The AIR Professional File

Fall 2023 Volume

Supporting quality data and decisions for higher education.

SPECIAL ISSUE EDITED BY HENRY ZHENG AND KAREN WEBBER FEATURING FOUR ARTICLES ON ARTIFICIAL INTELLIGENCE AND ADVANCED ANALYTICS

air | ASSOCIATION FOR INSTITUTIONAL RESEARCH

PREFACE

Artificial Intelligence and Advanced Analytics in Higher Education: Implications for Institutional Research and Institutional Effectiveness Practitioners

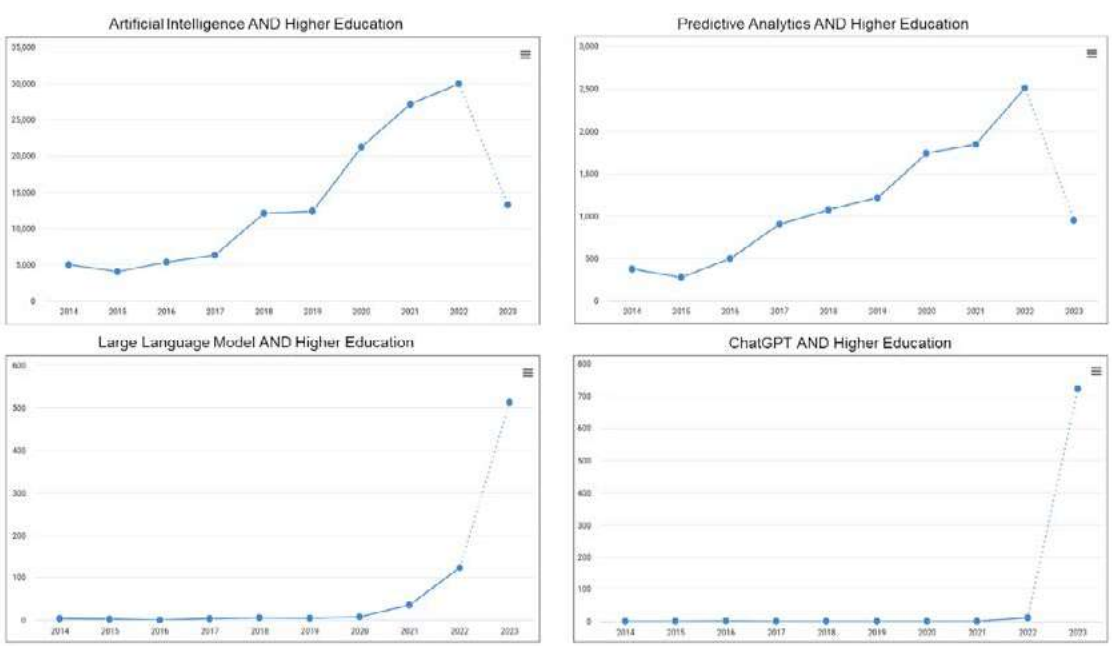
New technologies in our post-pandemic world have prompted substantial changes in every facet of higher education. The emergence of Big Data is one of several key facilitating conditions that accelerated the adoption of artificial intelligence (AI) and machine learning (ML) in key application areas. According to Gartner (2023), Big Data are the high-volume, high-velocity, and/or high-variety information assets that demand cost-effective and innovative forms of information processing that enable enhanced insight and decision-making, and process automation. Considerations for when, how, and why we use Big Data and forms of AI data-informed analytics are critical in institutional research (IR) and institutional effectiveness (IE).

Recently, Chat Generative Pre-trained Transformer (ChatGPT) and generative AI tools including those listed by Dilmengali (2023), have grabbed our attention for their novelty and ability to provide answers to questions in a conversational style. Although they have risks (Reagan, 2023), and refinements are being introduced constantly (as is inherent in a continuous learning model), we find the hands-on user experience of these AI chatbots simultaneously interesting and worrisome. ChatGPT bots and image-building tools such as DALL-E from OpenAI seem to be the latest in AI applications that have generated media hysteria. Other AI-supported systems have been used in higher education, however, including the Georgia Institute of Technology's use of AI Jill Watson (Goel & Polepeddi, 2019) for student tutoring and the U.S. Department of Education's use of a chatbot for federal financial aid (Aidan) (Federal Student Aid, n.d.). The soaring interest in ChatGPT and other AI tools signal that the AI/ML revolution is accelerating (McKendrick, 2021). According to Bill Gates (2023), there have been two technology revolutions in his lifetime: the first was the introduction of a graphical user interface as the forerunner of every modern operating system; and now there is a second revolution: "The development of AI is as fundamental as the creation of the microprocessor, the personal computer, the Internet, and the mobile phone. It will change the way people work, learn, travel, get health care, and communicate with each other" (Gates, 2023).

In this special volume of the biannual Association for Institutional Research's (AIR) *Professional File*, we briefly describe some of the key factors that helped drive the development of AI and ML in higher education; we also include a focus on the implications and opportunities for IR and IE professionals. Although this topic continues to evolve, we think it is important to forge ahead with some discussion, while acknowledging that some aspects of these new tools will change—and will change rapidly. Nevertheless, as critical colleagues on our campus and in policy agencies, we need to be engaged with others on this topic right away. We believe it is essential that IR/IE colleagues (who either already have or who want a seat at the table) contribute actively to discussions about AI in higher education. Being involved in these discussions with senior administrative officials and academic instructional staff members can help cement the perception that IR/IE professionals are knowledgeable, broadly skilled, and able to situate issues within the context of a specific campus environment (yes, IR/IE professionals are indeed multitalented). We could wait 6 to 12 months or more and see how the AI tools evolve, but we believe it is more valuable for IR/IE leaders to get engaged as soon as possible, considering the issues and implications, while being mindful of the likelihood that there will be changes to the tools, techniques, data governance, and other institutional policies.

According to Digital Science's Dimensions Database (dimensions.digital-science.com, accessed May 23, 2023), the number of publications in higher education related to AI in general as well as publications specific to large language models (LLMs), predictive analytics, and ChatGPT, climbed a steep trajectory in the past few years. As shown in Figure 1, publications about general AI and predictive analytics have been growing steadily since 2017, but publications about LLMs and generative AI models such as ChatGPT have exponentially increased only within the past year.

Figure 1. Scholarly Publications in Key Artificial Intelligence–Related Areas in Higher Education



If the speed that ChatGPT grabbed people's attention is stunning, the subsequent rush to leverage its growth is equally dazzling. Companies and organizations rushed to create plugins to ChatGPT. (A ChatGPT plugin is a software add-on that integrates other applications into the ChatGPT AI chatbot. Plugins allow a third-party software or content generator to tap into ChatGPT's capabilities for search optimization and conversational interaction.) As of June 17, 2023, less than 7 months since the official launch of ChatGPT, nearly 500 plugins have been published and connected to ChatGPT 4.0. For example, the plugin ScholarAI allows users to use ChatGPT's interface to answer questions on scholarly articles and research papers. The plugin SummarizeAnything helps users summarize books, articles, and website content. More plugins and similar products are likely to follow.

AI and other advanced analytics in higher education can serve to benefit students in a number of ways. Informed by the work of Zeide (2019) and Holmes and Tuomi (2022), we group the current AI and advanced analytic techniques available in higher education into four categories:

1| **Institutional use**, including marketing and student recruitment, estimating class size, optimizing course catalog descriptions, allocating resources, network security, and facial recognition

2| **Student support**, including academic monitoring, course scheduling, suggesting majors and career pathways, allocating financial aid, identifying students at risk, and supporting mental health

3| **Instruction**, including personalized learning, creating library guides, using generative language models (e.g., ChatGPT, DALL-E), and making grading more efficient

4| **Scholarly research**, including synthesizing literature, drafting grant proposals, and creating new knowledge in many disciplines (both within individual disciplines as well as cross-disciplinary collaborations)

During the early years when AI was introduced to higher education, both in the United States and in other countries, we saw some promising applications of AI and ML. Early adopters sought to enhance student success through tools such as online chat assistants, homework tutoring chatbots, or course learning systems that sought to gather student learning data from multiple sources. Some of the early tools were not user friendly, lacked comprehensive data, and/or did not have faculty buy-in and so did not remain viable. However, these early tools sharpened our thinking, and the ensuing refinements moved members of the higher education community forward on how digital technologies can contribute positively to the higher education mission.

Over the past few years, Georgia State University (GSU) has become well known for its success in gathering and using voluminous data points every day that are related to student characteristics (e.g., financial aid need) to predict and track student academic progress. Their extensive use of the data-enabled digital systems, in combination with human advisors, has produced a significant impact on student success and graduation. The GSU system was quite successful, and GSU now hosts the National Institute of Student Success (NISS), a national effort aimed at helping institution officials to identify potential challenges related to student access, finding ways to maximize impact and ensure success for all students.

A number of institutions are incorporating AI into teaching and learning as well as into campus operations. For example, team members at Rensselaer Polytechnic Institute have incorporated an AI-powered assistant into a language-immersive classroom that helps students learn to speak Mandarin (Su, 2018). According to Gardner (2018), leaders at Elon University are using an AI-based course planning and advising system developed by a tech company, Stellic, to plan courses, consider cocurricular activities, and keep students on the path to graduation. Also according to Gardner, leaders at the University of Iowa are using AI to monitor campus buildings for energy efficiency and to monitor for facilities problems. These and other examples of AI-based systems can promote student and institution success, but they also require staff to have robust technical skills and relevant ways of thinking about data.

An important concern about the use of Big Data or comprehensive predictive analytic models is the high potential for the unintended inclusion of bias, either through training data that do not fully represent the population under study or that fail to contextualize the results to a broader population. The unique changes that occurred during or as a result of the Covid-19 pandemic, as well as continued emphases on the need for diversified campuses, left many institution officials unable to reliably use historical data for predicting the future.

Along with applications in teaching and learning and overall student success, AI is growing its applications in research as well. We have an explosive list of AI applications in business and industry such as health care, banking, and retail customer service. AI is gaining strength in university endeavors such as Emory University's AI. Humanity Initiative and the Graz Center for Machine Learning. Both of these initiatives are focused on interdisciplinary efforts to consider ways in which AI can improve aspects of society. We believe that collaborative, interdisciplinary efforts like these will make dramatic improvements in our higher education systems and overall quality of life.

An ongoing concern about data analytics will be ensuring ample representation of the population under study and/or that the analyses are contextualized to the broader population. The unique changes that occurred during or as a result of the Covid-19 pandemic, as well as continued emphases on the need for diversified campuses, left many institution officials unable to use historical data to reliably predict the future. Vigilance with continued improvements in data security and unbiased models will continue as we progress in the use of AI in higher education, and IR practitioners must be an integral part of these discussions.

Foreseeing the significant changes and implications from AI-assisted education technology implementation in all aspects of education, the U.S. Department of Education issued a guidance document (U.S. Department of Education, 2023) acknowledging that AI poses both risks and opportunities in teaching, learning, research, and assessment. The report recommends several key considerations as key stakeholder continue to explore the use of AI in educational and other academic endeavors:

- **Emphasize humans-in-the-loop**: Keep a humanistic view of teaching front and center.
- **Align AI models to a shared vision for education**: Humans, not machines, should determine educational goals and measure the degree to which models fit and are useful.

- **Design AI using modern learning principles**: Connect AI algorithms with principles of collaborative and social learning and respect the student not just for their cognition but also for the whole human skillset.
- **Prioritize strengthening trust**: Incorporate safety, usability, and efficacy in creating a trusting environment for the use of AI.
- **Inform and involve educators**: Show the respect and value we hold for educators by informing and involving them in every step of the process of designing, developing, testing, improving, adopting, and managing AI-enabled edtech.
- **Develop education-specific guidelines and guardrails**: The issues are not only data privacy and security, but also new issues such as bias, transparency, and accountability.

Clearly, the growth of AI tools in the world around us will also impact current strategies and actions in higher education. Allowing only a short time to adjust, higher education officials must continue to consider its impact on student and institutional success. This special volume of the *Professional File* includes four thoughtful articles related to specific facets of AI and/or advanced analytics in higher education today. In this volume we seek (a) to bring attention to and provide an effective introduction to AI/ML developments in higher education; (b) to introduce IR/IE professionals to some of the latest developments in AI/ML, especially in generative AI, natural language processing, and predictive analytics; and (c) discuss policy, ethics, privacy, and IR/IE workforce implications of these new developments. Each article covers a specific facet or application of AI in higher education. Time and space do not allow us to cover all of the equally important topics, but we offer these topics as a starting point for future discussions.

In the first article, Kelli Bird describes promises as well as the cautions that must be considered in the use of predictive analytics to identify at-risk students. With her eyes wide open to the potential challenges of algorithmic bias and the need for a personal touch, Bird offers examples of success in student support that have occurred through carefully considered predictive modeling. Bird makes an excellent point that, as more-advanced analytics tools become available, the main challenge will not be whether the algorithms (i.e., from machines) are able to identify at-risk students better and more efficiently than humans. Instead, most of the challenges will surround the question of how humans will use the output that machines provide. This aligns with the U.S. Department of Education's key observation that humans, not machines, should determine educational goals and measure the degree to which models fit and are useful.

In the second article, Emily Oakes, Yih Tsao, and Victor Borden urge readers to consider how predictive analytics at large scale as well as applications of AI can be used to center the student voice in developing higher education access and policy development related to learning analytics and AI-embedded student supports. Like Bird, these authors remind readers to be mindful of the potential biases that can be inadvertently built into analytic models, and they urge researchers to ground data in a social justice framework. This cannot be a one-and-done approach, but instead must include a general framework that is used for all analytics tasks as well as the policies governing the collection, management, and implementation of data-based systems. Oakes, Tsao, and Borden's article aligns well with some of the keen observations made by Cathy O'Neil in her bestselling book, *Weapons of Math Destruction*, such as suggesting that, lacking a humanistic perspective, machine algorithms would rely on historical data and learning models that cause harm to those less favored by historical data and machine logics.

We know that academic advising is critical to student success, however, resource-constrained higher education institutions might not have the capacity to offer comprehensive student support that can yield success. Aspects of AI including LLMs enable large-scale collection of data and automated data systems to assist; authors of the third article describe an enterprise-level academic system called AutoScholar. Professor Rawatlal developed the system and colleague Rubby Dhunpath led the implementation of a multifaceted advising system that provides information to students as well as to their instructors, department leaders, and other administrative managers who seek to examine student success across a college or total institution. Authors Rawatlal and Dhunpath describe the AutoScholar system and acknowledge the importance of being able to provide advising information to students, regardless of institutional resources. They acknowledge the high benefits of a data-informed application that augments automated information with human judgement.

In the fourth and final article in this volume, Michael Urmeneta starts with a review of recent discussions on the potential impact of AI in higher education, the increasing proliferation of AI tools, and the need for ethics and accountability. Urmeneta reflects on transitions that helped carve out the path toward AI and advanced data analytics in higher education as well as on the need for ethics and accountability, and offers a cogent discussion on many important implications for IR and IE professionals. Although our landscape for ML and other forms of AI continues to evolve, Urmeneta reminds us that the future is here, and it is important that we understand the technologies, how we will use them, and how we will ensure that the data are used responsibly and with transparency. As those who are deeply embedded in the collection, storage, analysis, and reporting of data, IR and IE professionals must firmly understand the data, and how they are being used within a particular context and without black box designs. IR professionals can ensure ethical deployment, privacy and confidentiality of data, and guard against bias. We like Urmeneta's comment, "Being a passive spectator is neither optional nor tenable." With AI and advanced data analytics, we encourage IR/IE professionals to seize the day!

Although the first paper on AI was published more than 50 years ago and has been embedded in business and industry practices for a few decades, applications of AI are quite new in the higher education arena. We realize that we offer this volume to *Professional File* readers closer to the beginning of the journey into AI and advanced analytics in the higher education context. The months ahead will see a growth in publications on this topic in higher education, but we are confident that the articles herein can help *Professional File* readers to contemplate their role and ways to stay actively involved.

In its policy guidance document, the U.S. Department of Education (2023, p. 4) acknowledged, "AI is advancing exponentially, with powerful new AI features for generating images and text becoming available to the public and leading to changes in how people create text and images. The advances in AI are not only happening in research labs but also are making news in mainstream media and in educational-specific publications." With the rapid speed of AI-related developments, the U.S. Department of Education considered its policy guidance document not as a definitive document but rather as a starting point for discussion. Likewise, we believe that this volume of *Professional File* offers beginning conversations from the authors.

We hope you enjoy the articles in this volume. We believe that AI and advanced analytics will continue to grow in our world of higher education, and, as they grow, we hope you will contribute to the positive impact of AI for IR and IE practitioner success.

Henry Zheng
Karen Webber

ISSN 2155-7535

REFERENCES

Dilmengali, C. (2023). Top 35 generative AI tools by category (text, image, . . .). https://research.aimultiple.com/generative-ai-tools/

Federal Student Aid. (n.d.). Meet Aidan. https://studentaid.gov/h/aidan

Gardner, L. (2018, April 8). How A.I. is infiltrating every corner of the campus. *Chronicle of Higher Education.* https://www.chronicle.com/article/how-a-i-is-infiltrating-every-corner-of-the-campus/

Gartner. (2023). Information technology Gartner glossary. https://www.gartner.com/en/information-technology/glossary/big-data

Gates, B. (2023, March 21). The age of AI has begun. *Bill Gates blog*. https://www.gatesnotes.com/The-Age-of-AI-Has-Begun

Goel, A., & Polepeddi, L. (2019). Jill Watson: A virtual teaching assistant for online education. In C. Dede, J. Richards, & B. Saxeberg (Eds.), *Learning engineering for online education*. Routledge. https://www.taylorfrancis.com/chapters/edit/10.4324/9781351186193-7/jill-watson-ashok-goel-lalith-polepeddi

Holmes, W., & Tuomi, I. (2022). The state of the art and practice of AI in education. *European Journal of Education, 57*(4), 542–570. https://onlinelibrary.wiley.com/doi/10.1111/ejed.12533

McKendrick, J. (2021). AI adoption skyrocketed over the last 18 months. *Harvard Business Review*. https://hbr.org/2021/09/ai-adoption-skyrocketed-over-the-last-18-months

Reagan, M. (2023, February 27). The darker side of ChatGPT. *IIA blog*. https://iianalytics.com/community/blog/darker-side-of-chatgpt

Su, H. (2018, August 30). Mandarin language learners get a boost from AI. *RPI blog*. https://everydaymatters.rpi.edu/mandarin-language-learners-get-a-boost-from-ai/

U.S. Department of Education. (2023). Artificial intelligence and future of teaching and learning: Insights and recommendations. Office of Educational Technology. https://tech.ed.gov/ai-future-of-teaching-and-learning/

Zeide, E. (2019). Artificial intelligence in higher education: Applications, promise and perils, and ethical questions. *EDUCAUSE Review*, August 26, 2019. https://er.educause.edu/articles/2019/8/artificial-intelligence-in-higher-education-applications-promise-and-perils-and-ethical-questions

Table of Contents

Predictive Analytics in Higher Education: The Promises and Challenges of Using Machine Learning to Improve Student Success

Kelli Bird

About the Author

Kelli Bird is a Research Assistant Professor at the University of Virginia's School of Education and Human Development.

Acknowledgments

I am grateful to Ben Castleman, whose continued collaboration and mentorship has been instrumental in my exploration of this topic. I am also grateful for the long-standing partnerships with the Virginia Community College System and Bloomberg Philanthropies that have enabled us to do this work.

Abstract

Colleges are increasingly turning to predictive analytics to identify "at-risk" students in order to target additional supports. While recent research demonstrates that the types of prediction models in use are reasonably accurate at identifying students who will eventually succeed or not, there are several other considerations for the successful and sustained implementation of these strategies. In this article, I discuss the potential challenges to using risk modeling in higher education and suggest next steps for research and practice.

The AIR Professional File, Fall 2023

Article 161

https://doi.org/10.34315/apf1612023

INTRODUCTION

With persistently low retention and graduation rates at many colleges and universities, higher education administrators are increasingly looking for innovative ways to improve student success outcomes. As a result, predictive analytics are increasingly pervasive in higher education (Ekowo & Palmer, 2016). The most common and arguably the most impactful application of predictive analytics is to use a prediction model to identify students who are at risk of doing poorly in a course or of leaving college without completing, and to intervene with these students early before they are too far off track.[1] For instance, more than half of colleges and universities report using "statistical modeling to predict the likelihood of an incoming student persisting to degree completion" (Ruffalo Noel Levitz, 2021, p. 22). Once the at-risk students have been identified by the prediction model, then faculty or staff proactively reach out to these students with offers of additional supports, such as academic advising or tutoring. While these types of resources are typically available to students upon request (though perhaps at limited capacity), many students do not take advantage of them. Since colleges do not typically have the resources to provide all students with these extended supports—at the median community college, academic advisors are responsible for 2,000 students (Carlstrom & Miller, 2013)—the goal of predictive analytics is for colleges to efficiently target the resources to students who need the resources to succeed. I will refer to this application of predictive analytics as "risk modeling and resource targeting" throughout this article.

To administrators who have been searching for solutions to improve student success, risk modeling and resource targeting are tempting solutions. Because colleges often lack the analytic capacity to implement these methods, private industry has stepped in with solutions, and those solutions are now a $500 million industry. Roughly a third of colleges and universities have bought predictive analytics products, with each institution spending approximately $300,000 per year (Barshay & Aslanian, 2019). Despite this investment, however, there is no rigorous evidence to show that these methods (either proprietary or in-house applications developed by colleges themselves) are successful at improving student outcomes.[2] What's more, there are concerns that racially biased algorithms or poorly executed messaging could exacerbate, instead of mitigating, existing inequities (Acosta, 2020; Angwin et al., 2016; Burke, 2020; Engler, 2021). In this article, I will discuss the promises of predictive analytics in higher education, the challenges of predictive analytics (human vs. machine), obstacles to effective implementation, and recommendations for next steps for research and practice.

PROMISES OF PREDICTIVE ANALYTICS IN HIGHER EDUCATION

While the current research is lacking in rigorous evaluations of the impact of risk modeling and resource targeting on student success, an increasing body of literature demonstrates that algorithms can achieve relatively high levels of accuracy at

1. Colleges also use predictive analytics for enrollment management purposes, such as identifying high-target students for recruitment or offering generous financial aid packages. These enrollment management practices are designed to bolster the quality of a colleges' incoming class. In this article, I choose to focus on predictive analytic applications designed to support at-risk students.

2. Still, there are several anecdotes to suggest that current applications risk modeling and resource targeting are leading to improved student outcomes. Most notably is Georgia State University (GSU), which reports an 8-percentage-point increase in its graduation rate since implementing EAB's predictive analytics products. This implementation accompanied several other changes at the university, however (Swaak, 2022).

predicting student success. For a recent cohort of high school seniors, my colleagues and I compared the accuracy of a relatively simple logistic regression model with the students' professional college advisors at predicting the students' college enrollment outcomes (Akmanchi et al., 2023). We found that the logistic model is at least as accurate as the advisors for students who interacted with the advisors up to eight times. This is true even though advisors likely had much more pertinent information about the students' college search, such as the names of colleges where they had been admitted. In a separate line of work, my colleagues and I found that incorporating behavioral trace data from online learning management systems can significantly improve the prediction accuracy for new students—which is the population with the lowest retention rates and thus those for whom predictions could be most important (Bird et al., 2022). In recent University of Oregon applications, a more advanced machine learning (ML) algorithm (XGBoost) is roughly three times better at identifying at-risk students than relying on students' high school GPAs alone (Greenstein et al., 2023).

CHALLENGES OF PREDICTIVE ANALYTICS: HUMAN VS. MACHINE

There are many challenges to successfully deploying risk modeling and resource targeting in higher education. However, as the research I briefly discuss above demonstrates, the main challenge will *not* be whether the algorithms (i.e., machine) are able to identify at-risk students better and more efficiently than humans. Instead, most of the challenges surround the question of how humans will use what the output the machines provide. A quote from Pedro Domingos highlights this tension: "It's not man versus machine; it's man with machine versus man without. Data and intuition are like horse and rider, and you don't try to outrun a horse; you ride it."
For humans to harness the machine effectively, it is important to remember two important distinctions. First, much like a horse and rider, the human and machine have different objectives when it comes to predicting which students are at risk. Humans (administrators, policymakers, researchers, etc.) have complex objectives of increasing student success, improving equity, and ensuring the longevity of the colleges and universities. The machine's objective is much simpler: to make the best predictions possible using the information provided. Second, the human and machine have different responsibilities. The humans have the responsibility to rely on context when building the prediction models, since there are many subjective decisions to be made regarding sample construction, outcome specification, and predictors to include. Humans must also investigate potential biases within models, which I will discuss below. Once the predictions have been made and at-risk students have been flagged, the machine's job is done, but the human's job is not: people must decide how to communicate to at-risk students and which additional supports to provide. This is no simple undertaking, and requires significant engagement with colleges' faculty and advising staff. Allison Calhoun-Brown at GSU highlights the importance of the human work: "The innovation is not the technology. The innovation is the change that accompanies the technology" (Calhoun-Brown quoted in Swaak, 2022). In other words, if we want to improve student success outcomes, it is not a question of if we use predictive analytics, but instead *how* we use it.

OBSTACLES TO EFFECTIVE IMPLEMENTATION

One of the biggest obstacles that colleges face in implementing predictive analytics is effectively communicating to students (Acosta, 2020). You could imagine someone drafting this message: "Kelli, an algorithm flagged you as someone likely to fail English 101. Work hard to improve your grade." This message raises several concerns. A recipient might be concerned about their data privacy: How is the college using their personal data to determine their likelihood of failing? This type of messaging could also reinforce stereotype threats of not being "good enough" or "college material," and being labeled as likely to fail could become a self-fulfilling prophecy. Perhaps this message would be more appropriate: "Hi Kelli, this is Professor Smith. I noticed you've been interacting less frequently than some of your classmates. Let's set up a time to talk about how you're doing in the class." This message puts more of a human touch on the outreach, does not lead with the idea of failure, and provides a concrete next step on which the student can act. My colleagues and I are currently working with social psychologists to design effective messaging for an upcoming pilot program, which I describe below. Simply getting the communication right is not sufficient, however. Several recent low-touch nudge interventions with behaviorally informed messaging failed to improve student outcomes (e.g., Bird, Castleman, Denning, et al., 2021), so it is also imperative for students to be connected to the right supports to meet their needs.

Another barrier to successfully implementing risk modeling and resource targeting is achieving buy-in from faculty and staff. Among colleges and universities using statistical modeling to predict graduation, fewer than one-third of administrators thought it was a very effective strategy at improving student success (Ruffalo Noel Levitz, 2021). One of the reasons that faculty may distrust predictive analytics is their black box nature. Many prediction models in use are from third-party for-profit venders; their proprietary nature means that institutions have little understanding of what goes on under the hood. A recent GAO report specifically calls out these higher education models as needing more scrutiny from both their consumers and from regulators (Bauman, 2022).

Humans also may find it difficult to incorporate risk modeling due to the impersonal nature of the machine. Prediction models inherently rely on information from a large historical sample and generate predictions to optimize the accuracy for the group as a whole, as opposed to considering potential nuance in a particular individual's circumstance. In a recent pilot where my colleagues and I collaborated with a community college to improve transfer outcomes for their students, we incorporated an algorithm that generated personalized course recommendations that accounted for the probability that the student would succeed in the course. Despite significant collaboration on how the algorithm would select the courses to recommend, the advisors still changed roughly one out of three courses the algorithm had identified before communicating the recommendations to students.

Finally, many are concerned about the potential negative impacts of algorithmic bias to exacerbate, instead of mitigate, existing inequities. These concerns are not unfounded: several studies have found the existence of algorithmic bias in higher education prediction models (e.g., Baker &

Hawn, 2021; Yu et al., 2020).[3] When my colleagues and I investigated algorithmic bias in two models predicting course completion and degree completion among community college students, we find evidence of meaningful bias (Bird et al., 2023). Specifically, we find that the calibration bias present in the models would lead to roughly 20% fewer at-risk Black students receiving additional supports, compared with a simulated unbiased model.[4] Our exploration suggests that this bias is driven not by the inclusion of race or socioeconomic information as model predictors, but instead by success being inherently more difficult to predict for Black students. This result may reflect structural racism in K–12 education systems where many Black have access to fewer advantages. Specifically, model predictors based on past performance reflect that unequal circumstances would not be as powerful to predict a disadvantaged student's full potential. The algorithmic bias is particularly prevalent among new students for whom there is very little baseline information, suggesting that additional pre-matriculation data collection could mitigate bias in this case. We also find that the amount of algorithmic bias—and the strategies for mitigating the bias—can vary substantially across models; it is therefore imperative to address bias on a case-by-case basis.[5]

RECOMMENDATIONS FOR NEXT STEPS FOR RESEARCH AND PRACTICE

First and foremost, we need rigorous evaluations of different strategies that incorporate predictive analytics. My colleagues and I are planning a pilot program that we will evaluate through a randomized control trial, with three experimental conditions: (1) control (i.e., business as usual); (2) early-term predictions, in which community college instructors will be informed which of their students a prediction model flagged as being at risk, with the instructors receiving training in how best to communicate with those students; and (3) early-term predictions plus additional embedded course supports. We include the third condition recognizing that community college instructors likely face meaningful constraints in the additional supports they can provide students on their own. While randomized control trials are the gold standard of research, they are not the only rigorous method. For institutions interested in evaluating their predictive analytic applications, there are many researchers, including me, who would be happy to collaborate on designing a quasi-experimental study.

Another important topic for future research is to better understand which point(s) in the distribution of predicted risk would be most effective and efficient for intensive resource targeting. While students are typically lumped into categories based on their risk (e.g., two categories: at risk or on track; three categories: green, yellow, or red), the raw model output is a continuous predicted risk score ranging from zero to one. An immediate thought may be to target the students at highest risk, meaning those least likely to succeed. However, it might be quite difficult to get these students to engage with additional supports, and they may not have a high likelihood of success even when they are targeted. So perhaps students at a more moderate

3. Algorithmic bias has been found in other predictive analytic applications outside higher education, including criminal justice and health care (Angwin et al., 2016; Obermeyer et al., 2019).

4. Calibration bias occurs when, conditional on predicted risk score, subgroups have different actual success rates. In our application, this means that, at a particular point in the distribution of predicted risk scores, Black students have a higher success rate than White students.

5. Our related work also suggests that small changes in modeling decisions (e.g., choosing logistic regression versus XGBoost as the prediction model) can significantly change the sorting of students within the risk score distribution, and therefore have the potential to significantly alter which students would receive additional supports (Bird, Castleman, Mabel, et al., 2021).

risk level, or students just at the margin of success, would be a more appropriate targeting strategy. It is not clear where in the distribution of risk we would expect to see the most bang for the buck in terms of resources moving students from failure to success; thus future research could significantly improve the cost-effectiveness of risk modeling and resource targeting. It is important to note that the answer to this question will almost certainly be context-dependent. For example, at more-selective colleges with higher persistence and graduation rates, the best strategy would likely target those with the highest risk scores; at broad or open access institutions, however, there is a much wider range of students who could benefit from additional resources. Institutional research (IR)/institutional effectiveness (IE) professionals who are involved in institution assessment are positioned well to contribute important context of student success that would not only inform the design of student success supports tied to the risk models, but also estimate the institution's return on investment of these additional resources.

I also believe that ML has the potential to improve how we structure the targeted students supports. Struggling students have a variety of different needs that may be inhibiting their success: lack of academic preparedness, financial constraints, inflexible schedules, unfamiliarity with administrative processes, and so on. So how do we connect students to the right supports that they need? ML methods commonly used in the private sector such as market basket analysis (Aguinis et al., 2013) have a lot of potential to inform this question, although it would require colleges to invest in the collection of student support usage data. IR officials who are involved in campus-wide data governance could help colleagues think about data collection, management, and analytic uses of this and other student data, including the integration of this data collection into existing learning management systems or student success platforms that already track several other student behaviors (e.g., Blackboard).

Finally, it is imperative for us as an education research community to develop standards for ethical considerations relevant to these applications. Researchers and policymakers are increasingly recognizing the need for transparency and student rights with regard to artificial intelligence (AI) in education (e.g., Holmes & Tuomi, 2022; U.S. Department of Education, 2023), though additional considerations should be given to the technical aspects of algorithmic bias. There are many metrics that could be used to determine whether a model is generating fair predictions, and the choice of metric is critical since they can be at odds with each other (Kleinberg et al., 2016). In the paper I describe above (Bird et al., 2023), my colleagues and I chose to focus on calibration bias because we thought the most important type of bias in this application would be at-risk students from underrepresented or minoritized groups who are less likely to receive additional supports, compared to at-risk students from majority groups. However, this metric is less appropriate for an application where at-risk students are counseled out of college majors that are associated with the highest earnings (e.g., Barshay & Aslanian, 2019). We also need to develop standards for what level algorithmic bias is acceptable since reducing bias often leads to decreases in overall model accuracy, and it may not be feasible to achieve zero bias while still maintaining a high-performing model.

At this time predictive analytics has shown its promise at efficiently identifying at-risk students; with the possible inclusion of more-detailed data from learning management systems, these predictions will only improve (Bird et al., 2022). Still, there is much important work to be done to both unlock its full potential and to ensure its safe use. Before risk modeling practices and applications that use predictive analytics become too ingrained in our colleges and universities, it is critical that we use the momentum fueled by the various discussions I mention above to ensure a fruitful future for predictive analytics in higher education.

REFERENCES

Acosta, A. (2020). *How you say it matters: Communicating predictive analytics findings to students.* Report, New America. https://www.newamerica.org/education-policy/reports/how-you-say-it-matters/

Aguinis, H., Forcum, L. E., & Joo, H. (2013). Using market basket analysis in management research. *Journal of Management, 39*(7), 1799–1824. https://journals.sagepub.com/doi/10.1177/0149206312466147

Akmanchi, S., Bird, K. A., & Castleman, B. L. (2023). Human versus machine: Do college advisors outperform a machine-learning algorithm in predicting student enrollment? EdWorkingPaper 23-699, Annenberg Institute at Brown University. https://doi.org/10.26300/gadf-ey53

Angwin, J., Larson, J., Mattu, S., & Kirchner, L. (2016). Machine bias. ProPublica. https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing

Baker, R. S., & Hawn, A. (2022). Algorithmic bias in education. *International Journal of Artificial Intelligence in Education, 32*, 1052–1092. https://doi.org/10.1007/s40593-021-00285-9

Barshay J., & Aslanian S. (Hosts). (2019, August 6). Under a watchful eye: Colleges are using big data to track students in an effort to boost graduation rates, but it comes at a cost. [Audio podcast episode]. The Educate Podcast, apmreports.org. https://www.apmreports.org/story/2019/08/06/college-data-tracking-students-graduation

Bauman, D. (2022, June 3). Congress should scrutinize higher ed's use of predictive analytics, watchdog says. *Chronicle of Higher Education*. https://www.chronicle.com/article/congress-should-scrutinize-higher-eds-use-of-predictive-analytics-watchdog-says?cid2=gen_login_refresh

Bird, K. A., Castleman, B. L., Denning, J. T., Goodman, J., Lamberton, C., & Rosinger, K. O. (2021). Nudging at scale: Experimental evidence from FAFSA completion campaigns. *Journal of Economic Behavior & Organization 183*(March), 105–128. https://www.sciencedirect.com/science/article/abs/pii/S0167268120304819?via%3Dihub

Bird, K. A., Castleman, B. L., Mabel, Z., & Song, Y. (2021). Bringing transparency to predictive analytics: A systematic comparison of predictive modeling methods in higher education. *AERA Open, 7*. https://journals.sagepub.com/doi/10.1177/23328584211037630

Bird, K. A., Castleman, B. L., & Song, Y. (2023). Are algorithms biased in education? Exploring racial bias in predicting community college student success. EdWorkingPaper 23-717, Annenberg Institute at Brown University. https://www.edworkingpapers.com/ai23-717

Bird, K. A., Castleman, B. L., Song, Y., & Yu, R. (2022). Is Big Data better? LMS data and predictive analytic performance in postsecondary education. EdWorkingPaper 22-647. Annenberg Institute at Brown University. https://www.edworkingpapers.com/ai22-647

Burke, L. (2020, December 13). The death and life of an admissions algorithm. *Inside Higher Ed*. https://www.insidehighered.com/admissions/article/2020/12/14/u-texas-will-stop-using-controversial-algorithm-evaluate-phd

Carlstrom, A. H., & Miller, M. A. (Eds.). (2013). 2011 NACADA national survey of academic advising. Monograph No. 25, Global Community for Academic Advising. https://nacada.ksu.edu/Resources/Clearinghouse/View-Articles/2011-NACADA-National-Survey.aspx

Ekowo, M., & Palmer, I. (2016). The promise and peril of predictive analytics in higher education: A landscape analysis. Policy paper, New America. https://www.newamerica.org/education-policy/policy-papers/promise-and-peril-predictive-analytics-higher-education/

Engler, A. (2021). Enrollment algorithms are contributing to the crises of higher education. Part of series "AI Governance." The Artificial Intelligence and Emerging Technology (AIET) Initiative, Brookings Institution. https://reachhighscholars.org/Articles/Enrollment%20Algorithms%20-%20Brookings%20Institution%209.14.21.pdf

Greenstein, N., Crider-Phillips, G., Matese, C., & Choo, S-W. (2023). Predicting risk earlier: Machine learning to support success and combat inequity. Academic data analytics briefing document. Office of the Provost, University of Oregon. https://provost.uoregon.edu/analytics/student-success

Holmes, W., & Tuomi, I. (2022). State of the art and practice in AI in education. *European Journal of Education,* 57, 542–570. https://onlinelibrary.wiley.com/doi/10.1111/ejed.12533

Kleinberg, J., Mullainathan, S., & Raghavan, M. (2016). Inherent trade-offs in the fair determination of risk scores. Cornell University. https://doi.org/10.48550/arXiv.1609.05807

Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science, 366*(6464), 447–453. https://www.science.org/doi/10.1126/science.aax2342

Ruffalo Noel Levitz. (2021). *2021 effective practices for student success, retention, and completion report*. Ruffalo Noel Levitz. https://www.ruffalonl.com/papers-research-higher-education-fundraising/student-retention-practices-report/

Swaak, T. (2022, August 26). How higher ed is trying to improve student performance with data. PBS News Hour. https://www.pbs.org/newshour/education/how-higher-ed-is-trying-to-improve-student-performance-with-data

U.S. Department of Education. (2023). Artificial intelligence and future of teaching and learning: Insights and recommendations. Office of Educational Technology. https://tech.ed.gov/ai-future-of-teaching-and-learning/

Yu, R., Li, Q., Fischer, C., Doroudi, S., & Xu, D. (2020). Towards accurate and fair prediction of college success: Evaluating different sources of student data. In A. N. Rafferty, J. Whitehill, V. Cavalli-Sforza, & C. Romero (Eds.), *Proceedings of the 13th International Conference on Educational Data Mining* (pp. 292–301). https://files.eric.ed.gov/fulltext/ED608066.pdf

ABOUT SPECIAL ISSUES OF *THE AIR PROFESSIONAL FILE*

Special Issues of the *AIR Professional File* are guest-edited and feature themed journal-length articles grounded in relevant literature that synthesize current issues, present new processes or models, or share practical applications related to institutional research.

For more information about AIR Publications, including the *AIR Professional File* and instructions for authors, visit www.airweb.org/publications.

ABOUT AIR

The Association for Institutional Research (AIR) empowers higher education professionals to leverage data, analytics, information, and evidence to make decisions and take actions that benefit students and institutions and improve higher education. For over 50 years, AIR has been committed to building and sustaining strong data-informed decision cultures within higher education institutions.

Association for Institutional Research
Christine M. Keller, Executive Director and CEO
www.airweb.org
ISSN 2155-7535