LEADING STRATEGIES

The Coming of Age of Data Analytics in Higher Education

By Reid Kisling, Andrew Peterson and Robert Nisbet

Data analytics is undergoing an evolution through effective data use to support both operational and learning analytics models. However, this evolution will require that institutional leaders transform their data systems to best support the needs of application modeling and use their intuition to help drive the development of better analytical models for the future.

> *"Marley was dead: to begin with.... There is no doubt that Marley was dead. This must be distinctly understood, or nothing wonderful can come of the story I am going to relate."*
>
> —CHARLES DICKENS, "A CHRISTMAS CAROL," 1843

So it is with data analytics in higher education. One thing must be clearly understood before analytics can provide much benefit: institutions must change the way they view and use their data. This paradigm shift in thinking is absolutely necessary, or nothing good in the long term will come from efforts to develop analytical applications in higher education.

The purpose of this article is to describe that paradigm shift and to serve as a primer for those who haven't explored yet the power of data analytics to support institutional strategic enrollment management (SEM) efforts. A cursory review of core SEM resources will reveal that data is foundationally important to organizational decision-making and planning (Hossler and Bontrager 2014; Sigler 2017). However, institutional leaders are continuously challenged by the advent of new tools for data analytics and how to use them effectively for SEM planning and goals.

During the last 20 years, data analytics applications have been created in schools, usually in "digital sandboxes," to show the power of analytics in educational operations. A particular use case for higher education has been student retention, given the ability of analytics applications to unearth patterns of behavior that are not possible through standard means of data analysis. These patterns serve as a proxy for how students act (and perhaps think) in a given context. Yet, data analytics has been limited in many ways to these basic patterns of behavior.

Development of a synergy between the application of data analytics in education and the psychology of instruction in our schools and colleges is underway. The ability to tap into this synergy and put analytics to use in educational operations requires a change in how an institution views and manages its data. The traditional view of data in most schools is organized around archival and business purposes. A fundamental shift in this view is necessary to unlock the vast potential of the school's database to permit data-driven planning and decision-making.

To facilitate this paradigm shift, this article will explore:

- The evolution of education psychology during the last 100 years;
- The rise of data analytics in education;
- Current predictive analytics applications in education;
- The pressing need to apply data analytics in education and how to do it.

The Evolution of Educational Psychology

To understand the impact that data analytics has generated in education, it is critical to understand the progression in psychology and technology that has led to its development. Instructional design still requires a theoretical base and the craft of educational technology (Sawyer 2014). The historical phases in the development of instructional psychology over the past 100 years have moved from behaviorism characterizing educational theory to that of cognitivism and then to constructivism. This transition in educational theory is marked by an initial emphasis on overt behavior patterns (Tomic 1993), followed by a shift in focus to covert cognitive algorithms, and then to subjective perception (Jenkins 2000). The precision of behaviorism, the formalization of cognitivism, and the dynamics of constructivism condition the educational designer's focus to bear on the key aspects for instruction related to each phase.

Paradigms for Educational Data

Cross-currents in educational psychology began early in the 20th century with the behaviorist learning paradigm, which provoked studies based on cognition. The study of behavior as habitual responses to specific stimuli was the dominant science for education until the 1980s. It produced programmed instruction with an emphasis on immediate correct responses. When key experiments began to show the inadequacy of psychology without the concept of "mind," educational researchers and practitioners became serious about including the logical protocols of thinking as part of learning. While the inability to directly observe someone's thought processes resulted in its study being rejected in the past by materialistic science, the necessity of hypothetical constructs like cognition became clear. Even for prediction and control with humans, aspects of a learner's thinking pattern became necessary to capture and analyze.

At the time of the transition of the mainstream to cognitive psychology, computer science advances led to the suggestion of artificial intelligence. The idea of mimicking human thinking patterns became the model for designing information processing methodologies in every aspect of general psychology in the 1980s. But like behaviorism and despite the incorporation of internal constructs relating to human thinking, it remained a rather mechanistic approach; the concepts of insight, curiosity, challenge, etc., were still absent. Educational leaders in philosophy, psychology, and business were not satisfied with the lack of these concepts in education planning for the future. These developments laid the groundwork for the application of machine learning technology to educational psychology in the 21st century.

Beginning in the 1970s, Hubert Dreyfus at UC Berkeley continued to challenge the assumptions and conclusions from the AI researchers at MIT, Stanford, and elsewhere. With his analysis from *What Computers Can't Do* (Dreyfus 1972) still on the table, he yearned for education with more insight and action as one moved from novice to beginner to expert status. Another scholar who moved from behaviorism and cognitivism to constructivism was Omar K. Moore of Yale and the University of Pittsburgh. He was convinced by Godel's Incompleteness Theorem that a strictly behavioristic model was impossible. Based on a combination of insights from sociology, psychology and logic, he executed a 20-year research program to study the best environments for learning, including much interaction and data collection and analysis (Moore 1971; 1980).

Moore's four principles about learning (learning should be productive, include multiple perspectives, be personalized, and autotelic) represent various quality measures of the educational process. These quality measures can then be used to characterize various learning environments, but quantitative studies are needed to find non-intuitive patterns in the data sets. Data analytics in education can add metrics to this qualitative approach. Analytical classroom applications in online and on-campus venues can be used in many ways to promote the development of personalized instruction programs, similar to the development of personalized medical practices (Miner, *et al.* 2015).

The Rise of Data Analytics in Education

Data analytics is a broad category that includes any application that distinguishes patterns in data sets, which can be used to guide management operations in an organization. Data analytics in any field today begins with the "three Vs": volume, velocity, and variety. Powered by the unrelenting Moore's Law of increasing computing power year to year, the volume, velocity, and variety of data processing operations are rapidly increasing. The largest volumes of business data consume petabytes (1,000 terabytes) for all the records, transactions, and tables in an organization like Google. Velocity is increasing rapidly in all modes, by batch, near time, real time, and in streams. Academic data sets can be composed of a variety of data types, structured into tables, in unstructured text, and in semi-structured forms. Academic data analytic applications expose profile patterns that can be used to answer important business and educational questions.

The Three Vs Plus Two

In addition to the "three Vs" of increasing volume, velocity, and variety of data produced by "big data" operations, value is also important, along with the concept of "very interdisciplinary."

- **Volume** — This part of the data dynamic refers to the size of electronic storage forms, measured in multiple terabyte- or petabyte- class data, motivating the use of such highly parallel next-generation data management technologies as MapReduce, Hadoop, and NoSQL that can be used on much, much cheaper hardware.
- **Variety** — Big data goes beyond numbers in relational databases, a.k.a. "structured data." Such "unstructured" data sources include web search log files, tweets, call center transcripts, telecom messages, email, and data from sensor networks, video, and photographs. The multi-structured nature of big data in part accounts for its large volume and often high degree of "messiness" and "noisiness."
- **Velocity** — Because much of it emanates from sensors, web search logs, real-time feeds, or mobile devices, very large data sets are generated continuously, particularly in online organizations at a very fast rate (*e.g.*, Google).
- **Value** — Delivery on strategic goals for the organization regarding the very positive impact on revenue.
- **Very Interdisciplinary** — The effective use of analytical applications requires a team with diverse capabilities and expertise. A fully functional team might include these competencies: business consultants, subject matter experts (SMEs), educational technologists, statisticians, and database programmers.

Education at Apple: The Synthesis of Instruction and Descriptive Analytics

As a practitioner and business expert at Apple from the Silicon Valley, John Couch embraced a proactive learner approach with emphases of challenge, collaboration, and context. He operationalized the insights of Dreyfus and Moore into the development of the Apple Education ecosystem (Couch and Towne 2018; Peterson 2017). With both computer technology and constructivist education philosophy, Apple created tools (*i.e.*, the user interface) that combined an effective communication capacity with normal computer operations. Contemporary predictive analytics combines similar elements of user intuition plus machine learning processing. Thus, predictive analytics operations can comport well with constructivist educational psychology, including immersive learning with interactive online social simulations.

The Apple Education ecosystem provides a form of data analytics that is descriptive, not predictive. Charts, graphs, tables, and trends are composed from the instructional data to guide instructor's evaluation of student progress. The greater need, however, is useful information gleaned from analytical operations to predict various outcomes in the educational process and prescribe appropriate actions based on the predictions.

It is very common to find that some of the most important predictor variables in analytical models are those that the analyst derived from existing variables, based on intuition and business domain expertise. The two dominant development paths in modern predictive analytics are automation and incorporation of human thinking and intuition. These development paths appear to be contradictory, but in practice, elements of both must be included in future analytical applications.

Predictive Analytics in Education

The descriptive analytics capabilities of the Apple Education ecosystem are useful to provide information to answer the "what" category of questions. These descriptive applications are suitable for a starting point, but they beg more profound questions about "how well" and "when" things happen. Predictive analytics (PA) in education includes applications of two forms: (1) operational analytics (*e.g.*, student retention and donor development); and (2) learning analytics (student performance in the learning environment). Operational analytics applications are focused on the business aspects of the school while learning analytics applications are focused on optimizing success in educational activities (*i.e.*, instructional effectiveness, student performance).

Operational Analytics

Almost all of the early operational analytics applications in schools and colleges addressed student retention (Manyanga, Sithole, and Hansen 2017). The authors recount the descriptive modeling activities for student retention as beginning in the 1970s, but the first predictive analytics models didn't appear until 2010.

By 2015, Western Seminary recognized that they had a problem with student retention. Recognition of this problem led to developing a proof-of-concept analytics model for student retention in 2015 to explore the extent of student attrition ("churn") in the past and predict student churn rates in the future. Analysis of the past decade of data showed that as many as 80 percent of Western students in degree-granting programs left the school without completing a degree (defined as student churn). This loss of students, the income they represent, and the lack of program continuation toward completion of students' intended goals constituted a major problem for the school. Based on model results that revealed some important predictive factors of student churn, interdiction strategies were introduced (*e.g.*, increase in the number of points of student contact) to reduce the churn rate.

The student churn model was updated in a 2019 study supported by the In Trust Center for Theological Schools. Results of this study showed that the student churn rate had decreased from about 80 percent in 2015 to 49 percent in 2019. The interdiction strategies put in place during the previous four years worked. This study also showed the power of text analysis by identifying an important predictor variable as the presence to the word "probation" in the text of a comment field in the student database (something that the authors believe had not happened to date in retention analytics studies). The information in this database field was available to any staff who might see and read it, but it was not available to the analytics algorithm until text mining data preparation was performed to tag it as a candidate predictor variable. The increases in opportunities to serve many more students with degrees in those programs and the increase in student revenue were very significant, and they were crucial to maintaining the ongoing educational operations of Western Seminary.

Education costs in the United States have increased faster than health care costs. The average college student debt load stands currently at about $29,800, but some students amass nearly a quarter of a million dollars in educational costs (Hess 2019). Simultaneously, most schools are under greater scrutiny to document success levels in the workplace to justify the high cost of education. Parents and students are becoming increasingly focused on relating the high cost of tuition to clear results. Despite the provision of significant government funding in education, it is possible that an education "bubble" will burst soon, similar to what happened with the tech bubble in 2000 and the housing bubble in 2008, and many schools may have to close. The results of the COVID-19 pandemic may be precipitating this effect now, as Gordon College in Massachusetts announced that it would reduce its tuition cost for the 2021–22 academic year by 33 percent (Gordon College 2020). Thus, efficiencies must be provided to maximize student retention to ensure the survival of academic programs and as revenue protection measures. Data analytics provides the means to achieve this goal. This current new focus in education parallels the perceived needs in business that led to the development during the last 20 years of customer relationship management (CRM) applications for customer acquisition, retention, and purchasing growth. Education must follow the lead of business to optimize efficiencies in operations activities ranging from strategy formation to performance growth to evaluation of benefits.

Student retention studies like these represent the "low-hanging fruit" of opportunities in schools and colleges to leverage predictive analytics' power to provide immediate and tangible benefits to the institution. Successes like these in operational analytics set the stage for the application of predictive analytics to the educational learning process itself, known as "learning analytics."

Learning Analytics

Learning analytics (LA) is a rapidly developing application of predictive analytics that focuses on analyzing data gathered from classroom instruction activities to predict outcomes related to instructional effectiveness and student performance. LA models can be applied to answer questions related to the effectiveness of various instructional activities. Analysts can search through prepared data sets to find critical patterns to help them formulate new instruction plans that include appropriate feedback to promote student success. Progress in instruction can be monitored and amplified with proper interventions at an appropriate time based on analytical results. Analytical models in LA can be applied to provide patterns and relationships specific to and can enhance education at all levels, ages, and venues in conjunction with faculty input.

It is important to understand the potential opportunities and limitations of applying LA models. One potential benefit of LA is that it can provide a more personalized and sustainable instruction model than can be offered by traditional means. For example, an "engagement index" can be applied and used to assess and monitor the effects of increasing the number of student touch points. The explosion of online learning provides a rich venue for the development of such data analytics applications. LA can also be applied to predict student performance, based on various predictive factors.

Many of the early models in Learning Analytics (LA) were performed in India and Eastern Europe. Most LA student performance models classified performance into groups, often just pass vs. fail. Prior statistical regression models performed poorly, possibly because the data sets used violated one or more of the assumptions implicit in regression theory (particularly, the assumption of a linear nature of data relationships). One of the earliest classification models of student performance was performed by Osmanbegović and Suljic (2012) for University of Tuzla students in Bosnia and Herzegovina. This model predicted whether a student in a business informatics class would pass or fail using three machine learning algorithms: Naïve Bayes (overall accuracy = 77 percent), a C4.5 decision tree algorithm (overall accuracy = 74 percent) and an artificial neural network algorithm (accuracy = 71 percent). The most important predictor variables among the models included GPA, entrance exam score, diversity of study notes materials (including notes of other students), and the average weekly number of hours devoted to study. The predictive effects of GPA and of the entrance exam scores are rather intuitive. The finding that showed the importance of the proper use of study materials is logical, but it may not be immediately intuitive in the minds of school administrators. Such non-intuitive predictor variables can be used to guide the development of interdiction programs with faculty, designed to increase levels of performance for students at risk of failing.

The Pressing Need to Apply Data Analytics in Education and How to Do It

The sharply rising costs of education (including the cost of student attrition) and the current constraints on college operations posed by the COVID-19 pandemic pose massive challenges to school administrators. New ways must be crafted to meet these challenges, and many of them require the input of information gained from data analytics operations. Operational analytics modeling operations for student retention and even donor development offer a large potential to assure the financial survival of the school. Millions of dollars have been retained for Western Seminary by reducing the student churn rate from 80 percent to 49 percent in four years, based on results of two student churn models. Without those monies, the school might very well have had to close its doors. Learning analytics operations can provide critical information to optimize the learning environment and student performance in it. Student performance models can illustrate key practices of successful students to increase the performance of other students. While operational analytics must be data-driven to optimize the business operations of the college, learning analytics must be competency-driven to succeed in moving the "center of gravity" of student performance upward. As students learn more, they will find greater success in the job market and recognize the great worth of the educational system based on analytics that provided it.

Database Systems in Education to Serve Analytics

Database systems in schools and colleges were developed in the past to serve two primary purposes: (1) as a repository for general student records (including grades and other educational activities); and (2) to support accounting systems (financial and records of program completion). It has only been in recent years that institutions have begun collecting and maintaining broader records of student engagement (*i.e.*, CRM activity, learning management system [LMS] assessments). The original purposes defined the way database structures were designed and may have restrictions due to hardware space limitations (including memory cost in past years).

In addition to natural limitations that existed in the past (and may still undergird the structures of today's applications), these older data structures were designed to track information about specific student programs resulting in granting a degree rather than to track general information about a given student. For example, a student who has elected to suspend an academic program for financial or family reasons will "stop out." Many students incur many stop-outs in their programs while some students enroll in sequential degree programs (*e.g.*, M.S. and Ph.D). The result of multiple programs is to add multiple records to the database for a given student ID.

Information from these multiple records for a given student is currently composed of reports generated with Structured Query Language (SQL) reporting programs. To support PA efforts, information accessed by these programs could be collected together to form a master student table, with one row per student. This new student table is analogous to the customer table in a business, composed of many line items of information in the accounting tables. The student ID can function as a relational key in the student table to point to records in other tables of the database containing information specific to a given student ID.

In the Western Seminary In Trust project, the number of stop-outs for a given student was a significant predictor. This number represents a value that could be calculated and stored as a field in the master student table from where it is immediately available for analysis by a modeling algorithm. However, in many of our institutional data systems, such predictor variables for PA models are not stored but must be compiled separately to support PA efforts. Many other fields like this could be added to the student record to facilitate analysis. Table 1 shows a typical student courses table.

For analytical purposes, the information in multiple records for the same student must be aggregated or combined mathematically to yield values in multiple fields of the same record. If this data preparation is not done, it must be done every time a new model is built. Indeed, data preparation is the most time consuming part of PA efforts. Table 2 shows a combined student analytical record, which is much more suitable for use by data analytics modeling algorithms.

Information in the student analytical record table can be updated each night, and be available for use on the next day, based on information present in the student courses table. Some of our institutions have begun utilizing data warehouses that store data that can be used for PA purposes, while many such data warehouses are simply storage structures for historical summary data useful for trend analysis. In this way, the student analytical table is *dependent* upon the student courses table. The diversity of information related to students may require multiple tables to be populated with data aggregated or computed from other tables in the academic database. These tables will contain keys to link them together with each other, but not with the tables in the main student records database. Such a multiple table data structure is called a *dependent analytical data mart*.

TABLE 1 ➤ Typical Student Courses Table in a Traditional Student Records Database

RecordID	StudentID	Degree	Term	CourseID	Grade	StopOut
1	1	M.S.	F2017	3	A	
2	1	M.S.	W2018	7	B	
3	1	M.S.	S2018	6	A	
4	1	M.S.	F2018	4	C	
5	1	M.S.	W2019	12	B	
6	1					Yes
7	1	Ph.D.	S2019	23	B	
8	1	Ph.D.	F2019	34	A	
9	1	Ph.D.	W2020	41	A	
10	2	Ph.D.	F2019	3	A	
11	2	Ph.D.	W2020	9	B	
12	2	Ph.D.	S2020	15	A	

TABLE 2 ➤ An Example of a Student Analytical Record Table, Suitable for Use by Modeling Algorithms

StudentID	Degree1	Degree2	GPA1	GPA2	#StopOuts
1	M.S.	Ph.D.	3.20	3.66	1
2	Ph.D.		3.66		0

IBM SPSS Modeler, SAS Enterprise Miner, Rapid Insight, and KNIME analytical packages include data preparation nodes that can easily integrate data inputs from multiple tables in the dependent analytical data mart, without impacting response time on the main student records system. This independence is complete when the analytical data mart is dedicated to a separate database server, updated each night automatically through the institutional network.

The required paradigm shift in thinking by student database managers requires a shift from the previous focus on student data as input for search and reporting purposes to a new focus on provision of data for analytical purposes. Sometimes, these two purposes run counter to each other. Therefore, search-and-retrieval and reporting operations can be dedicated to one computer system optimized for those purposes. In addition, a separate computer system with its separate analytical data structures can be optimized to serve analytical needs.

The "Last Mile" in Deployment of Data Analytics Systems in Education

Academic data must be adequately prepared; as much as 90 percent of the project time will be spent in data access, data integration, data cleansing, and other data preparation jobs before modeling operations can even begin (Nisbet, Miner, and Yale 2017). These data preparation operations can be performed automatically in the dependent analytical data mart operations to provide input information for data integration tasks in analytical modeling operations. This change in data infrastructure constitutes the "last mile" in the data pathway (analogous to the "last mile" in a telecommunications network). Those "last mile" implementation problems in deployment can kill a project in any organization, particularly in a higher education institution. Many business models just sit on the shelf because they can't be implemented in the ongoing business operations of a company. We must approach developing a data analytics capability in a school as a *system*, not just as a group of individual processes. These processes will almost never work together unless their needs and feeds are coordinated together as a system in the overall planning process before the individual processes begin.

Summary and Prospect

Data analytics has proven to provide valuable information to administrators for increasing student retention and increasingly to instructors to improve the learning environment. Analytical applications have been applied successfully to other nonprofit organizations to drive donor development operations; they can benefit academic organizations as well. There are, however, few examples of donor development models in higher education. Organizations like the American Red Cross and the Paralyzed Veterans of America (PVA) have used data analytics for more than 20 years to increase donation receipts. The University of California at Irvine includes a PVA data set to train data scientists in the Accelerated Certificate Program in the Division of Continuing Education.

The development of database systems optimized to support analytical operations is a crucial factor for success in developing analytical applications in education. Otherwise, modeling operations will be very cumbersome and inefficient. This inefficiency will augur poorly for the application of data analytics in many areas of operation. Academic and enrollment data managers must shift their focus to view data, not just a record of student achievement but also as a source for data analytical operations. This paradigm shift may spawn the development of a dependent analytical data mart to provide input data efficiently for analytical purposes.

Despite the importance of data analytics in education, the human element provided by educational administrators and faculty is critically important in an educational program to assure that graduates are prepared properly for their future job responsibilities. Schools must provide learning environments that are tuned more closely to specific human needs and perceptions of students. Such an operation to match student expectations with academic results is very similar to the use of recommendation models by Netflix and Amazon Prime Video for matching past viewings to probable future viewings by a customer. Successful graduates compose the only end result that will assure program sustainability in education.

Improvements in student recruitment, achievement, and retention can greatly improve the financial viability of an institution. Increased personal contacts can enhance the degree to which students engage their educational program to facilitate learning. Increased engagement of donors driven by patterns learned in analytical studies can greatly influence giving behavior leading to increased giving receipts. Data analytics, when planned and executed properly, can be one of the most cost-effective means to achieve those ends. These analyses can generate significant increases in the quality and quantity of the learning process in schools and colleges.

As SEM professionals seek to support efforts for improved planning and mission fulfillment across the institution, it is incumbent upon these leaders to become conversant in the language of predictive analytics so that these models can indeed be used to refine and support institutional SEM plans. SEM professionals may think that they must possess all of the skills of a data scientist, but this isn't necessary (Henke, Levine, and McInerney 2018). Instead, SEM leaders would do well to begin with a cursory understanding of these issues and develop the ability to help others with deeper analytic capabilities translate institutional data and intuition into actionable models to benefit their institutions.

References

Couch, J., and J. Towne. 2018. *Rewiring Education: How Technology Can Unlock Every Student's Potential.* Dallas, TX: BenBella Books.

Dreyfus, H. L. 1972. *What Computers Can't Do: The Limits of Artificial Intelligence*. New York: Harper & Row.

Henke, N., J. Levine, and P. McInerney. 2018. You don't have to be a data scientist to fill this must-have analytics role. *Harvard Business Review*. February 5. Retrieved from: <hbr-org.cdn.ampproject.org/c/s/hbr.org/amp/2018/02/you-dont-have-to-be-a-data-scientist-to-fill-this-must-have-analytics-role>.

Hess, A. 2019. Here's how much the average student loan borrower owes when they graduate. *CNBC*. May 20. Retrieved from: <cnbc.com/2019/05/20/how-much-the-average-student-loan-borrower-owes-when-they-graduate.html>.

Hossler, D., and B. Bontrager. 2014. *Handbook of Strategic Enrollment Management*. San Francisco: Jossey-Bass.

Jenkins, E. W. 2000. Constructivism in school science education: Powerful model or the most dangerous intellectual tendency? *Science & Education.* 9: 599–610.

Manyanga, F., A. Sithole, and S. Hansen. 2017. Comparison of student retention models in undergraduate education from the past eight decades. *Journal of Applied Learning in Higher Education.* 7: 29–41.

Miner, L., P. Bolding, J. Hilbe, M. Goldstein, T. Hill, R. Nisbet, N. Walton, and G. Miner. 2015. *Practical Predictive Analytics and Decisioning Systems for Medicine: Informatics Accuracy and Cost-Effectiveness for Healthcare Administration and Delivery Including Medical Research*. London: Academic Press.

Moore, O. K. 1980. About talking typewriters, folk models, and discontinuities: A progress report on twenty years of research, development, and application. *Educational Technology*. 20(2): 15–27.

———. 1971. The clarifying environments program. *Educational Technology*. 11(2): 73–77.

Nisbet, R., G. Miner, and K. Yale. 2017. *Handbook of Statistical Analysis and Data Mining Applications*. 2nd ed. San Diego: Academic Press.

Osmanbegović, E., and M. Suljić. 2012. Data mining approach for predicting student performance. *Economic Review: Journal of Economics and Business*. 10(1): 3–12.

Peterson, A. 2017. Big data in education: New efficiencies for recruitment, learning, and retention of students and donors. In *Handbook of Statistical Analysis and Data Mining Applications*, edited by R. Nisbet, G. Miner, and K. Yale. San Diego: Academic Press.

Sawyer, R. K. 2014. *The Cambridge Handbook of the Learning Sciences*. 2nd ed. Cambridge Handbooks in Psychology. Cambridge: Cambridge University Press.

Sigler, W. 2017. *SEM Core Concepts: Building Blocks for Institutional and Student Success*. Washington, D.C.: American Association of Collegiate Registrars and Admissions Officers.

Gordon College. 2020. *The Gordon Game Change*. Wenham, MA: Author. Retrieved October 8, 2020 from: <gordon.edu/gamechange>.

Tomic, W. 1993. Behaviorism and cognitivism in education. *Psychology*. 30(3/4): 38–46.

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