, Vianden and Barlow (2014) comment that "students who develop positive attitudes or emotions towards their institution are more likely to persist and graduate than their peers who do not connect with their college or university on an emotional level" (p. 16). It is these connection emotions that serve as the glue that adheres the student to a particular college or university.

But if one rewinds back to the initial stages of student recruitment and cultivation, it is not difficult to apply trust and commitment themes to the college search process for the student. Most colleges and universities have complex communication plans in place that seek to do exactly what business pursues in its customers—build brand loyalty and cultivate those students who are "on the fence" or considering other colleges. It is often the student (and family) who is looking to develop trust in the school (through information gathering on the internet, e-mail messages, social media, physical marketing materials). This trust is further deepened when the student first receives a positive affirmation of enrollment and visits the campus. If schools are able then to parlay authentic marketing messages along with an experience to match, this equates to success for the college or university.

Customer Relationship Management (CRM)

One significant way to incorporate technology into an EM plan is through the use of a CRM. First "developed in the middle of the 1990s in information technology" (Rababah et al., 2011, p. 220), CRM has been described as the "process of attracting and retaining profitable customers" (Ackerman & Schibrowsky, 2008, p. 321). However, appealing to students is but one part of the utility of CRM. Today's CRM also serves to cultivate students through the admissions and funnel where the developer of the communication plan designs messages that attract and keep prospective students captivated in the institution over a long time frame.

Utilization of CRM, according to Shani and Chalasani (2013), are described as a process where there is an "integrated effort to identify, maintain, and build up a network with individual consumers and to continuously strengthen the network for the mutual benefit of both sides, through interactive, individualized, and value-added contacts over a long period of time" (p. 44). CRM is readily differentiated from e-mailing in that the system is programmed by the user (the college), is often automated, and is designed to communicate to multiple student cohorts (i.e., inquiries into the school, applicants, and deposited students). High-performing CRM effectively links front office (marketing and customer service) with back office (strategic operations, logistics, implementation processes) into deliberately planned touch points with prospective students (Chen & Popovich, 2003; Fickel, 1999).

Despite the popularity of CRM at colleges and universities nationwide, use and implementation of CRM in higher education has never been a simple and easy process. According to a study carried out in 2014 by the American Association of Collegiate Registrars and Admissions Officers (AACRAO), which described the state of CRM use in higher education, research discovered that 64% of colleges and universities nationwide utilize at least one CRM, but major impediments to implementation such as the learning curve among employees to master the system remain barriers toward full integration of such communications systems (Kilgore & Bloom, 2014). This same report indicated that 75% of colleges report that their school is not maximizing the use of their CRM (Kilgore & Bloom, 2014). Another study by Hanover Research in 2014 described how colleges appear to be relying more heavily on CRM for outreach to students, but implementation of a CRM does not always equate to success (p. 6).

CRM has revolutionized the process of personalizing contact with students in a way that is dynamic (Park & Kim, 2003) and strategic. Bligh and Turk (2004) noted that CRM needs to be seen not as just a technology initiative, but instead approached strategically (p. 5). Messaging to prospective students can now be tailored with different messages for different cohorts. Further, colleges can track or drill down within e-mails in order to determine, for example, how many students opened the e-mails or clicked on a particular embedded link. This is important because the mechanisms that schools now interface with students are much more technological and predicated in developing numerous messages for specific populations. Antiquated one-size-fits-all approaches have been rapidly replaced by high-tech CRM that is now fully automated, can be effectively programmed to identify student cohorts, and immediately send communication to these individuals at the stroke of a key. While messaging and outreach are important, they leave out one key component: linking CRM and predictive analytics into one seamless strategic procedure. Guided by a goal to effectively combine the messaging (driven by past historical data connected with yield conversion, student interest and "intent" for student matriculation into the college), significant strides at Brockport were made in realizing these goals over the past few years. In 2014–2015, Brockport set out to purposefully integrate predictive modeling with the CRM in a meaningful and substantial way to better communicate both electronically (CRM) and in print with prospective students and their families. Within this process, CRM was recognized as a leveraging opportunity to scale down significant investments in marketing (print) and rapidly transition to a more economical path (electronically) while communicating in a purposeful and targeted way to prospective students.

PROGRAM OBJECTIVES

The program objectives developed for our CRM/predictive modeling integration were predicated upon a strategic need to better understand existing institutional data. Essentially, Brockport was both focusing on expanding the enrollment funnel and seamlessly connecting predictive analytics at the inquiry and admit stage of the funnel to the technology already implemented by way of a CRM. Therefore, the program objectives were clear: (a) make full use of the existing CRM in a much more dynamic way; (b) develop credible predictive modeling at the lead, application, and admission to deposit stages of the admissions funnel; (c) successfully integrate both elements into a comprehensive strategic initiative that drew on the mathematical (data-driven environment) and the human side of personalizing (providing exemplary customer service); and (d) drive down overall administrative costs associated with a "one-size-fits all approach to marketing the college. With over 12,000 applicants, trying to reach out and meaningfully personalize the college experience with every student applicant was beyond program resources. However, the predictive modeling approach allowed Brockport to take the data or variables that predicted ultimate student enrollment and apply this to current student applicants. By drilling down to an individual level, the true likelihood for student enrollment at the college could be revealed for the first time. Once student likelihood was ascertained, the integration of CRM at the individual college admissions counselor level was a natural evolution and represented a significant leap in the way Brockport could reach out and cultivate student interest from inquiry to applicant, to deposit, to matriculation.

PROGRAM DESIGN

Armed with experience in both CRM development and predictive modeling, the college set out to design a plan that would effectively integrate mathematics with communication and outreach. The design for creating a statistical model for predictive analytics and further integrating with a CRM platform were therefore purposeful and deliberate. In 2015, Brockport implemented two predictive models for two different student cohorts. These cohorts included (a) first-year applicants seeking admission for fall 2015 and (b) leads with an entering class designation of fall 2016.

COLLABORATIVE OUTREACH WITH OPERATING UNITS AT COLLEGE

Early in the planning process within the Enrollment Management division, Brockport recognized a need to assemble a team cross-divisionally to assist in developing accurate statistical models. Therefore, the following departments took part in this collaborative effort: Undergraduate Admissions, Institutional Research and Planning, and Information Technology. Each of these offices played a critical role in data integrity. To achieve core objectives of this program, each office was identified as a key stakeholder in the ownership of our big data as well as the gatekeepers of such issues as security and flow (data extraction) of the information.

DEVELOPMENT OF FIRST STATISTICAL MODEL

The first statistical model was developed in-house in the spring of 2015. This model was designed to measure application-to-enrollment likelihood among fall 2015 first-year students. Data extraction, assessment, interfacing between the predictive model score and the CRM, all coding, and dissemination to admissions staff was managed by the assistant director of admissions. The tactical implementation of the yield strategy was carried out by admissions representatives. Further data interpretation as well as strategies to deploy the data in a meaningful way were managed by senior admissions staff.

A statistical binary probit model was developed, which utilized linear regression with the objective to essentially tease out those variables most likely to have an impact on a student's ultimate enrollment at the college. Binary probit models "estimate the effect of a particular variable of interest on a binary outcome when potentially confounding variables are controlled" (Karlson, Holm, & Breen, 2012, p. 287). By examining variables individually and determining the relative strength of the parameters, we were then able to develop a model that utilized a dependent variable (enrollment) with numerous independent variables (i.e., visited campus, major, etc.). Output from the modeling was demarcated on a scale from 0 to 1, where 0 represented a student who had statistically no probability to attend, and 1 where a student, no matter what marketing interventions occurred, would likely come to the college. Based on prior statistical modeling, when viewed on a normal curve, there was a natural bell-shaped curve that illustrated where students who have high modeling scores were much more likely to attend the college than students who had lower predictive modeling scores. This was not entirely surprising, but it served to validate our resolve to attempt to move students from the left side (least likely to attend) of the normal curve to the right side of the normal distribution (more likely to attend). However, this approach left some crucial questions unanswered. Do we focus on students with low predictive modeling scores and try to move them to the middle of the normal curve? Or do we attempt to keep the higher predictive modeling scored students as our VIP group? In the end, a determination was made to attempt to move all those students with moderately high scores into the higher scoring areas (tiers) of the model when we rescored. In other words, we understood that low scoring students were unlikely to attend no matter what efforts we put into the recruitment cycle. Conversely, those students who scored very high were likely to attend even if we were to reduce our print and electronic communications. Therefore, we focused exclusively on students in the middle where we had a greater opportunity to influence and move them to a higher predictive modeling score. After our first scoring, we found that there was significant skewing to the left side of the normal distribution and in order to attain symmetry (50% distribution on the right side of the normal curve and 50% on the left side of the normal curve) it was essential to engage in specific interventions through CRM as one vehicle to influence students.

However, defining students as having scores in the 0 to 1 range is problematic for admissions recruitment staff. For example, what is the relative difference between 0.207 and 0.0207? Mathematically, of course, there is a significant difference between these numbers, but for admissions staff, understanding who they were to contact would be more readily understood by defining the numerical ranges of each category and letting staff simply contact students within their "bucket." To better equip admissions staff, project planners employed a simple categorical system that described the scores by quartile. For example, students with the least likelihood to attend the college were defined as category D or those students from .0001 to .01, students in category C had scores between .0101 and .032, students in category B fell within a range of .0321 to .0999, and, finally, those students between .10 and .9605 were coded in category A. We then placed the actual counts of students in each of these categories so that they were distributed relatively uniformly. Once the students were coded with scores, they were uploaded into the CRM for more targeted recruitment efforts. Within the CRM, reporting dashboards were developed for staff and supervisors, and new system views (dashboards) were created to display the scores on each student record. Table 1 illustrates how advisors could click on the link in any of their score categories to generate a contact list of students who met those criteria. Each staff member had unfettered access to their dashboard and could interface with the predictive model score categories through a simple point and click. This action then called up all of their applicants by model score, and aggressive personalized communication approaches could be taken by each individual counselor. Pragmatically, this approach was far superior to past ways of contacting students through nonstrategic scattershot means.

In Table 1, the predictive model scores are also represented on an individual contact screen, so when an advisor was working with a prospective student, they had immediate access to their scores and likelihood to attend the college. With over 6,000 accepted first-year students and an office of 12 advisors, our outreach needed to be targeted. Students in category A were prioritized for immediate phone call outreach, while categories B through D received personalized e-mails from their advisor. Once the advisors had completed calls to all category A students, they successively moved on to categories B through D and beyond depending on their recruitment region.

Table 1. Dashboard Report

Assigned Staff	Predictive Model Score Category A	Predictive Model Score Category B	Predictive Model Score Category C	Predictive Model Score Category D
Counselor A	72	201	224	118
Counselor B	164	122	105	75
Counselor C	97	79	75	55
Counselor D	70	40	33	29
Counselor E	109	70	30	33
Counselor F	94	118	102	88
Counselor G	278	196	76	65

Table 2 illustrates the main independent variables utilized within the logistic regression model that were used to best describe the dependent variable being that of enrolled.

Specifically, each of the variables used in the logistic regression model are explained in greater detail below:

1. *Personicx Segmentation Cluster (XCLUST).* This variable is made up of several factors within the appended Acxiom data. The clusters represent a combination of Net Worth, Income, Geographic Type (Urban, Suburban/Towns, Rural). Clusters break U.S. households into one of 70 clusters within 21 life stage groups based on specific consumer behavior and demographic characteristics.
2. *Student County Code (XCNTY2).* County where student resides.
3. *Academic Interest or Major (Y-MAJOR)*. Major of interest selected by student when providing their contact information to NRCCUA (name purchasing vendor) via their My College Options Survey.
4. *Mid-Sized City Preference (COLCH_MIDSZECITY).* Via the NRCCUA survey, students who identified the type of city/town they preferred for college/university surrounding.
5. *Campus Environment Preference (YENVIR).* Students can select a preference of "Conservative," "Moderate," or "Liberal." This does not represent political leanings, but more so the policies in place regarding student behavior, housing, etc.
6. *Household Setting Type (XSETTYP).* Household setting would identify the surroundings of a student's "home" as being urban, rural, or suburban.
7. Student Zip Code (YZIPCD). Student home zip.
8. *General College Prep Flag (PREP_GENRLPREP).* Students identifying whether they take a general college prep curriculum in high school.

Table 2. Variables Used in the Logistic Regression Model Predicting Enrollment

Variable	Description
XCLUST	Personicx Segmentation Cluster
XCNTY2	Student County Code
YMAJOR	Academic Interest or Major
COLCH_MIDSZECITY	Mid-Sized City Preference Flag
YENVIR	Campus Environment Preference
XSETTYP	Household Setting Type
YZIPCD	Student Zip Code
PREP_GENRLPREP	General College Prep Flag

A second model (Table 3) was developed in the summer of 2015 in conjunction with an enrollment consulting firm. This model comprised (a) 3 years of campus enrollment data, (b) survey data from the National Research Center for College and University Admissions (NRCCUA), and (c) third-party demographic and behavioral data and was developed to help guide our class of 2016 name purchase and through quantifiably measured lead-enrollment likelihood. Numerous variables were tested in the model, and in Table 2 the most predictive are illustrated and explained. This predictive model score was applied against the entire NRCCUA student database, scoring each candidate on their likelihood to enroll at the college. Using this model, we were then able to strategically purchase student names that had a better than average likelihood of actually attending the college. Once the names were obtained we statistically were able to gauge the strength of our model. Table 2 illustrates the logistic regression coefficients, standard errors, *t*-stats, *p*-values, and strengths of each variable. Relative strength was determined by the absolute value of the *t*-statistics of the model. This was computed by dividing a variable's *t*-stat by the sum of all of them. Therefore, the relative strength of the Personix Cluster (XCLUST) at 18.6% indicates that this variable is a strong predictor for student enrollment. The strength of the variables gradually is reduced for other variables such as county and major, but the key takeaway from this exercise was that there were at least five significant variables that, when applied to student data, are statistically more likely to predict student enrollment.

Students and scores were again uploaded into the CRM to further drive population segmentation within our communication strategy. All prospective students received a digital communication plan. However, students with a score of 0.6 or higher received up to three additional printed marketing brochures to supplement

Table 3. Logistic Regression Coefficients, Standard Errors, *t*-Stats, *p*-values and strengths of each variable					
Variable	**Coefficient**	**Standard Error**	***t*-stat**	***p*-value = Pr(>|z|)**	**Strengths**
Intercept	6.261965877	0.917768811	–6.823	0.000	
XCLUST	61.62192171	11.00580397	5.599	0.000	18.6%
XCNTY2	33.76279471	6.882609434	4.906	0.000	16.3%
YMAJOR	0.296447238	6.87E-02	4.315	0.000	14.3%
COLCH_MIDSZECITY	0.554978429	0.140223635	3.958	0.000	13.1%
YENVIR	1.309155358	0.411013361	3.185	0.001	10.6%
XSETTYP	77.11289633	23.91652544	3.224	0.001	10.7%
YZIPCD	0.043302641	0.017324702	2.499	0.012	8.3%
PREP_GENRLPREP	0.375480519	0.150908021	2.488	0.013	8.2%

their digital plan. We continued to use these scores throughout the admission cycle. Event invitations, physical mailings, phone calls, text messages, and other direct marketing were largely driven by the predictive model scores as well as their engagement with our office.

EFFECTIVENESS OF PROGRAM IMPLEMENTATION

The most significant areas of improvement with implementation of this strategy was twofold: bringing in a record class of 2015 first-year students, and a realization of significant savings in our recruitment budget for the 2015–2016 fiscal year.

For the Entering Class in Fall 2015

In 2015, our initial foray into predictive modeling–CRM integration strategy, adoption among the 12 members of our admissions team was strong. Using the dashboard reports in the CRM, supervisors regularly followed up with their team to ensure that students were contacted in the prescribed fashion and time frame. Further, the model was effective at predicting enrollment likelihood of first-year applicants and assisted us in actively segmenting and prioritizing personal outreach throughout the spring yield season. The scores were applied to 6,636 freshman applicants.

For the Entering Class in Fall 2016

Under the theory that we could purchase fewer names at a higher chance of enrollment, this ultimately paid significant dividends for our office. Using the enrollment management consulting firm's predictive model, we were able to successfully reduce overall expenditures on our class of 2016 name purchase by 33.3%. By leveraging the scores to drive our direct mail strategy, we realized savings of over $50,000 in printing and postage of marketing materials, which represented a 40% decrease in costs as compared to the previous year. In 2016, we were further able to decrease our cost of recruitment by $60 per deposited student from 2015. The return on investment (ROI) increased by 12.4% from 2015 to 2016, which represented an increase of approximately $1 million in net tuition revenue for the college. From an operational perspective, the program has been a successful recruitment strategy with the Enrollment Management division. While final enrollment data won't be available until September, our preliminary analysis indicates that we are exceptionally well positioned with respect to the first-year class to substantially exceed budgeted goal.

OUTCOMES

When the effectiveness of the program was assessed, we were gratified to see that all of the planning and hard work by numerous constituencies at the college paid significant dividends. Our efforts to seamlessly connect predictive modeling and CRM were very successful, and, as a result, we were pleased to welcome the largest class of first-year students in over 30 years to the college this past fall while increasing both diversity and academic quality! In every score category, our enrollment yield exceeded the predicted rates, most notably in categories B and C (see Table 4).

This demonstrated that by curtailing major investments in print materials and segmenting messaging to students who mathematically had a greater likelihood to attend Brockport was successful. In 2015, we discovered that when we initially scored admitted students, in March of that year, 75% of the students who had deposited were in category A, 15% in category B, 10% in category C, and 0% in category D. As we increased CRM messaging and targeted print materials of varying intensity after March, our final enrollment effectively expanded deposits in categories B and C, which was a desired outcome. Admissions outcomes demonstrated that category A students ultimately encompassed 56% of final enrollment, 28% of enrollment in category B, 14% in category C, and 2% in category D.

Another significant outcome related to overall college retention efforts that the college has been involved with. A 2013 white paper by Eduventures found that implementation of predictive analytics as related to a data-driven decision-making culture at a college or university yielded numerous positive outcomes including an improved retention rate (p. 4). Indeed, we have experienced an increase in student retention as this number effectively increased from 81.9% in fall 2014 to 82.5% or a net gain of 52 students in the first-year class alone.

Conclusion and Implications for Practice

This research study sought to identify approaches associated with the successful adoption of predictive analytics and CRM within the higher education industry. Predictive modeling and CRM, when used at colleges and universities, have been documented to achieve success in overall enrollment management efforts (Campanelli, 2007; Fredette, 2013; Mokhtarian, 2013; Oguntoyinbo, 2015). However, it is critical for higher education institutions to consider a planning process if there is an aspiration to integrate CRM and predictive analytics. For future planners, it is recommended that teams of individuals (or key decision makers) gather to methodically plan out how they would utilize CRM and predictive modeling, set a timetable to implement these facets of EM, and then determine how to effect a successful seamless integration between these two quantitative and technological tools.

The implications for practice are numerous and include recommendations that can be applied to any enrollment management operation large or small. Our research and strategic planning, along with razor-focused implementation was invaluable in our success. Through the process we learned that successful integration and application of predictive modeling and CRM relies on the expertise of numerous individuals often dispersed throughout the campus. Creating a data-driven culture is never an easy task, but with dedicated staff, credible data, a strong implementation plan, and a road map for success, this can be accomplished at any college or university. By expanding the current research related to SEM and predictive modeling as well as integration with CRM, we hope that this will continue to generate discussion on these important concepts. By better understanding the capabilities of CRM when combined with quantitative approaches toward SEM, this places EM professionals in a much better position to not only better understand their students but also more effectively determine their enrollment behavior from prospect to matriculation. Ultimately, enrollment behavior is not an exact science, but through the use of quantitative data analysis and with skilled professionals, practitioners in EM are in a much better position to both better understand their students and ultimately yield a strong entering class.

Table 4. Application to Enroll Yield

Application Score Category	Application	Admit	Enroll	Predicted Application-to-Enroll Yield	Actual Application-to-Enroll Yield
A	1,610	1,526	531	31.8%	32.9%
B	1,725	1,542	260	5.8%	15.0%
C	1,599	1,196	132	1.9%	8.2%
D	1,702	190	19	0.3%	1.1%
Total	6,636	4,454	942	9.8%	14.1%

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