Academic Advising Approaches for Student Success in Developmental Education

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Developmental, or remedial, education—in which incoming college students deemed to be not college-ready (usually in mathematics and/or language arts) are remediated—has long been a difficulty for colleges and community colleges in particular. In recent years, however, there has been an explosion of new research and techniques related to developmental education.

Placement into either developmental or college-level courses is also the subject of much research. The traditional model for college placement is that the prospective student takes a placement test to determine if they can meet the required level and, if they do not, is placed in a developmental course of study to be completed prior to college-level work. This paper reviews the literature around trends and research in the academic advising and placement process.

Review of Literature

Student Success in Traditional Developmental Education

The literature raises many concerns about the negative impact of traditional developmental education on student success. Scott-Clayton (2012) found that placement exams are better at predicting which students will succeed in college than who would fail and that multiple methods of placement would be more effective and could help more students be successful. Once a student has been placed into a developmental course, Park et al. (2016) found that taking developmental education classes has a significant impact on degree and career completion and that many students simply do not ever take the core or gateway classes. In fact, less than half of the students complete their developmental education series of courses, and nearly one third simply do not take the developmental education course at all (Bailey, Jeong, & Cho, 2010). Hu et al. (2016) determined that developmental education acts more as a hindrance than a help to incoming college students. Even new first year experience courses were found to not help students move through developmental education faster or improve academic achievement (What Works Clearinghouse (ED) & Development Services Group, 2016).

Trends in Academic Advising for Developmental Education

Despite the bleak outlook on traditional developmental education, there is much activity around alternative approaches for developmental education, many of which are summarized by the Core Principles for Transforming Remedial Education: A Joint Statement (Charles A. Dana Center, Complete College America, Education Commission of the States, & Jobs for the Future, 2012), credited for being the impetus behind (Waschull, 2018) Florida's 2013 developmental education reform measures—which made placement tests optional for high school graduates and required measures for developing corequisite support classes (Venezia & Hughes, 2013)—among others. As a result of those reform measures, Hu et al. (2016) found that fewer students took developmental education courses but more passed them and that while more students both took and failed gateway courses, the ratio of all first-time college students who passed gateway courses increased.

Multiple Measures for Placement. Many colleges are beginning to use multiple, alternative measures to traditional placement testing to evaluate students' ability to be successful in college-level courses. These measures often include some of the following: high school GPA, standardized testing, specific skills testing, and noncognitive assessments (Barnett & Reddy, 2017; Gaertner, Conley, & Stolz, 2016; Scott-Clayton & Belfield, 2015). These measures are combined differently, but can be summarized as the following three primary methods: "conjunctive," where all measures must be passed; "compensatory," where one measure can compensate for others; and "complementary," where the best result among the available measurements is used (Brookhart, 2009). The literature shows that using multiple measures is more accurate than placement testing alone. For example, a pilot study in California showed tremendous improvements in placement accuracy for both math and English (Scott-Clayton & Belfield, 2015) and Nunez (2015) found that high school GPA was the best overall predictor of student success at an Illinois community college.

Pathways for Gateway Courses. Guided pathways and meta-majors are another significant area of interest in developmental education. This model is designed to “help students explore career and college options and choose a program of study or broader ‘meta-major’ and develop a program plan early on.” (Jenkins, Lahr, & Fink, 2017, p. 1) Several states are considering or have already enacted legislation requiring meta-majors and/or guided pathways (Fulton, 2017). Other similar pathways projects, such as the Carnegie math pathways, are also underway and showing promising results. Six years after implementation, students are earning college credit at triple the rate and in half the time compared to standard developmental math sequences (Huang, 2018).

Noncognitive Assessments. There is also much research being performed around so-called noncognitive factors, referring to “attributes, dispositions, social skills, attitudes, and intrapersonal resources, independent of intellectual ability” (U.S. Department of Education, Office of Educational Technology, 2013, p. v). Farrington et al. (2012) categorized these factors as follows: “academic behaviors,” “academic perseverance,” “academic mindsets,” “learning strategies,” and “social skills” (p. 10). Robbins et al. (2004) found that a number of noncognitive factors—most notably “academic self-efficacy and achievement motivation”—were predictive of college success. Allen, Robbins, and Sawyer (2010) argue that measuring for noncognitive factors as part of the advising and admission process will help institutions better design and implement interventions to promote student success.

Predictive Modeling, Artificial Intelligence, and Machine Learning. Using machine learning (ML) and artificial intelligence (AI) to develop predictive models is an area of intense interest for many higher education institutions. Examples of applications include the following: identifying students for whom access to more scholarships would be retained at a higher rate (Yates & Chamberlain, 2017), analyzing students' past interactions to predict their chances of success with a semester's class schedule to automate the advising process (Al-Sarem, 2015), and analyzing learning management system log files to determine study habits and develop virtual tutors to assist students (Arroyo & Woolf, 2005). More research is needed on the specific and long-term effects of AI and ML on student success.

Creative, Human Advising. Despite the incredible achievements and promise in the areas of ML and AI, there exist—and quite likely always will exist—aspects of academic advising that are uniquely suited to humans. When advanced or monotonous calculations are automated by computer logic, people can then be freed up to perform the human tasks (Aoun, 2017, p. 47). In their study of jobs most likely to be replaced by automation, Frey and Osborne (2017) summarized some of these human tasks, stating that "occupations that involve complex perception and manipulation tasks, creative intelligence tasks, and social intelligence tasks are unlikely to be substituted by computer capital over the next decade or two." (p. 27) Indeed, they found that education was one of the least likely to be computerized in the near future (p. 37). Creativity, "the ability to come up with ideas or artefacts that are new, surprising and valuable," (Boden, 2003, p. 1) is perhaps the most human of traits. Boden ultimately determines that, although computers can appear to be creative or appraise creative works, computers lack the ability to actually be truly creative (p. 21). For example Sony's Flow Machines, an AI music-generation program, needed to be programmed to learn music so it could mimic it (Gaca, 2016), an example of an algorithm that appears to be creative but fails to come up with something “new, surprising and valuable.”

Discussion

The research shows that student success can be improved by considering more factors in the academic advising process, including the student’s past performance, standardized test scores, selected pathway or meta-major, noncognitive factors. To accurately account for all these factors, ever more complicated data models—including and especially leveraging AI and ML—will be needed. However, rather than relying on automated, more complex versions of cut scores, advisors should be encouraged and empowered to use their creativity to help students succeed.

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