Journal of Strategic Management Education 14: 37-60.

Analytics Driven Management Education

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Abstract. Management education has come a long way since Sir Isaac Pitman initiated the first correspondence course in the early 1840's. Nevertheless, the business school universe continues to evolve due to the ongoing impacts of globalization, new learning technologies, changing demographics, and unprecedented economic uncertainty. To that end, the increasing use of analytics in business to improve efficiency and performance suggests that similar possibilities exist for schools of business. Specifically, analytics holds considerable promise for enhancing student recruitment and retention, student learning outcomes and employment opportunities, and institutional efficiencies. The purpose of this article is to highlight best practices in the use of analytics throughout the management education community of practice.

Keywords: Learning analytics, educational data mining, academic analytics, management education, student success, employment opportunities, student recruitment and retention.

1. Introduction

Management education has entered a seminal period that is being driven by competition, globalization, economic uncertainty, demographics, and technology. Speed and agility, which are two key characteristics associated with today's analytics-driven business universe, are being given considerable attention throughout academia as a template for the future. Specific business based-analytics trends that hold out significant promise for business education include: 1) Product/service offerings adjusted quickly to meet changing customer demands, 2) Increased use of cloud-based technologies, and 3) Real-time analysis for increased system efficiency and transparency (Lueth, 2016). Business schools can adopt similar processes to better meet the changing demands of the business community. Today, both industry and the public sector are looking for graduates that are web-savvy, agile, and proficient with big data. With the continued expansion of the Internet and mobile technologies, these pleas are gaining a new level of urgency. A growing number of management educators are now calling for a fundamental shift in the way business education is organized and delivered (Rubin, 2013; Shejwalkar, 2016; Thomas, H., 2012; Waddock, 2013). This assessment is underscored, in part, by the exponential growth in online programs (Allen, 2016). Other factors driving this transition embody: 1) an increasing focus on experiential learning, 2) a burgeoning demand for fast track and limited residency programs, 3) an expanding number of peer school strategic alliances, 4) an escalating interest in program customization and flexibility, and

5) a growing interest in critical thinking and cultural diversity (Anderson, 2014; Hardy, 2015; Worthington, 2017). Even the accrediting bodies are weighing in on this debate. For example, the Association to Advance Collegiate Schools of Business (AACSB) is calling for more flexible delivery formats, with students having more control over their curriculum, strengthening international partnerships, expanding internationalization within the curriculum, and connecting various global activities through a comprehensive collaboration strategy (AACSB, 2016). Naturally, as with any significant transition, there are a wide variety of challenges, opportunities, and potential risks associated with fundamentally changing the course of business management education.

> The era of big data and analytics is upon us and is changing the world dramatically. The field of information systems should be at the forefront of understanding and interpreting the impact of both technologies and management so as to lead the efforts of business research in the big data era. We need to prepare ourselves and our students for this changing world of business (Baesens, 2016).

Many successful companies, including SMEs, have already developed an analytics-based and data informed decision-making culture (Ogbuokiri, 2015). The fundamental goal, of course, is to improve the decision-making process and thus enhance organizational performance. To that end, Performance Management Analytics (PMA) is receiving increased attention throughout the business universe. (Schlafke, 2013; Sharma, 2017). The PMA construct can be defined as an evidence-based approach to management decision-making and execution using business analytics. The first study illustrated how performance analytics can be applied to validate causal relationships among input, process, and output components with the goal of integrating these results into the firm's overall business strategy. This approach can be readily transferred to academe since many of the performance elements are very similar. The second study found that the use of performance management analytics in the HR sector can substantially reduce bias and thus increases employees' interest in improving outcomes. Moreover, the HR community, as an example, needs employees (i.e., end users) with the right skill sets, systems that communicate throughout the organization, and an IT environment that supports the analytics proposition (Marler, 2017). This same approach can be used in academe whereby "students" are added to the list of end users in the latter characterization. Furthermore, several recent studies on employee retention can serve as templates to address the challenges associated with student retention (Presbitero, 2016; Younge, 2015). These analyses reported that effective employment retention plans, such as better aligning the employee's values with the mission and vision perspectives of the organization, can have a positive impact on the firm's value and overall performance.

> The biggest barriers companies face in extracting value from data and analytics are organizational; many struggle to incorporate data-driven insights into day-to-day business processes. Another challenge is attracting and retaining the right talent—not only data scientists but business translators who combine data savvy with industry and functional expertise (Bughin, 2016).

Employment opportunities for graduates with a technical background (e.g., STEM) will continue to grow due to the increasing use of analytics throughout industry and government. Recent estimates suggest that the demand for graduates with deep analytical skills will approach 200,000 in the United States by 2020, with requirements for supporting personnel reaching nearly five times this estimate over the same period (Kao, 2017). To provide perspective, business schools in the United States graduate approximately 100,000 MBA students per year and most of these graduates cannot be classified as possessing deep analytics skills (Murray, 2012). Furthermore, the number of students graduating with an MS in Analytics (or equivalent) in the United States can be measured in terms of a modest percentage of MBA graduates. Because of this mismatch between supply and demand, the bidding war for new and experienced analytics talent will increase dramatically (Miller, 2017).

> By now it's obvious that universities and colleges can't crank out data scientists fast enough to keep up with business demands. And they certainly can't produce experienced analysts from a two- or four-year programme (Sing, 2016).

The basic proposal, as outlined in this paper, is to apply the analytics paradigm presently in use throughout business and government to management education for the specific purposes of enhancing student learning and employability. Traditionally, learning analytics has been defined as the science of discovering and communicating meaningful patterns in data and developing actionable plans with the objective of optimizing student learning performance (Barneveld, 2012; Cooper, 2012). The proposed approach extends the traditional learning analytics definition to include institutional operations such as student recruitment and placement. The construct will be referred to as the Analytics-Driven Management Education (ADME) model. Students enrolled in a management education program, given the current business environment, need to develop technical analysis capabilities and problem-solving skills to remain competitive in the globalized marketplace. ADME supports achieving these goals in the following ways:

- Providing a conceptual setting for improving student's managerial decision-making skills
- Increasing student performance though the use of analytics-based intelligent tutors

- Enriching team group dynamics and outcomes
- Identifying students at risk and developing intervention plans
- Improving student recruitment, retention, and employment opportunities

This paper is organized as follows: 1) a review of the ADME model, 2) an example that illustrates the use of analytics in detecting students at risk, and 3) an overview of ADME implementation strategies. This article's primary contribution to management education is to identify how the learning analytics model can be used to improve recruitment, enhance student learning outcomes, and advance employment opportunities.

> Business analytics is a fast-growing job market for business school graduates. Our findings indicate that business schools still have a long way to go before they reach higher levels of business analytics maturity and that they are not yet in an ideal position to serve the presumed industry needs (Turel, 2016).

2. ADME Model

The ADME model embraces many options for delivering content to students in both individual and collaborative contexts and supports the transition from the three pillars of traditional management education - fixed time, fixed location, and fixed learning pace - with a more flexible and dynamic learning environment. ADME builds on the burgeoning fields of learning analytics, academic analytics, and educational data mining. The term *Learning Analytics*, denoting the measurement, collection, analysis, and reporting of data about learners, for purpose of optimizing the learning process, was initially defined at the first Learning Analytics and Knowledge Conference (Chatti, 2012). The basic construct behind learning analytics is to collect student data (i.e., performance and characteristics) on a continuous basis and analyze the data for the primary purpose of improving learning opportunities and outcomes via customized learning plans. Academic analytics can be defined as a methodology for collecting and analyzing institutional data with the objective of improving the overall decision-making process (Goldstein, 2005). Specific academic analytics applications include: strategic planning, demand forecasting, capacity planning, faculty and student recruitment and retention, and post-graduation employment.

> Academic analytics reflects the role of data analysis at an institutional level, whereas learning analytics centers on the learning process, which includes analyzing the relationship between learner, content, institution, and educator (Long, 2011).

The primary goal of educational data mining is to apply sophisticated modeling tools to discover new insights into how students learn (Baker, 2009; Soh, 2013). Data is typically gleaned from student and administrative information (e.g., test performance and background), interactive learning environments (e.g., learning management systems), and cloud-based collaborative systems (e.g., simulations). The resultant models, which are developed from the assembled database, can be used to forecast students and student groups learning practices and behaviors. Educational data mining systems are usually hierarchical in structure in the sense that they capture data from individual key strokes or voice commands through to degree completion (Bienkowski, 2012). The complex nature of many of these factors calls on the use of advanced techniques like ensemble modeling, classification and regression trees (CART), neural nets, and decision trees (Dhingra. 2017; Satyanarayana, 2016).

Figure 1 – ADME Overview Structure

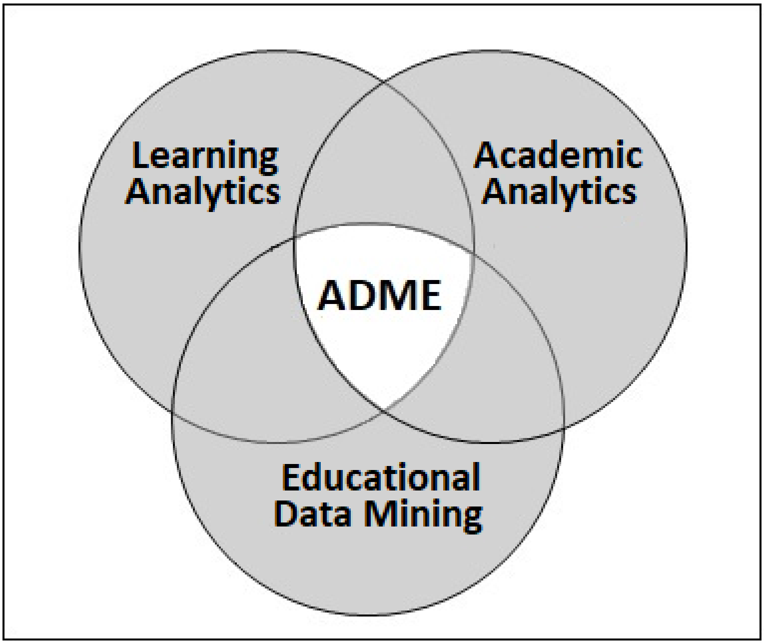

Figure 1 highlights the overall ADME paradigm, which is designed to assess and integrate the various key aspects of the management education universe, such as, student recruitment, student learning, student employment, and institutional operations. Some specific benefits associated with the ADME model include (Avella, 2016; Siemens, 2013):

- **Gaining a competitive advantage** – Provides business school administrators with the capability to better manage their strategic and tactical resources and thus enhance overall value for both the student and institution. Analytics has emerged as a platform to both effectively process data and suggest specific courses of action.

- **Meeting the demand for analytics talent** – Offers a vehicle to address the growing demand for analytics-based talent. Specifically, analytics can be used to help reorient the MBA curriculum towards an evidence-based pedagogy which will increase the number of graduates with the requisite technical background currently in demand by the business community.

- **Improving learning efficiency through integration** – Enhances the learning process both within and between courses via content and process integration. Student performance is continuously monitored over the course of their studies, which facilities the development of customized learning constructs.

- **Enhancing student yield** – Supports a more dynamic approach in student recruitment in the face of increased competition. Data driven models can be used to improve both yield and retention rates, which includes both identifying students at risk and designing effective intervention plans.

> Cognitive models map the actual tasks that students engage with during learning to the underlying knowledge that is required to complete those tasks. Cognitive models are an important basis for the instructional design of automated tutors and are important for accurate assessment of learning (Liu, 2017).

Many business schools are now facing increased competition and more demanding customers (Ziegler, 2017). These forces tend to drive up the cost of student acquisition and retention. The emergence of the Internet generation as the new student body, which are web savvy and heavily engaged in social media, requires institutions to develop a real-time and interactive approach to student recruitment and retention. Until recently, the processes used by most business schools has been on data warehousing, which tends to provide a backward perspective e.g., assessing student performance after the fact. In contrast, the emphasis with predictive analytics is forward looking, with a special interest in non-quantitative measurements (e.g., tweets, blogs). While the explosion of social networks and the corresponding information flows have added a new level of complexity to the assessment process the opportunities for gleaning new insights via analytics have also improved (Holmes, 2014). Presented in the following sections are three specific applications, which are designed to highlight the ADME paradigm: 1) student recruitment, 2) student retention, and 3) post-graduate employment.

2.1. Student Recruitment

Recent evidence suggests that analytics can assist in student recruitment and retention by leveraging the fact that some counselors are extremely successful in dealing with certain types of students (Han, 2014; Maldonado, 2017). Matching prospective students based on given characteristics (e.g., educational background) to a specific counselor can significantly increase yield rates. Analytics can be used to look at past relationship data and develop an assignment schedule that optimizes recruitment outcomes. Additionally, analytics can be employed to expand diversity by identifying a broader range of candidates with interests that coincide with the institution's overall mission and vision. Predicting academic performance is an essential ingredient of the recruitment process. This subject has been examined extensively (Oadme, 2014; Pratt, 2015; Truell, 2006). In business undergraduate programs the predictive factors include high school GPA, curriculum strength, SAT scores, and subjective score assessments For MBA and related MS programs standard predictor variables include some combination of incoming GPA, GMAT scores, work experience, and leadership (Deis, 2010). The ability to consider many additional and more complex factors using predictive analytics represents the new frontier in student recruitment (Rajni, 2015).

Yield management, used within the context of academia, is the technique of understanding, anticipating, and influencing prospective student behavior to grow enrollments and thus revenue (Maltz, 2007). In a university setting, yield management is often characterized as enrollment management. Yield management has seen considerable success in a variety of business contexts including professional sports (Shapiro, 2016). Student seats are a perishable resource just like airline seats or hotel rooms. Once the school term starts an unfilled seat equates to lost revenue. Yield management provides the platform to increase enrollment rates by examining patterns and proactively developing actionable strategies that improve inquirer-to-enrollment conversion rates.

> Over the past decade, institutionally-funded financial aid (or "tuition discounts") have been the fastest-growing item within most public four-year college and university operating budgets. The data suggests that aid indeed can be leveraged for revenue generation. However, this relationship is only sustainable to a certain point. When unfunded tuition discount rates exceed approximately 13 percent, institutions may experience diminishing revenue returns to this financial aid investment (Hillman, 2012).

Scholarships and early enrollment discounts are but two vehicles for filling seats. Yield management models can be used to support the entire recruitment process (i.e., advertising, initial inquiries, applications, acceptances, enrollments). Today, many college applicants engage in a reversal of the classic practice of airlines overbooking flights. That is, they apply to many schools and select the “best’ offer based on a variety of criteria. This behavior places each institution at risk in the sense that they have committed resources in the form of scholarship offers, which could limit their ability to proffer additional scholarships given budget constraints. Again, this is where predictive analytics can play an important role by identifying which prospective students are most likely to accept scholarship offers or early enrollment discounts. This identification process can be further enhanced via personalized calls from an alumnus or faculty member. The task of advertising also lends itself to the yield management process. Typically, a business school has a wide range of promotional options including TV, radio, alumni outreach, information socials, and a variety of cloud-based materials (e.g., interactive videos). This allocation of resources decision process falls into the prescriptive analytics arena. In general terms, prescriptive analytics is all about assigning scare resources to a number of competing alternatives in a timely manner and has seen extensive use in scheduling radio and TV spots (Venkatachalam, 2015). Schools of business can use the same analytics approach to optimize advertising budget allocations.

2.2. Student Retention and Enhanced Learning

The same modelling processes used in student recruitment can also be employed to identify students at risk early on and to develop interventions based on modifying the pace and nature of content delivery through artificial intelligent agents (Bagheri**,** 2015; Najar, 2016). The evidence to date suggests that early invention can have a positive impact on student learning performance (Hussey, 2015). One very telling variable in this regard is freshman performance. Current date suggests that nearly one-half of United States universities experience a freshman attrition rate of 25 percent (Rebbapragada, 2017). Time is often of the essence since waiting until midterm exam results to intervene can often prove problematic. The data indicates that continuous assessment encourages student engagement, which in turn enhances student learning outcomes (Lyman, 2018; Parkin, 2014). In this regard, web-based learning management systems (LMS) offer an effective vehicle for both detecting early on students at risk (e.g., weekly quizzes) but also for providing modifying content based on specific student characteristics. This capability is particularly helpful for online programs where a sense of isolation is often the norm. Specifically, providing continuous performance metrics as well as monitoring the extent of student engagement within the LMS can help identify those students that require additional assistance.

Recent studies suggest that a LMS platform equipped with a prediction model can provide automatic and timely reports, allowing the pace and nature of content delivery to be modified to meet the specific needs of the students, especially those that are struggling (Lo, 2014). This capability can help reduce student drop outs that occur do to either a lack of persistence or a failure to meet institutional standards (Dominguez, 2016; Y. Hu, 2014). In many instances departing students are not viewed as future candidates by the institution (Harvey, 2017). This is an area where the administration and faculty need to re-think current policies and develop a more dynamic strategy for enhancing retention rates. Rehabilitating a current student is much more cost effective than having to recruit a replacement (Vander Schee**,** 2009). Additionally, some success has been found in reducing dropouts by engaging students in career planning early in the matriculation process and providing virtual office hours (Belser, 2017; Gregori, 2018). This success can be further enhanced by providing internships on an on-going basis. By reducing drop outs, through a combination of technical support, administrative initiatives (e.g., career planning), and reduced course loads, the economics associated with recruitment and retention can be better optimized.

The experiences gained from online management education programs, the fastest growing segment in business schools today, suggests that students that engage early with recently released material tended to outperform their laggard classmates (Mori, 2016). The capability to monitor student activity digitally represents one of the significant advantages of online programs compared to the traditional classroom format. Typically, online-based student engagement can be classified into two broad categories: 1) low level (e.g., number of logins), and 2) high level (e.g., quiz performance). Predictive analytic models using data extracted from the server logs of student activity (e.g., login frequency) can be employed early in the term to automatically generate specific notifications for the student to remain current. These notifications can be supplemented with the use of electronic badging, which has been found to have a positive effect on increasing student engagement (Huttenlocher, 2014). Additionally, course content and pace could be modified to reflect laggard behavior as well as student performance on early practice quizzes. Again, the goal is to mitigate the potential for students to drop out due either to self-selection or failing to meet institutional standards.

> Learning analytics (LA) is an emerging discipline that aims at analyzing students' online data to improve the learning process and optimize learning environments. The most important predictors were factors reflecting engagement of the students and the consistency of using the online resources. The analysis of students' online activities by means of LA techniques can help early predict underachieving students, and can be used as an early warning sign for timely intervention (Saqr, 2017)

An analysis of Massive Open Online Courses (MOOC) dropout rates can provide even more insights into the need to enhance student engagement on a continuous basis (Bozkurt, 2017; Onah, 2014). By some estimates less than ten percent of students enrolled in a MOOC complete the course (Henderikx, 2017). This large imbalance between the number of dropouts and the number of students that complete the course and the variance in student engagement on a weekly basis represents a major analytic challenge. Some success in this regard has been found using Interpreting Linear Models where the dropout prediction algorithms are updated each week based on prioritizing features and characteristics differently (Nagrecha, 2017).

Purdue University's Signals project has applied analytics to the problem of improving student success and, hence, to enhancing retention and graduation rates (Arnold, 2012; Howard, 2017). This project has led to the development of success algorithms with intervention messages sent to students based on performance via dashboards. These algorithms can also be used to help identify students at risk (Macfadyen, 2010; Wise, 2014). Furthermore, data mining tools which often include decision trees, rule induction, and neural networks, can be employed to 1) select student groups with similar characteristics and reactions to learning strategies, 2) detect student misuse and lurking, 3) identify students who, in multiple choice tests, are hint-driven, 4) locate students who exhibit low motivation and find alternate means of reaching them, and 5) predict probable student outcomes (Duarte, 2014; Kala, 2017; Oyerinde, 2017). To this end, some specific factors that contribute to academic success or failure include the following (Horton, 2015; Kless, 2013):

- **Academic perseverance** is that quality that allows students to continue trying to do something even though it is difficult to accomplish
- **Academic mindset** relates to students' beliefs about their intelligence or academic ability, which influences their academic tenacity
- **Learning strategies** are approaches used by individuals to actively learn or facilitate acquisition, understanding, the transfer of new knowledge and skills, and the use information to solve problems
- **Social skills** are components of behavior that help an individual understand and adapt to a variety of social settings

Detecting the presence or absence of these characteristics is a central ingredient of the ADME model. The successful detection and prediction of student performance allow educators to design specific intervention plans using both unstructured and structure data. A recent study, using only unstructured student text data from online class discussion forums, revealed that both the probabilistic latent semantic analysis and hierarchical latent Dirichlet allocation models produced significantly better results than chance in predicting students' final grades, which improved with additional data collected over the duration of the course (Ming, 2012). However, recording and maintaining student data over the course of their studies represents a major challenge. As a result, the issues of interoperability and data collection performance must be addressed early in the system design process (Dogero, 2017).

Student entropy is another potentially useful metric for monitoring performance. The idea of entropy was first applied to the study of thermodynamics in the late 1850s. In that context it was used to characterize the amount of energy in a system that was no longer available to perform work. Subsequently, the definition was expanded as a more general measure of randomness and disorder. In more modern times, the theory of entropy has been extended to the study of financial markets (Billio, 2016; Dimpfl, 2013; Pincus, 2008; Maasoumi, 2002). The basic idea is that more volatile securities have a greater entropy state than more stable securities. Two fundamentally different phenomena exist in which time-based securities data deviate from constancy: 1) Exhibit larger standard deviations and 2) Appear highly irregular. These two phenomena are not mutually exclusive and as such, both can be used to characterize the uncertainty associated with fluctuations in security data. In fact, two distinct time series can possess the same standard deviation but different entropy levels. The standard deviation measures the extent of deviation from centrality, while entropy provides an insightful metric for delineating the extent of irregularity or complexity of the data set. Evaluating the subtle but complex shifts in series data is a primary prerequisite for exploiting the potential information contained therein. One entropy metric, approximate entropy (ApEn), has been found to be robust to outliers and can be applied to times series with 50 observations or more with good reproducibility. A second measure of system complexity that has also seen widespread use is called sample entropy (SaEn). The literature is replete with detailed discussions of these alternative measures of entropy (Thuraisingham, 2006). The basic ApEn and SaEn entropy models consist of three inputs: 1) time series, 2) matching template length (M), and 3) matching tolerance level (r). Entropy has also been used in the early detection of atrial fibrillation and sports performance (Alcaraz, 2010; Couceiro, 2014). These two seaming diverse entropy applications have one core characteristic in common, the measurement of human performance. It is postulated that these same entropy assessment techniques can be applied to the early detection of students at risk. For example, a student's entropy can be measured from weekly quizzes on multiple subjects over multiple periods.

The increased use of analytics throughout academe raises a number of ethical concerns, which includes protecting student privacy (Rubel, 2016; West, 2016). These concerns are somewhat similar in nature to customers engaging in web commerce. A core issue is the extent to which a student should have some input as to how their administrative data and performance data will be used. Some principles to help guide this conversation include the following (Slade, 2013): 1) students should be seen as collaborators and not merely sources of data, 2) student identity should be viewed as a combination of permanent and dynamic attributes, 3) institutions of higher education should be transparent regarding the purposes for which student data will be used, and 4) students should have some input on the use of their data. To this end, identity authentication and secure data transfer practices represent two major technical challenges. The authentication of identity is the process of ensuring that the recipient of student education records has the approved authorization while data transfer is based on the latest encryption technology.

2.3. Post-Graduation Employment

An ADME-based curriculum offers the student both a customized and an integrated knowledge experience. This is particularly important for online and hybrid types of programs (Shum**,** 2012; C. Hu, 2012). The primary learning goal throughout the management education universe should be on developing generalized problem-solving skills that can be easily transferred to the employment marketplace. The curriculum should be designed to create an environment where the student becomes comfortable in using decision support tools and processing "big data". The Assurance of Learning for Graduate Employability Framework (ALGEF) is a model for supporting curriculum design with the primary goal of improving graduate employability. This framework is predicated on the following principles (Beyrouti, 2017**;** Yorke, 2006):

- Employers generally view a graduate's achievements related to the subject discipline as necessary, but not sufficient for them to be recruited.

- Employers may find the actual subject discipline to be relatively unimportant. Achievements outside the boundaries of the discipline (e.g., "soft skills") are generally considered to be important in the recruitment of graduates.

- Employability refers to a graduate's achievements and should not be confused with the actual acquisition of employment, which is highly dependent on the state of the economy.

- Employability derives from complex learning and is a wider ranging concept than simply key skills and knowhow.

- Employability skills are not job specific but are skills that cut horizontally across all industries and vertically across all jobs.

An analytics-driven curriculum should be geared towards producing graduates that are inculcated in the current and future demands of the business community. By using the ADME template, business schools can better align a graduates' performance and background with the business needs at a given time, which are currently focused on big data analytics.

> Companies today are seeking employees who understand the business domain in which decisions are made and who possess depth and breadth of understanding of the analytics to optimize decisions. But the reality is the demand for individuals grounded in analytics, particularly in data mining and predictive analytics, and with a solid foundation in a business discipline far exceeds the supply of graduates (Stanton, 2015).

Presented below are some major industry trends that need to be incorporated into the basic business curriculum (Brock, 2017; Halper, 2011; Vidgen, 2016; Vila, 2012):

- **Providing Solutions Across the User Spectrum** – Traditionally the primary users of predictive analytics were statisticians. Today, there is a shift toward managers as users, and the business universe is looking for graduates that can fill this demand.

- **Supporting Unstructured Data Analysis** – Managers realize they can gain significant insight from mining unstructured data (e.g., text), that when used in conjunction with structured data, can provide additional inputs into the decision-making process.

- **Big Data** – As organizations gather greater volumes of disparate kinds of data (i.e., both structured and unstructured), they are looking for solutions that can be scaled. Interoperability continues to be a major problem in both commerce and government.

- **Open Source** – Open source solutions are becoming increasingly important to the predictive analytics market because they enable the wider community to engage in innovation. Several adoption obstacles include having a shared vision, establishing coding standards, and ensuring risks are minimized.

- **Cloud Computing** – Cloud computing is one of the most significant recent developments to impact the global business marketplace, as it provides the opportunity for firms to lower their IT expenses. Cloud computing, also known as on-demand computing, provides computing resources that are delivered as a remote service over a network to host and manage a user's data, software, and computational activities.

The management education curriculum (undergraduate and graduate) must be designed to incorporate these trends. For example, a large gap currently exists between many business school graduates and the business community in terms of understanding the role of big data. To that end, a critical component that many business programs lack are core courses focusing on data analytics. Students need to be trained to manage data flows and to use applications to create data visualizations, which are now a core element of modern business practice (Henry, 2015). Students also need to have a better understanding of the role of open source solutions and cloud-based computing.

3. Identifying Students at Risk: An Example

To illustrate the risk assessment process outlined above performance data was collected on 251 students engaged in a fully employed MBA program at a major business school. Some specific characteristics of the program included: 1) small classes with 30 students or less, 2) students with significant work experience, 3) multi-campus locations, and 4) courses offered both in a traditional setting and online. The "At Risk" target variable was: *Students have the skills to analyze business situations in an integrated, multidisciplinary way and recommend solutions.* This construct was characterized based on the faculty's assessment of a number of performance factors, e.g., business simulations. This candidate "At Risk" factor is only one of many possibilities including being dismissed from school, dropping out of school, and being on probation. The resultant survey data revealed that approximately 12 percent of the students in the sample failed to meet the expectations associated with this goal. Table 1 highlights the various model variable mnemonics and corresponding descriptive statistics for the assembled database. Traditional delivery is defined primarily as in-class instruction. These statistics reveal, for example, that 44 percent of the database consisted of women and that the average working experience was eight years. Furthermore, 88 percent of the students were engaged in a quantitative oriented course, e.g., analytics, finance, and accounting. These statistics are consistent with their overall proportions in the MBA program. The target variable (expectations) was re-characterized as a dummy variable (1= meets or exceeds expectations, 0 = does not meet expectations).

Table 1 – Selected Variable Mnemonics and Descriptive Statistics (N=251)

Mnemonic	Definition	Mean	S.D.
Delivery	Online=1, Traditional=0	0.70	-
Quant	Quantitative Course=1, Other=0	0.88	-
Work	Years of Working Experience	8.00	5.00
IGPA	Incoming Grade Point Average	3.15	0.44
Wave	Wavier Yes=1, No=0	0.53	-
Gender	Female=1, Male=0	0.44	-
Period	2nd Year student=1, 1st Year student=0	0.73	-
Expt (target)	**Expectation Level-Goal #1***	0.88	-

*1 = meets or exceeds expectations, 0 = does not meet expectations

Table 2 – Correlation Matrix (Kendall- Tau)*

	IGPA	Work	Expt
IGPA	1		
Work	0.02	1	
Expt	0.15*	0.06	1

* Significant at the 0.01 level

Table 2 reports the Kendall-Tau correlation coefficients for the continuous predictor variable set and the dummy target variable Expt. The correlation data revealed that incoming GPA is statistically significant at the 0.01 level.

In many similar educational assessment applications ordinal logistic regression (OLR) is often the method of choice (Romero, 2010). However, the relatively small sample size (N=251), coupled with the relatively small portion of students that did not meet expectations (12 percent) called for more robust analytical methods. Accordingly, two more powerful analytics techniques were employed: neural nets (NN) and classification regression trees (CART), which are receiving increased attention throughout the educational community of practice (Kayri, 2015; Kirby, 2014).

A classification analysis of the assessment database using both NN and CART is highlighted in Table 3. Typically, a portion of the database is used to train the model and the remaining data is used for predictive or classification purposes. Often an 80 percent to 20 percent ratio (training to holdout) is used (Nguyen, 2001). However, the relatively small sample size precluded this approach in the present study. The paired numbers in the table are the NN and CART estimates, respectively.

Table 3 – Comparison of NN and CART Classification Analysis

	Actual 0[1]	Actual 1[2]	Total	%	
Predict 0	29/28	52/38	81/66	36/42	PPV[3]
Predict 1	0/1	170/184	170/185	100/99	NPV[4]
Total	29	222	251		
%	100/97	77/83			
	Sensitivity	Specificity			

[1] Does not meet expectations, [2] Meets or exceeds expectations,
[3] Positive predictive value, [4] Negative predictive value

A positive predictive value is the probability that a student classified as not meeting expectations will not meet expectations. In contrast, a negative predictive value is the probability that a student was classified as meeting expectations when they did meet expectations. The results from both models suggest that very few students requiring an intervention will be missed. For example, the NN model correctly identifies all 29 students that did not meet expectations based on the predictor variable set. Again, the purpose of these discussions is to illustrate an analytics-based approach for identifying students at risk and not a detailed evaluation on the efficacy of a specific analytics model. In both models, the variables IGPA and Work explained most of the variability in the target variable. The relative importance of IGPA as a predictor of student performance in management education is consistent with similar studies (Christensen, 2012; Howell, 2014). The results from the above discussion outline an approach for relating student characteristics (e.g., work experience) to learning outcomes. These models can also be used to identify additional customized learning resources for struggling students (Kirkwood, 2014). However, recognizing the potential of this methodology is only the first step. Of equal importance is the design of effective intervention implementation strategies.

4. Implementation Strategies and Issues

Developing and executing a viable ADME implementation strategy turns out to be as important as formulating the overall ADME system design structure. As with most business decisions the two basic options are: 1) develop an analytics staff, which could have significant internal budget and operations implications and 2) outsource the implementation task. The trades-offs association with the make or buy decision have been extensively examined (Leiblein, 2017). Some factors that need to be considered in the implementation process, regardless of the make or buy decision, are highlighted below (Janardhanam, 2011; Pardo, 2017):

- **Relative Advantage**: The degree to which ADME will offer benefits surpassing those of its predecessor.

- **Compatibility**: The level at which ADME acts in accordance with previously experiences and the requirements of future adopters.

- **Complexity**: The degree to which ADME is difficult to understand or use.

- **Trialability**: The level at which ADME can be used and pre-tested prior to universal adoption.

- **Observability**: The degree to which the outcomes are evident to the adopter and external viewers.

- **Speed:** The timeframe in which ADME can be adopted.

- **Culture:** The degree to which intuition based on previous experiences is still the driving factor in the decision-making process.

The functionality of social media provides opportunities to enhance the effectiveness of the ADME paradigm. Nevertheless, there are ongoing concerns about using social media across the learning universe since many of the communication devices are not part of the institutional enterprise systems (i.e., Shadow IT). Ethical issues related to student online behavior, information privacy, control, and ownership are also of concern (Coll, 2011; Joosten, 2013). Additionally, the institution must establish and maintain a robust wireless connectivity infrastructure. The types of effective learning activities designed within the social media universe are predicated upon mobile connectivity, which requires coverage across the teaching and learning spaces to enable students to connect, collaborate, and interact via their own mobile devices (Antonczak, 2014). In summary, the adoption of the ADME paradigm will vary considerably between institutions.

5. Conclusions

Dramatic change is in the wind throughout the management education universe. Business schools must be able to respond quickly to changing requirements from both the business community and students. In today's business world, organizations are increasingly turning to analytics to gain a competitive edge. The business universe is looking to analytics to help address many of the issues associated with today's global economy. Data management is the number-one challenge in the adoption of the business analytics paradigm. Many business and government institutions continue to lack the proper analytical talent. In this new environment, graduates need both technical analysis and problem-solving skills. Management educators must take responsibility to meet this growing demand by providing relevant courses, programs and learning venues. Specifically, these challenges provide schools of business with an excellent opportunity to increase the use of analytics in all operational phases and thus be in a better position to meet this growing unfilled demand.

To this end, the ADME paradigm embraces many options for delivering content to students in both individual and collaborative contexts and supports the transition from the three pillars of traditional management education - fixed time, fixed location, and fixed learning pace - to a more flexible and dynamic learning environment. ADME builds on the burgeoning fields of learning analytics, academic analytics, and educational data mining. Student recruitment and retention, student learning success, and post-graduation employment are but three areas where the ADME model can improve the overall performance of the business management universe. The era of big data, which has caused a massive seismic shift in the business community, has now reached the shores of management education. Traditionally, many schools of business have at best, taken a descriptive analytics approach to the issues associated with big data, which exists in abundance. The transition to a predictive analytics strategy where performance is forecasted alleviates many problems, including concerns about student privacy, faculty and administration resistance, and new technological developments. This new perspective will allow business schools to better align their product mix with the real needs of the business community for years to come.

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