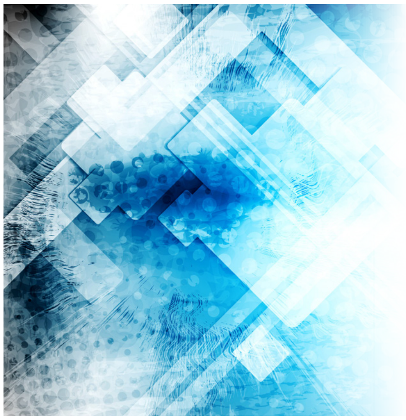

Abstract

This article explores the challenges that students face in navigating the curricular structure of post–secondary degree programs, and how predictive analytics and choice architecture can play a role. It examines Degree Compass, a course recommendation system that successfully pairs current students with the courses that best fit their talents and program of study for upcoming semesters. Data are presented to demonstrate the impact that this system has had on student success. In particular the data will show that by closing the information gap, this system is able to close the educational achievement gap for low–income and minority students.

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How Predictive Analytics and Choice Architecture Can Improve Student Success

It has been a longstanding reality that success in higher education is very uneven across the population of the United States. Consistently over the last three decades racial minority, low–income, and first generation students have earned post–secondary degrees at substantially lower rates than their counterparts. Although the degree–attainment rates for these three groups have increased over that time horizon, those improvements have not kept pace with the degree attainment rates of students in general (NASH & The Educational Trust, 2009; NCES, 2012; U.S. Census Bureau). The most recent IPEDS data show that whilst 49 percent of white students who began college in 2007 graduated with at least an associates degree in 6 years, 37 percent of their African American counterparts, and 33 percent of Hispanic students graduated. While the rate at which low–income students enroll in higher education has doubled since the 1970s the graduation rate for these students has only grown from 7 percent to 10 percent (NASH & The Educational Trust, 2009; Postsecondary Education Opportunity.[1]) First generation students begin to trail their peers as early as their first year, earning 18 credits, on average, compared to the 25 credits earned by students whose parents have degrees (Chen & Carroll, 2005). In fact, similar patterns emerge for minority, low–income, and first generation students in every success metric governing student progress through college when compared with their white, higher–income or non–first generation peers (Kelly, 2005; Lumina Foundation, 2014; NASH & The Educational Trust, 2009).

These attainment gaps appear to be significantly influenced by information gaps. First generation, low–income and minority students often do not have the advice system that surrounds students whose parents or other relatives have been to college. Information is certainly available to these students, but without knowledge of the structure and nomenclature of higher education they are unable to even frame the questions that would enable them to become informed (Diamond et al., 2014; Hagelskamp, Schleifer, & DiStasi, 2013; Kadlec, Immerwahr, & Gupta, 2014).

[1] http://www.postsecondary.org/

The process of navigating institutions from admission to graduation involves large numbers of crucial decisions, and once again, the information gap plays its part in the achievement gap. Despite the advantages to having a clear direction of study (Jenkins & Cho, 2012), one third of first generation students begin college without identifying a major or program of study, whereas only 13 percent of their peers with college–going parents do so (Chen & Carroll, 2005). Students select their majors with little information about what is involved in successfully completing the program, and often discover too late that the picture they had of that discipline is very different from the reality (Kirst & Venezia, 2004; Smith & Wertlieb, 2005). Low–income and minority students express less knowledge of programmatic demands than their peers. Although students may think that they have an interest in a particular area, they receive little information about whether their academic abilities create a realistic chance of successfully completing that program. What is more, they may associate each discipline with a limited number of careers, and often eliminate disciplines from their list of choices because those jobs are unappealing, without realizing the true variety of career opportunities that lie on the other side of graduation.

First generation, low–come and minority students often do not have the advice system that surrounds students whose parents or other relatives have been to college.

As challenging as the factors involved in choosing the right degree program are, navigating a degree program is no less crucial or challenging. Each student must choose from a variety of courses that satisfy the requirements of their general education core, and then their various degree program requirements. Ideally students would make strategic decisions about which courses are most likely to lead to their success. Instead, they are faced with making choices between courses that, ahead of time, they are not in a position to distinguish between. Indeed higher education has been described as a "post–experience good" (Diamond et al., 2014), since not only is it difficult to envisage or evaluate the experience of studying a particular course or program before hand, the true benefits of that study may not be understood until long into the future. Advisors are often well equipped to provide valuable advice in their own field. But, most programs require students to take courses from across the full spectrum of disciplines, and advisors find themselves challenged to offer useful advice in disciplines far from their own. As higher education funding has become more and more depleted, even access to this advice is far from guaranteed (Kadlec et al., 2014).

Yet access to advising is vital as nationwide, college students take up to 20 percent more courses than are needed for graduation on average – not motivated by a desire for a diverse curriculum, but because they had to rethink their plans several times. In an environment in which time to degree has considerable implications for a student's likelihood of successfully graduating, a semester of extra coursework plays a crucial factor, especially for students who attend part time, or for whom financial impacts weigh heavily (Complete College America, 2011).

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Information and choice clearly have a significant impact on a student's ability to navigate through a degree successfully. But this significantly raises the stakes on the ways in which the information is presented and how the choices are framed. Schwartz (2004) has argued for a paradox of choice – that having too many options can lead to a decision paralysis. Tversky and Kahneman have carefully analyzed how decisions are made in the face of an abundance of choice (Kahneman, 2011; Kahneman & Tversky, 1979; Tversky & Kahneman, 1974). They, and others, have found that when presented with too many choices people fall back on a variety of rules–of–thumb, anecdotal evidence, or rely on cognitive ease and the halo effect. Often, poorer choices are made in situations of an abundance of choice, using these fall back methods, than in situations with more limited choice. In fact the literature on choice overload suggests that too many options can result in several adverse experiences including a depletion of cognitive resources and post–decision feelings of regret (Reed, DiGennaro Reed, Chok, & Brozyna, 2011; Schwartz, 2004). Given the multiplicity of choices entailed in selecting from a college's array of majors or programs, and then satisfying the curricular requirements they require, these adverse experiences may play a significant part in student success, especially for at–risk populations. In fact it seems that a more focused choice structure would be far more effective and preferred (Diamond et al., 2014; Kadlec et al., 2014; Reed et al., 2011; Schwartz, 2004).

While these educational achievement gaps have remained stubbornly present, one promising avenue of attack seems to be the use of predictive analytics to provide individualized information to each student, and so to more evenly level the information playing field.

Predictive analytic techniques move from a retrospective reporting data stance toward the use of large data sets to make detailed predictions about the future. These predictive models enable strategic action to be taken in the present to potentially provide significant improvements in the future. In this vein an appropriately designed system could use the perspective of the past to better inform students, and conversations between students and advisors. Such a system could allow advisors and students to make plans for future semesters, illuminated by the knowledge of courses or even majors in which past students with similar programs, grades and course histories had found success. It could also provide a focused choice architecture in which students could choose from a more limited selection of majors or courses that have been individualized to them, whilst leaving all possibilities available.

Recent Work to Respond to this Challenge

My recent work at Austin Peay State University and now at the Tennessee Board of Regents has, in part, been focused on finding ways to empower student choices by creating choice architectures that improve the information available to each student. The concept was to combine predictive analytics with behavioral economics to create an environment that would help students and advisors select impactful courses. We were intentional in providing an interface that neither restricts nor prescribes their choices, but instead empowers choice by creating an information source with a larger than human viewpoint and supported by data from previous choice patterns (Denley, 2012).

Recommendation systems implemented by companies such as Netflix, Amazon and Pandora are a familiar feature of life today. We decided to create an interface in that vein, and developed a course recommendation system (Degree Compass) that successfully pairs current students with the courses that best fit their talents and program of study for upcoming semesters. The model combines hundreds of thousands of past students' grades with each particular student's transcript to make individualized recommendations for each student. However, the recommendations in this system had to be made within the confines of each student's degree structure, and in a fashion that aligned more closely to the concerns of effective advising if it truly were to level the information field. In contrast to systems that recommend movies or books, these recommendations do not depend on which classes students like more than others. Instead it uses predictive analytics techniques based on grade and enrollment data to rank courses according to factors that measure how well each course might help the student progress through their program. In their 2009 book, Thaler and Sunstein discuss strategies to better structure and inform complex choices (Macfadyen, Dawson, Pardo, & Gasevic, 2014). Degree Compass was designed with this in mind to create a choice architecture to nudge students toward course selections in which the data suggest they would have the most productive success, but using an interface that would minimize choice overload.

While these educational achievement gaps have remained stubbornly present, one promising avenue of attack seems to be the use of predictive analytics to provide individualized information to each student, and so to more evenly level the information playing field.

[2] Degree Compass is now a commercially marketed product, available from D2L Incorporated

The algorithm liaises with the institution's degree audit system to find the courses that would satisfy some as yet unsatisfied degree requirement, if the student were to take that course. From these courses that could apply directly to the student's program of study, the system selects those courses that best fit the sequence of courses in their degree, recommending courses that are curricularly more central before those which are more specialized. That ranking is then overlaid with a model that predicts the courses in which the student will achieve their best grades. In this way, the system most strongly recommends those courses which are necessary for a student to graduate, core to the institution's curriculum and their major, and in which the student is expected to succeed academically.

The recommended course list is conveniently displayed in a web–based interface on the secure side of the institution's information portal. This interactive interface provides information on each recommended course's curriculum and requirements, what role that course plays in the student's degree, as well as class availability in upcoming semesters. The student is able to filter the list to show only classes that are offered online, or face–to–face, or only at particular campuses to refine their decisions according to some practical constraints.

The concept was to combine predictive analytics with behavioral economics to create an environment that would help students and advisors select impactful courses.

The strength to which the system recommends each particular class is communicated by a star rating. A five star class is one that, amongst the presently available courses, best fits the student's curricular constraints, and is one in which the student is predicted to earn as good a grade as they might earn in any other course that would fulfill their requirements. It does not necessarily mean that they will get an A grade. Indeed the interface does not reveal predicted grades to the student. However, all of this information is available to advisors as a tool for academic advising that supplements the information available when providing advice to their advisees.

The interface also provides a majors recommendation system called MyFuture. For a student who has already identified their major, MyFuture provides information about concentration choices and degree pathways, as well as links to prospective career paths, job availability and O*Net statistics for graduates in that major. For a student who is yet to choose a major, or is thinking about changing their major, it provides a list of majors in which that student is predicted to be the most academically successful. Again, for each of these majors, information is provided about concentration choices and degree pathways as well as prospective career paths and job availability. MyFuture uses data–mining techniques to identify the courses that are the best indicators of success in each of the institution's programs – the courses that capture the flavor of each major – and uses Degree Compass' technology to predict course grades and find the majors in which each student will be the most academically successful.

The system was developed in collaboration with faculty, advisor and student input to create an interface that would be able to supplement the advising process. The interface itself was developed to allow commonly utilized functionality in a familiar format. When developing the grade prediction engine for these tools, we chose the data sources on which to base the predictions carefully. Since one of the objectives was to try to impact the performance of subpopulations for which there has been an achievement gap in the past, we chose not to use any demographic information in the model. We also chose to make the system faculty–agnostic by not disaggregating the grading patterns of different faculty. Conversations with faculty members suggested that by doing this there would be greater faculty involvement in the project, and greater utility for the tool.

What the Data Say about the Impact of Degree Compass

We developed a strong assessment structure to assess the impact of Degree Compass on student success (Denley, 2013). Data collected as part of the Degree Compass project fell largely into three categories. First, because courses are recommended to students based on curricular fit, together with a prediction of the grade that student would earn if they were to take the class, it is crucial to collect data that establish the accuracy of the grade predictions. Degree Compass was built to track the predicted grade as well as the earned grade for each student in each semester in each class in which they were enrolled. Secondly, given that advice from Degree Compass is useful only if it is consulted, the system used click–traffic data to provide information about the system's use. Focus groups and surveys also provided feedback about the usability of the interface and other features that users might consider informative. Finally, the aim of the project was to empower students to make more advantageous choices in their education that would help them move effectively through their curriculum. Consequently we measured student success and progression through their curricula.

Instead it uses predictive analytics techniques based on grade and enrollment data to rank courses according to factors that measure how well each course might help the student progress through their program.

Our initial results for the 10,873 students at Austin Peay State University (APSU) were very encouraging. However, it was important to establish that our modeling techniques could calibrate themselves to differing institutional settings and student populations. Generous support from Complete College America and the Bill and Melinda Gates Foundation allowed us to replicate the system at three other schools in Tennessee – two community colleges and one university – adding another almost 40,000 students. Fortunately, the results from all three campuses replicated the ongoing grade prediction resolution achieved at APSU. Data from Fall 2012 showed that the average predicted grades in the university settings were within 0.59 of a letter grade of the awarded grades, and 89 percent of those who were predicted to pass the course indeed passed. In the community college setting, average predicted grades were within 0.64 of the awarded grades, and 90 percent of students who were predicted to pass the course did so. These results confirmed that the grade prediction engine successfully predicts grades in settings across the higher education spectrum, from a rural community college to an urban research university.

Of course, the motivation behind this work was not to predict grades, but rather to provide a choice architecture in which students and advisors could make more nuanced decisions about degree programs. Using Degree Compass as part of academic advising at APSU has steered students towards more classes in which they would more readily succeed, both by passing the course in greater numbers and also achieving higher grades. A comparison of student grades before the introduction of the system with those today shows a steadily increasing ABC%, with grade results across the institution today more than 5 standard deviations better than those in Fall 2010. This very statistically significant shift was apparent across the student body, from freshmen to seniors. We saw similarly significant increases for several subpopulations, including African American students (an increase of 2.1 percent, with 2.89 standard deviations) and Pell recipients (an increase of 3.9 percent, with 7.7 standard deviations). These figures are not results from a sampling of the student population, but include the entire undergraduate student body.

The performance data above clearly demonstrate that students in both the university and community college settings progress more effectively through their degree programs when they follow a course sequence informed by data–analytics.

While it is still early to make general connections between Degree Compass and graduation rates, since the system was introduced at APSU in Spring 2011, the six–year graduation rate has increased from 33 percent to 37.4 percent, with the greater gains for low–income students (increased from 25 percent to 31 percent) and African American students (increased from 28.7 percent to 33.8 percent).

On a more granular level we carried out a detailed analysis of the data to connect Degree Compass recommendations with student successes in their classes and progression through their degrees. Historically, the grade distributions across all four campuses, of all students, showed a picture in which 63 percent of the time a student received an A or a B grade in their course. Using Degree Compass, a much larger proportion of the students who were predicted to earn a B or above were actually awarded that grade. Indeed, on each campus more than 90 percent of students who took a course in which they were predicted to get at least a B actually earned an A or a B grade. The analysis shows that this effect was evidenced at every school and at every course level from developmental classes through upper–division courses.

It is clear that in a model that uses the past to influence the future there is the danger of perpetuating or even reinforcing existing stereotypical trends. However this need not be the case. One of the reasons we chose not to employ demographic information as part of the predictive modeling was precisely to build in safeguards against such phenomena.

For each of the institutions the number of earned credits was highly correlated with number of recommended classes that were part of a student's semester schedule. For instance, those students who took a 12–hour schedule that contained no recommended classes earned only 2.5 credits on average, compared with 10.5 credits for those students whose entire schedule was crafted from recommended courses (see Figure 1). Analysis of other attempted loads showed similar results. With correlation coefficients ranging from 0.7 to 0.9, this connection translates into significant gains when students take recommended classes in comparison with taking classes that are not recommended.

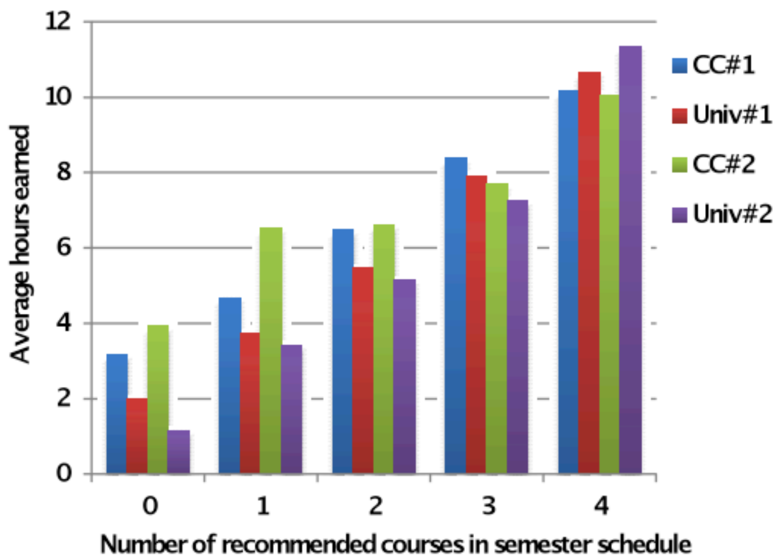

Figure 1. Comparison of average earned hours in a 12–hour schedule disaggregated by the number of recommended classes.

Further analysis of attempted and earned hours revealed that the achievement gap between the average hours earned by white students and average hours earned by African American students reduced significantly for those students who took classes recommended by Degree Compass. For instance among students who attempted 12 hours, white students earned 10.06 hours on average, while their African American peers earned 8.06 hours on average. As we have seen, this is the familiar achievement picture nationally. However, for those students who took 12 hours of courses all of which were recommended by Degree Compass, all students did better, regardless of ethnicity. White students earned 11 hours while African American students earned 10.3 hours on average. The 20 percent achievement gap was more than cut in half (see Figure 2). We see much the same picture for low–income students. Among students who attempted 12 hours, low–income students earned 8.35 hours on average, while their peers earned 10.07 hours on average. However, for those students who took 12 hours of courses, all of which were recommended by Degree Compass, low–income students earned 10.3 hours while their peers earned 11.04 hours on average. Once again, all students did better, and again the achievement gap was cut in half.

Conclusion

Degree Compass has crystalized a number of topics concerning the role that predictive analytics might play in higher education and student success initiatives in particular. First, as a proof of concept, it is now apparent that student success interventions powered by predictive

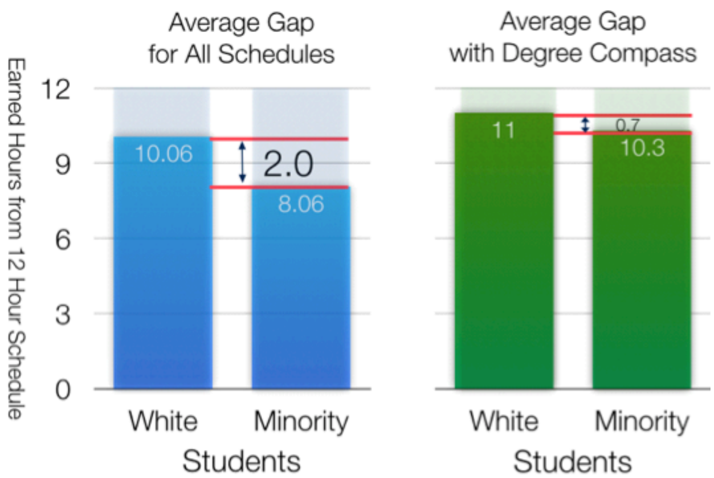

Figure 2. Comparison of average earned hours from a 12–hour schedule disaggregated by race for students in general and students who took only courses recommended by Degree Compass.

analytics are capable of moving the needle on degree completion. The performance data above clearly demonstrate that students in both the university and community college settings progress more effectively through their degree programs when they follow a course sequence informed by data–analytics. Furthermore, there have been precious few approaches that have been able to appreciably close the educational achievement gaps for race and income, and fewer still that can be scaled. Once again, the data suggest that this approach is one that is effective and can be broadly applied at scale.

This approach, however, has highlighted a number of educational issues. It is clear that in a model that uses the past to influence the future there is the danger of perpetuating or even reinforcing existing stereotypical trends. However this need not be the case. One of the reasons we chose not to employ demographic information as part of the predictive modeling was precisely to build in safeguards against such phenomena. The system is designed to be able to use additional data sources as they become available. However, the data that we have collected so far seem to suggest that our current approach has been successful.

In a similar vein, by nudging students towards courses in which they are predicted to have greater success there is the possibility that we may erode academic rigor by systematically steering students towards the easy classes. It may be interesting to contemplate whether when a student takes a class in which they have an increased likelihood of success they are taking an easier class. The experience in the class is as much a function of the student's preparation or talent as it is the challenge of the course. Indeed, as faculty we are all guilty of following the easier route and studying a topic in which we had talent and insight rather than taking the academically more challenging route of choosing a subject for which we had no affinity.

This is not computerized decision making, but technology–informed choice.

One of the important features of Degree Compass is that it only suggests courses that satisfy existing degree requirements. The curriculum is only as rigorous as the courses that can be taken to navigate it, and those remain unchanged. Consequently, the courses that are suggested by the technology are courses that any student might always have chosen and any advisor might always have advised a student to take. The issue comes down to how a student's or advisor's knowledge of the curriculum might inform that choice. It is also an important observation that the suggestions are just that. This is not computerized decision making, but technology–informed choice. The software provides additional information which the student and advisor are then able to use to make more informed decisions. The influence of a plausible default is an important aspect of this, and is an intentional feature of the choice architecture provided in the interface, but the choices that the student and advisor make are still their free choice.

The system only ever suggests courses that satisfy unmet degree requirements. This has the potential to reduce the numbers of excess hours that students currently take. By only suggesting courses that meet degree requirements there is the possibility that the students' experience of the aspect of discovery and intellectual curiosity in the educational process may be stifled. However, transcript analysis shows that more often than students choosing courses off their curricular path because of intellectual curiosity, they actually take these classes simply because the course they would like to choose is unavailable. Since the data now clearly support that students taking the courses that they need is a crucial aspect of student success, it is incumbent on us to offer the classes that students need, when they need them. If we employ predictive technology to ensure that the skeletal structure of the degree is seamlessly available to students, we create the flexibility for more intellectual curiosity should the student choose.

In fact, a deep dive into data at the Tennessee Board of Regents has allowed me to create strategic insights into the structure of the system and how students succeed and fail. These insights are being used to inform changes to system policy, as well as direct broad–scale system initiatives.

Here we have concentrated on seeing how individualized analytics can be used to help optimize course and curricular selections, but there are many other ways in which these kinds of technology can be utilized across higher education. This work demonstrates how predictive analytics can provide a larger–than–human viewpoint that can inform student choice. We are starting to see how these kinds of recommending systems can empower decisions by program coordinators, and institutional leadership. In fact a deep dive into data at the Tennessee Board of Regents has allowed me to create strategic insights into the structure of the system and how students succeed and fail. These insights are being used to inform changes to system policy, as well as direct broad–scale system initiatives. It seems likely that over the coming years we will see more and more ways in which predictive analytics and data–mining technology coupled with behavioral economics will play roles in higher education on every scale (Johnson et al., 2013; cf. O'Reilly & Veeramachaneni, 2014).

References

Chen, X., & Carroll, C. D. (2005). *First generation students in postsecondary education: A look at their college transcripts.* NCES 2005–171. Washington, DC: National Center for Educational Statistics.

Complete College America. (2011). *Time is the enemy*. Washington, DC: Author.

Denley, T. (2012). Austin Peay State University: Degree Compass. In D. G. Oblinger (Ed.), *Game changers: Education and information technologies* (pp. 263–267). Louisville, CO: EDUCAUSE.

Denley, T. (2013). Degree Compass: A Course Recommendation System. *EDUCAUSE Review Online*. Retrieved from http://www.educause.edu/ero/article/degree–compass–course–recommendation–system

Diamond, A., Roberts, J., Vorley, T., Birkin, G., Evans, J., Sheen, J., & Nathwani, T. (2014). *UK review of the provision of information about higher education: Advisory study and literature review*. Leicester, UK: HEFCE.

Hagelskamp, C., Schleifer, D., & DiStasi, C. (2013). *Is college worth it for me?: How adults think about going (back) to school*. New York, NY: Public Agenda.

Jenkins, D., & Cho, S–. W. (2012). Get with the program: Accelerating community college students' entry into and completion of programs of study. New York, NY: Community College Research Center.

Johnson, L., Adams Becker, S., Cummins, M., Estrada, V., Freeman, A., & Ludgate, H. (2013). NMC horizon report: 2013 higher education edition. Austin, TX: The New Media Consortium.

Kadlec, A., Immerwahr, J., & Gupta, J. (2014). *Guided pathways to student success: Perspectives from Indiana college students & advisors*. New York, NY: Public Agenda.

Kahneman, D. (2011). *Thinking, fast and slow*. New York, NY: Farrar, Straus and Giroux.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47*(4), 263–292.

Kelly, P. J. (2005). *As America becomes more diverse: The impact of state higher education inequality.* Boulder, CO: National Center for Higher Education Management Systems.

Kirst, M. W., & Venezia, A. (Eds.). (2004). *From high school to college: Improving opportunities for success in postsecondary education*. San Francisco, CA: Jossey–Bass.

Lumina Foundation. (2014). *A stronger nation through higher education*. Indianapolis, IN: Author.

Macfadyen, L. P., Dawson, S., Pardo, A., & Gasevic, D. (2014). Embracing big data in complex educational systems: The learning analytics imperative and the policy challenge. *Research & Practice in Assessment, 9*(2), 17-28.

National Association of System Heads (NASH), & The Educational Trust. (2009). *Charting a necessary path: The baseline report of public higher education systems in the Access to Success Initiative*. Washington, DC: Authors.

National Center for Education Statistics (NCES). (2012). *Higher education: Gaps in access and persistence study.* Washington, DC: Author.

O'Reilly, U. M., & Veeramachaneni, K. (2014). Technology for mining the big data of MOOCs. *Research & Practice in Assessment, 9*(2), 29-37.

Reed, D. D., DiGennaro Reed, F. D., Chok, J., & Brozyna, G. A. (2011). The "tyranny of choice": Choice overload as a possible instance of effort discounting. *The Psychological Record, 61*(4), 547–560.

Schwartz, B. (2004). *The paradox of choice: Why more is less*. New York, NY: HarperCollins.

Smith, J. S., & Wertlieb, E. C. (2005). Do first–year college students' expectations align with their first–year experiences? *NASPA Journal, 42*(2), 153–174.

Thaler, R. H., & Sunstein, C. R. (2009). *Nudge: Improving decisions about health, wealth, and happiness*. New York, NY: Penguin Group.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science, New Series, 185*(4157), 1124–1131.

U. S. Census Bureau. (2006). *Current population survey, October supplement, 1972–2006*. Washington, DC: Author.